DEVELOPING AND EVALUATING A BUSINESS ANALYTICS READINESS AND CAPABILITY MATURITY MODEL FOR ERP SYSTEMS: AN EMPIRICAL STUDY OF THE GREATER CHINA REGION

A Thesis submitted by

Wai Yip Freddy WONG
(BSc, MSc, MPhil, MBA)

For the award of

Doctor of Philosophy

2024

ABSTRACT

Many organisations in the Greater China Region (GCR) invest significant resources in their enterprise resource planning (ERP) systems, integrating or embedding advanced BA functionalities. The justification for this research is based on the importance of understanding and measuring BA readiness and capability of organisations using ERP systems. The success of an organisation in making data-driven decisions to achieve business success can be indirectly measured by their perceived BA capability and success, which significantly impact the organisation's overall success. To address this research problem, the study formulated a set of research questions to address the key gaps identified in the literature, with an emphasis on CSFs, measurement dimensions, and empirical validation of BA Readiness and Capability Maturity Model for ERP systems. The research gaps include (1) a lack of research on CSFs for ERP BA readiness, (2) limited understanding of how to apply CSFs with methodological rigour for BA capability measurement, and (3) limited exploration and empirical application of CSFs supported by Item Response Theory for assessing ERP BA readiness and BA capability in organisations using ERP systems. Addressing these research gaps is of great significance in advancing the understanding of ERP BA readiness and maturity, potentially leading to profound positive impacts on organisational success in this context. The study addresses three sets of high-level research questions and eight sets of low-level research questions, each targeting a specific research gap. The development and evaluation of a BA readiness and capability maturity model (BARCMM) for organisations using ERP systems involved developing a quantitative survey instrument based on existing literature. Rasch analysis assigns items to five maturity levels, while hierarchical cluster analysis classifies organisations into different maturity levels. The BARCMM integrates into a structural equation model. It predicts how BA readiness and capability influence the perceived success of BA initiatives in ERP systems, demonstrating a positive and significant relationship. This research contributes both theoretically and practically by providing organisations in the GCR with a rigorous means to assess BA readiness and BA capability maturity during ERP adoption and usage. Further research is needed to validate the model in other geographical regions and minimise biases associated with self-assessment questionnaires.

CERTIFICATION OF THESIS

I, Wai Yip Freddy Wong, declare that the Thesis entitled *Developing and Evaluating a Business Analytics Readiness and Capability Maturity Model for ERP Systems: An Empirical Study of the Greater China Region* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Date: 21st June 2024

Endorsed by:

Dr. Michael Lane
Principal Supervisor

Dr. Rohan Genrich
Associate Supervisor

Student and supervisors' signatures of endorsement are held at the University.

ACKNOWLEDGEMENTS

My deepest and most genuine gratitude is owed to Dr. Michael Lane and Dr. Rohan Genrich, my principal and associate supervisors, for their advice, support, encouragement, and insight throughout my studies. I also extend my sincere thanks to Dr. Albert Scott, who was my principal supervisor from 2015 until his retirement in 2019. I am grateful to Dr. Sophie Cockcroft, who served as my associate supervisor from 2019 to 2022.

I am honoured to have received the Best Conference Paper Award for our joint paper titled *Systematic Review of Methodological Approaches for Designing, Assessing and Validating Business Analytics Maturity Models*, co-authored with Dr. Lane and Dr. Cockcroft, presented at the International Conference on Information Resources Management in 2021 (see Appendix K). This recognition has been a significant milestone in my academic career. I am deeply thankful to Dr. Lane and Dr. Cockcroft for their invaluable contributions and collaboration, as well as to the conference organisers and reviewers for this honour.

I would also like to acknowledge and express my gratitude to my co-author, Dr. Lane, for his significant contributions to our joint paper titled *Critical Success Factors Classification Framework for Measuring Maturity of Organisations using New Generation ERP Systems: A Systematic Literature Review*, presented at the Forty-Fourth International Conference on Information Systems in Hyderabad, India, and nominated for the Best Full Research Paper Category. Dr. Lane's expertise and collaborative effort were invaluable, and his contribution greatly enhanced the quality of the paper.

I would also like to express my sincere gratitude to the participants and organisations that participated in the study.

This research has been supported by the Australian Government Research Training Program Scholarship.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

1PL	One-Parameter Logistic
2PL	Two-Parameter Logistic
3PL	Three-Parameter Logistic
AI	Artificial Intelligence
ASUG	American SAP User Group
BA	Business Analytics
BACF	Business Analytics Capability Framework (Cosic et al. 2015)
BACMM	Business Analytics Capability Maturity Model (Cosic et al. 2012; Cosic et al. 2015; Cosic 2020)
BAMMs	Business Analytics Maturity Models
BARCMM	Business Analytics Readiness and Capability Maturity Model (The proposed BA readiness and capability maturity model for organisations using ERP systems)
BI	Business Intelligence
BIMMs	Business Intelligence Maturity Models
BPI	Business Process Improvement
BPM	Business Process Management
BPO	Business Process Optimisation
BPR	Business Process Reengineering
CMM	Capability Maturity Model
CMMI	Capability Maturity Model Integration
CSFs	Critical Success Factors
DMM	Data Management Maturity
EBSE	Evidence-Based Software Engineering
ERP	Enterprise Resource Planning
ERPMMs	Enterprise Resource Planning Maturity Models
EUC	Euclidian Distance
GCR	Greater China Region
IIA	International Institute for Analytics

IoT	Internet of Things
IRT	Item Response Theory
IS	Information Systems
IT	Information Technology
KPA	Key Process Area
KPI	Performance Indicator
ML	Machine Learning
MM	Maturity Model
NCA	Necessary Condition Analysis
PIS	Participant Information Sheet
PLS-SEM	Partial Least Squares Structural Equation Modelling
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QCA	Qualitative Comparative Analysis
RBT	Resource-based theory
RPA	Robotic Process Automation
SLR	Systematic Literature Review
SSD	Statistical Squared Distance
STA	Set Theoretic Approach

LIST OF TERMINOLOGY

Bootstrapping	Bootstrapping is a statistical method for estimating the precision of sample estimates by resampling with replacement from the original dataset (Tibshirani & Efron 1993; Streukens & Leroi-Werelds 2016).
Business Analytics	Business Analytics (BA) is viewed as a study of business data using statistical techniques and programming for creating decision support and insights for achieving business goals (Schniederjans et al. 2014).
Business Intelligence	Business intelligence (BI) can be defined as a set of processes and technologies that convert data into meaningful and useful information for business purposes. While some believe that BI is a broad subject that encompasses analytics, business analytics, and information systems Bartlett (2013).
Capability Maturity Model	The Capability Maturity Model (CMM), developed at Carnegie Mellon University in 1991, aimed to improve software processes. Since then, maturity models have been used to enhance capabilities in areas such as project management, knowledge management, and information technology (IT) (Teah et al. 2006; Brookes & Clark 2009; Becker et al. 2010).
Capability Maturity Model Integration	Capability Maturity Model Integration (CMMI) is a framework that contains best practices for developing products and services originating in the software industry with the CMM for Software from 1993. The latest integrated version, CMMI for Development 1.3, was published in 2010 and combined concepts from software development, systems engineering, and product development, with two additional CMMIs for Acquisition and Services (Software Engineering Institute, 2010).
Greater China Region	The Greater China Region (GCR) includes Mainland China, Hong Kong, Macau, and Taiwan, sharing significant cultural, economic, and historical ties with Chinese civilisation despite different political statuses (Copper 2003; Cheung 2017).
Hierarchical Cluster Analysis	Hierarchical cluster analysis, also known as hierarchical clustering, is primarily used in data mining, statistics, and other fields to identify natural groupings within a dataset (Abonyi & Feil 2007).
Item Response Theory	Item Response Theory (IRT) is a paradigm for investigating the relationship between an individual’s response to a single measurement item and their performance on an overall measure of the ability or trait that item was intended to measure (Van der Linden & Hambleton 1997; Reise & Revicki 2014).

Level-based maturity models	Level-based maturity models define a set of distinct maturity levels that organisations can assess and work towards achieving in a flexible manner, with each level representing specific criteria and requirements organisations must meet to progress to the next level (Van Steenbergen et al. 2013; Lasrado et al. 2015).
Perceived BA Capability	Perceived BA Capability refers to an organisation's subjective assessment of its ability to effectively utilise business analytics tools and techniques (Conboy et al. 2020; Vishnubhotla et al. 2021; Chatterjee et al. 2024).
Perceived ERP BA success	Perceived ERP BA success is a critical metric for evaluating the effectiveness of ERP and BA systems, offering actionable insights to improve user satisfaction and system performance (Chien & Tsaur 2007; Holsapple et al. 2019).
Rasch Analysis	Rasch analysis, also known as Rasch modelling, the Rasch measurement model, or the Rasch algorithm, is a specific application of Item Response Theory (IRT) (Boone, W. J. & Noltemeyer, A. 2017; Andrich & Marais 2019; Liu et al. 2024)
Resource-based theory	Resource-based theory (RBT), also known as Resource-Based View of the Firm, Resource-Based Model, posits that organisations develop internal capabilities to enhance their competitive advantage (Barney 1996). As a strategic management framework, RBT emphasises that a firm's internal resources are crucial to gaining a competitive edge. It asserts that unique resources and capabilities, such as skills, knowledge, and assets, enable a firm to outperform its competitors.
Stage-based maturity models	Stage-based maturity models define a sequential progression of distinct maturity stages that organisations must navigate through, with each stage representing a higher level of organisational capability and characteristics that must be achieved, building upon the previous stage (Van Steenbergen et al. 2013; Lasrado et al. 2015).

CHAPTER 1: INTRODUCTION

Chapter 1 sets the stage for the PhD research project presented in this thesis and delineates the central research problem under examination. First, the background to this research is provided in Section 1.1, contextualising the study within a broader framework. Then, Section 1.2 outlines the research motivation. It emphasises ERP adoption and BA integration for decision-making. Additionally, it highlights the need to assess organisational readiness and capability for BA in ERP systems to capture business value. Section 1.3 establishes the foundational knowledge for examining the research problem, objectives, and questions. This section outlines the significance and implications of the corresponding research objectives and questions. The research is divided into three phases: Phase I, Phase II, and Phase III. In Research Phase I, a systematic literature review (SLR 1) was conducted. This review aimed to develop a CSF classification framework for measuring ERP maturity. It also incorporated dimensions for Industry 4.0 integration. Research Phase II involved two SLRs. SLR 2 explored methodological approaches for designing and validating BAMMs. SLR 3 examined methods for assessing BA maturity in ERP systems. The findings from these phases informed the design of the Business Analytics Readiness and Capability Maturity Model (BARCMM). Research Phase III focused on the design, assessment, and validation of BARCMM. This was achieved through empirical data collection and analysis using PLS-SEM to confirm the relationships between BA maturity, perceived ERP BA success, and perceived BA capability. Section 1.4 justifies the research by emphasising the vital integration of ERP systems with BA. It addresses the different levels of ERP readiness and BA capability, how organisational maturity affects BA readiness and capability within ERP systems, and the need for a customised maturity model to evaluate ERP BA readiness and capability. Section 1.5 elaborates on the research gaps this thesis aims to address, formalised in a set of research objectives and specific research questions that will guide this investigation. Section 1.6 describes and justified the research methodology that is used to conduct this study. Section 1.7 sets out the scope and specific research setting of boundaries and context of this study. Finally, Section 1.8 provides a concluding summary, bringing together the key insights and structural elements presented in this chapter. Figure 1.1 shows the structure of Chapter 1.

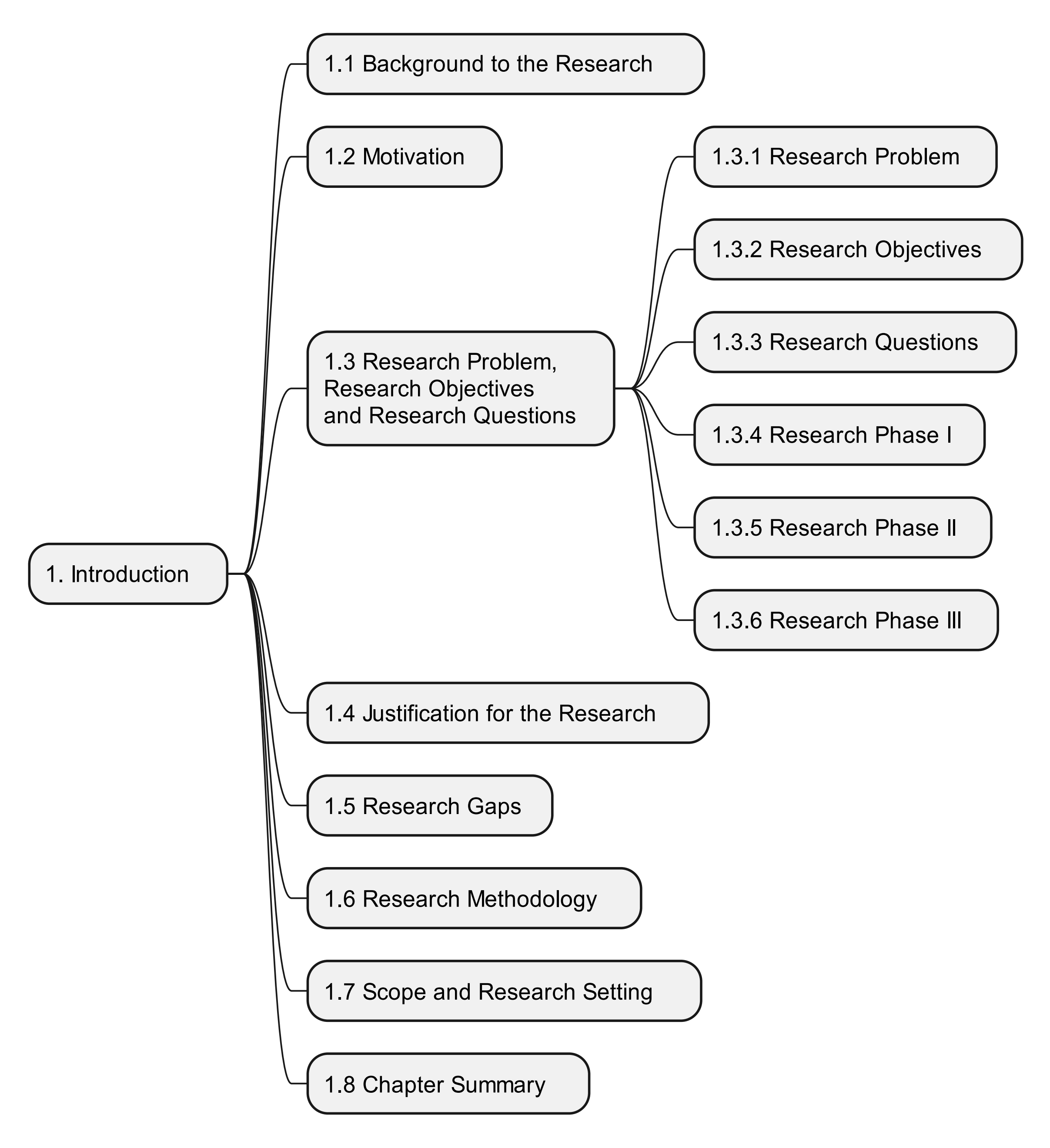

Figure 1.1 Structure of Chapter 1

1.1. Background to the Research

Business intelligence (BI) emerged in the 1990s, encompassing applications that extract, transform, and visualise data, enabling effective analysis of data subsets (Chen et al. 2012). Business analytics (BA), gaining prominence in the late 2000s, is the key analytical component of BI, emphasising data analysis to inform decision-making using statistical and quantitative methods, explanatory and predictive models, and fact-based management (Davenport & Harris 2007). While BI research has focused on technical aspects, the managerial and strategic dimensions of BA have been underexplored (Hawking & Sellitto 2010; Yeoh & Koronios 2010; Tripathi et al. 2020). Hawking and Sellitto (2010) proposed a model for assessing BI system success in ERP systems, identifying shared critical success factors (CSFs) with ERP systems.

There is a lack of research on managerial and strategic CSFs for the successful implementation of BA in ERP systems. The CSFs influencing organisational readiness and capability for effective BA use in ERP systems remain under-researched. According to Hawking and Sellitto (2010), CSFs vary by Solution type, Application, Temporal perspectives, and BI maturity stage, highlighting the need for further empirical investigation. Chaveesuk (2010) identifies a research gap in the managerial and strategic dimensions of BI and BA in ERP systems, suggesting the need for comprehensive studies on success factors. Recent studies by Ahmad et al. (2023) and Abu Madi et al. (2024) provide contemporary insights into CSFs and the impact of business analytics on organisational outcomes. Maturity models offer a structured approach to assessing organisational readiness and progress in BA capabilities. By identifying CSFs, organisations can map their progress through maturity stages, ensuring strategic alignment and optimising BA utilisation (Muntean et al. 2019). This approach links the importance of BA in ERP systems with maturity models for continual improvement and strategic alignment.

Rasch analysis, also known as Rasch modelling or the Rasch measurement model, is a specific application of Item Response Theory (IRT) (Boone, W. J. & Noltemeyer, A. 2017; Andrich & Marais 2019; Liu et al. 2024). It is a probabilistic model used to analyse categorical data, especially for assessing responses within a scale or instrument (Wendt et al. 2011). The Rasch model focuses on modelling the probability of endorsing an item based on a person’s ability and the item's difficulty (Stemler & Naples 2021). It assumes that the probability of a correct response depends only on the difference between the person's ability and the item's difficulty, highlighting the hierarchical ordering of items along the underlying trait (Bond 2015; Seamon et al. 2019). Rasch analysis provides insights into item responses and latent traits, enabling precise measurement and evaluation across various fields.

Lahrmann et al. (2011) proposed a rigorous approach for constructing maturity models using Rasch analysis combined with hierarchical cluster analysis. Rasch analysis measures variables such as abilities and attitudes for psychological and educational assessments, supporting the design of capability maturity models (Cleven et al. 2014). Hierarchical cluster analysis provides a structured method for allocating capability to organisations at various maturity levels, reducing subjectivity in defining these levels (Lahrmann et al. 2011). Raber et al. (2013b, 2013a) developed an empirically grounded maturity model based on Lahrmann et al.'s approach, using the BI Maturity Instrument to determine if higher BI maturity correlates with greater business benefits.

This research, building on the work of Lahrmann et al. (2011) and Raber et al. (2013b, 2013a), aims to develop the Business Analytics Readiness and Capability Maturity Model (BARCMM) to assess BA readiness and capability maturity in organisations using ERP systems. It provides a rigorous methodology for evaluating organisations' readiness to leverage BA and their maturity in using BA capabilities within ERP systems. A systematic review of existing BIMMs and BAMMs informed the development of the BARCMM conceptual model. Chapters 3 and 4 describe the methodology in detail. The measurement instrument, based on Raber et al.’s BIMM approach, uses Rasch Analysis to assess BA readiness and capability maturity, while Hierarchical Clustering Analysis determines item difficulty and assigns items to maturity levels. Chapter 4 provides a detailed example of using the instrument to assess BA readiness and capability maturity.

The Greater China Region (GCR), comprising Mainland China, Hong Kong, Macau, and Taiwan, shares significant cultural, economic, and historical ties with Chinese civilisation despite differing political statuses (Copper 2003; Cheung 2017). This region was chosen for the study because many organisations use ERP systems with business analytics functionalities. Additionally, there is a lack of empirical research on the BA maturity of organisations using ERP systems in the GCR.

This research aims to contribute to a deeper and more holistic understanding of the relationship between the BA maturity level and perceived success of organisations leveraging ERP systems and BA tools.

1.2. Motivation

This study is motivated by the need to understand and measure BA readiness and capability within organisations using ERP systems in the GCR. Despite the widespread adoption of ERP systems, which enhance process management and resource utilisation, there is limited research on how organisations can effectively leverage BA within ERP systems to gain competitive advantages (Davenport 1998; Markus & Tanis 2000; Laudon & Laudon 2019, p.15).

BA has become integral to ERP systems, providing insights for informed decision-making and process optimisation (Elragal & Hassanien 2019; Yahaya et al. 2019). However, organisations may vary in their readiness and capability to utilise BA effectively, even with the same ERP system. This variation can impact their ability to realise the full business value from BA (Muntean et al. 2019). Therefore, this research aims to develop and evaluate a model to assess BA readiness and capability maturity, offering organisations a benchmark for continuous improvement.

Perceived success, which reflects an individual's assessment of achieving goals, and perceived BA capability, which represents an organisation’s self-assessed ability to use BA tools effectively, are crucial for evaluating system performance and user satisfaction (Geneste & Weber 2011; Tladi 2017; Vishnubhotla et al. 2021). Understanding these perceptions helps organisations align their strategies and optimise BA utilisation to improve overall performance and achieve business value (Wixom & Todd 2005; Jo & Park 2023).

This research builds on previous studies and aims to contribute valuable insights into the relationship between BA maturity and perceived success, particularly within the GCR, addressing a significant research gap in this area.

1.3. Research Problem, Research Objectives and Research Questions

1.3.1. Research Problem

The development and evaluation of a BA readiness and capability maturity model for organisations using ERP systems in the GCR is crucial. This research aims to address gaps in the understanding and application of critical success factors for ERP BA readiness and capability, including methodological rigour and the use of

Item Response Theory for assessment. Given the dynamic and competitive nature of the GCR market, organisations encounter unique challenges and opportunities that impact their ERP implementations. While many organisations have advanced ERP systems with embedded BA functionalities, their readiness to use these systems and integrate with suppliers' ERP systems varies significantly. This variation affects their ability to optimise processes, manage resources, and leverage data for competitive advantage. The research problem therefore centres on developing a BA readiness and capability maturity model. This model will measure ERP BA readiness and assess BA capability. By using this model, researchers and practitioners can rigorously classify organisations into their maturity levels, benchmark against industry sectors, and identify areas for improvement to enhance their BA capabilities. Organisations with higher BA maturity are more likely to achieve greater business success through improved data-driven decision-making and strategic actions.

1.3.2. Research Objectives

The research objectives aim to develop and evaluate a Business Analytics Readiness and Capability Maturity Model (BARCMM) to identify and understand the strengths and weaknesses of organisations using ERP systems in the GCR regarding their Business Analytics readiness and capabilities. Additionally, the model will provide support to assess their current maturity levels and identify necessary improvements in their ERP BA readiness and BA capabilities.

The objectives of the research are:

(1) To identify CSFs for ERP BA readiness, develop effective measurement methods, determine dimensions for assessing ERP maturity models, and explore additional factors for evaluating the maturity of organisations using new-generation ERP systems for the BARCMM.

(2) To identify CSFs for BA capability, explore measurement methodologies, assess adaptability of BA maturity models to new-generation ERP systems, and review current BAMM research for empirical design and validation for the BARCMM.

(3) To investigate the relationship between ERP BA readiness and BA capability, develop and test a maturity model for BA capability in ERP systems, measure

organisations' BA maturity using IRT, enhance the reliability of measurement items, and examine the correlation between BA maturity, perceived BA capability, and perceived ERP BA success in organisations in the GCR for the BARCMM.

1.3.3. Research Questions

The research questions that align with the objectives and focus on developing and evaluating the BARCMM for measuring the BA readiness and capability of organisations using ERP systems in the GCR are outlined as follows:

Objective 1: To identify CSFs for ERP BA readiness, develop effective measurement methods, determine dimensions for assessing ERP maturity models, and explore additional factors for evaluating the maturity of organisations using new-generation ERP systems for the BARCMM.

- RQ1: What are the critical success factors that contribute to ERP BA readiness, and how can ERP BA readiness be effectively measured?
- RQ1.1: What are the main dimensions of critical success factors that can be used as measurement items to assess ERP maturity models?
- RQ1.2: What are the additional dimensions of critical success factors that can be used as measurement items to assess the maturity of organisations using new generation ERP systems?

Objective 2: To identify CSFs for BA capability, explore measurement methodologies, assess adaptability of BA maturity models to new-generation ERP systems, and review current BAMM research for empirical design and validation for the BARCMM.

- RQ2: What are the CSFs that contribute to BA capability, and how can BA capability be measured?
- RQ2.1: What are the main methodological approaches used to design, assess, and validate BA maturity models?
- RQ2.2: How can the BA maturity level of organisations using a new generation of ERP system be determined by adapting existing BA maturity models?

- RQ2.3: What is the state of research on BAMMs, and how can they be empirically designed, assessed, and validated?

Objective 3: To investigate the relationship between ERP BA readiness and BA capability, develop and test a maturity model for BA capability in ERP systems, measure organisations' BA maturity using IRT, enhance the reliability of measurement items, and examine the correlation between BA maturity, perceived BA capability, and perceived ERP BA success in organisations in the GCR for the BARCMM.

- RQ3: How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?
- RQ3.1: How can the BA maturity of an organisation be measured using item response theory (IRT) as a rigorous and quantitative approach?
- RQ3.2: How can IRT be used to improve the reliability of the measurement items in assessing BA maturity levels of organisations?
- RQ3.3: To what extent is BA maturity an indicator of perceived BA capability and Perceived ERP BA success in an organisation?

1.3.4. Research Phase I

The research is divided into three phases: I, II, and III. In Research Phase I, the first systematic literature review (SLR 1) was carried out to develop a CSF classification framework for measuring the maturity of organisations using ERP systems. It is believed that there are common CSFs in ERP that are also applicable to BA. The CSFs used as measurement items in the ERP BA profile questions in BARCMM will be developed based on the results of SLR 1 in Chapter 2, where RQ1.1 and RQ1.2 will be addressed. In Chapter 2, SLR 1 addressed RQ1.1 by identifying and categorising CSFs into dimensions for assessing ERP maturity models, specifically related to ERP implementation and post-implementation success, and also explored RQ1.2 by extending the dimensions to accommodate Industry 4.0 integration, resulting in a more comprehensive set of dimensions with sub-dimensions for contemporary ERP Maturity Models, making them relevant to Industry 4.0 and various ERP contexts while also identifying related research papers.

1.3.5. Research Phase II

In Research Phase II, two SLRs were conducted in Chapter 2. SLR 2 was conducted on methodological approaches for designing, assessing and validating business analytics maturity models. SLR 3 was conducted on measuring business analytics maturity in ERP systems. The findings from SLRs 2 and 3 will inform the design and implementation of the BARCMM to be discussed in Chapter 4.

In Chapter 2, SLR 2 explores methodological approaches for developing, evaluating, and validating BAMMs in general. It emphasises the importance of model validation in accurately assessing Business Analytics maturity. Through a systematic literature review, it identifies a lack of consensus in maturity level assessment methods. The review reveals Rasch analysis and set theory as primary design approaches, with Cluster, Additive Logic, and Minimum Constraints being common assessment methods. Validation often involves variance techniques using regression and correlation coefficients. The rigorous approach developed by Raber et al. (2013b), which applies Rasch analysis and cluster analysis for assessing maturity levels in BIMM, is also potentially applicable to constructing BAMMs. The chapter emphasises the need for more empirical research to comprehensively validate BAMMs, addressing the gap between academia and practice. Additionally, it sets the stage for the development and evaluation of the Business Analytics Readiness and Capability Maturity Model (BARCMM) discussed in Chapter 4.

In Chapter 2, SLR 3 focused on examining methodological approaches for designing, assessing, and validating BA maturity models, specifically for the new generation of ERP systems with advanced embedded BA functionalities. SLR 3 addresses research questions RQ2.1 and RQ2.2, focusing on methodological approaches for designing, assessing, and validating BA maturity models for organisations using ERP systems. To address RQ2.1, an effective and rigorous method involves the use of Rasch analysis in conjunction with cluster analysis. This approach provides strong support for the rigorous design, development, and evaluation of capability maturity models, which are crucial in assessing and validating BA maturity models. It is worth noting that this method draws from previous research by Cleven et al. (2014), Lahrmann et al. (2011), and Raber et al. (2013a, 2013b). For RQ2.2, determining the BA maturity level of organisations using new-generation ERP systems can be achieved through two primary methods. The commonly adopted approach employs additive logic, where maturity levels are computed by assigning weights to various factors, which can be defined by experts or predefined. However, for a more rigorous and repeatable assessment, Rasch Analysis, coupled with Cluster Analysis, is recommended. This method assumes that organisations with higher maturity levels are more likely to successfully implement desired capabilities. It is important to ensure the validity of results by randomly selecting participating organisations that encompass a range of capabilities.

1.3.6. Research Phase III

In Research Phase III, the focus in Chapters 4 and 5 is on the design, assessment, and validation of the proposed BARCMM. Phase III comprised (1) the design of the BARCMM, (2) the development of measurement instruments for Surveys 1 and 2, (3) the collection of empirical data from Surveys 1 and 2, (4) the analysis of the empirical data, and (5) the validation of empirical results using PLS-SEM. Phase III activities in the research process, along with the corresponding chapters for Surveys 1 and 2, are provided in Figure 1.2. This involves addressing RQ3.1 on using inductive methods to allocate survey items and organisations to a BA capability maturity continuum, RQ3.2 on evaluating and improving the BARCMM measurement instrument through surveys and item anchoring, and RQ3.3 on confirming the hypothesised positive relationships between BA maturity, perceived ERP BA success, and perceived BA capability. The empirical study also presents the results of applying the validated BARCMM model to organisations in the GCR in Chapter 5.

In Chapter 4 and Chapter 5, to answer RQ3.1, an inductive approach using Rasch analysis was used to allocate (1) survey items measuring BA capabilities and (2) organisations in terms of their BA capability to a continuum of difficulty. Then hierarchical cluster analysis was used to assign (1) BA capability survey items and (2) respondent organisations to five maturity levels. To answer RQ3.2, two subsequent surveys were designed and revised to illustrate how the measurement instrument can be evaluated by the item-fit statistics and the person-item map, and how the results of an initial survey (Survey 1) and subsequent survey (Survey 2) can be compared and improved using item anchors.

To answer RQ3.3, structural equation modelling was then used to test hypothesised relationships (H1) “BA maturity level is positively associated with Perceived ERP BA success” and (H2) “BA maturity level is positively associated with perceived BA capability”. This is to confirm the assumption of our BA maturity model that organisations with a higher level of maturity will be more capable of using BA to achieve greater benefits and success.

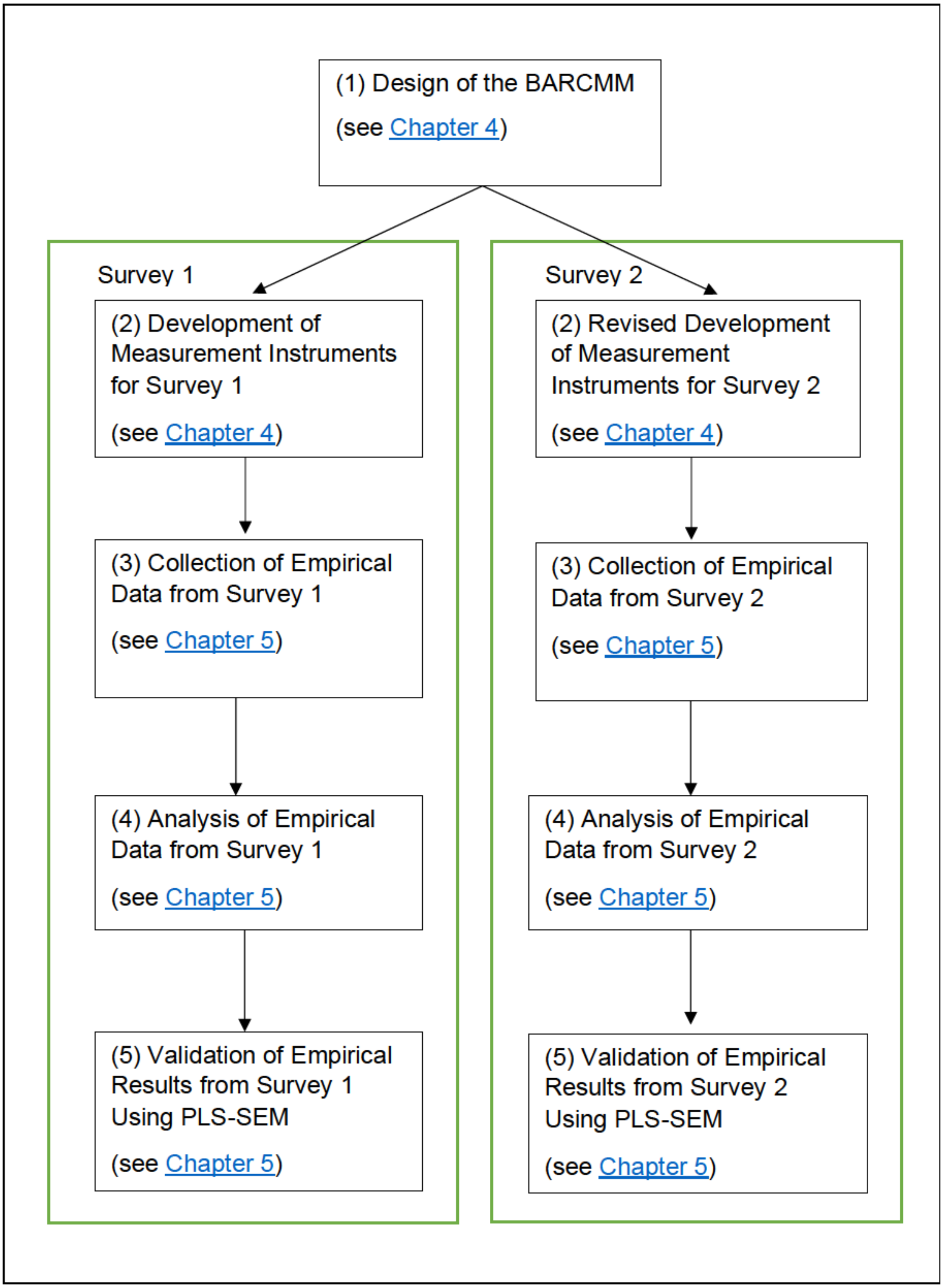

Figure 1.2 Phase III Activities in the Research Process

1.4. Justification for the Research

The justification for conducting this research is grounded in the overarching importance of the following four aspects:

(1) **The Integration of ERP Systems and Business Analytics**:

Many organisations have adopted ERP systems as a cornerstone and digital spine of their operations (Appelbaum et al. 2017). These systems are instrumental in resource management, enabling organisations to streamline their processes and enhance overall efficiency. However, the true potential of ERP systems increasingly lies in their ability to provide data-driven insights and improved decision making through embedded BA features (Popoola et al. 2024). These insights empower organisations to optimise and automate their operations for improved productivity and profitability.

(2) **Varied Levels of ERP Readiness and BA Capability**:

Organisations exhibit a spectrum of readiness in adopting and utilising ERP systems, with staff, stakeholders, and departments showing varying levels of readiness (Ngai et al. 2008). This variance affects their capability to apply Business Analytics for valuable insights, improved decision-making, and business enhancements (Appelbaum et al. 2017). Current literature lacks comprehensive studies on the CSFs for BA readiness and capability in ERP systems. Existing generic BA maturity models often overlook the ERP context. Identifying these CSFs is essential for effective ERP implementation with enhanced BA capabilities. This identification helps organisations focus resources on crucial areas for successful ERP use. It also ensures that BA implementation aligns with organisational goals, improving decision-making and performance (Shi & Wang 2018). The research addresses gaps in the literature, such as the need to identify ERP BA readiness CSFs and validate BA maturity models. It also highlights the importance of adapting models for new-generation ERP systems.

(3) **The Impact of Organisational Maturity Levels on BA Readiness and Capability within ERP Systems**:

Organisational maturity levels significantly affect BA readiness and capability within ERP systems. As organisations grow, their readiness to utilise BA functionalities in ERP systems can vary. This variation can be seen in two competing organisations within the same industry using ERP systems with pre-built BA functionalities but differing in maturity levels of organisational readiness. These differences influence their usage and integration of ERP systems with supply chain partners (AlMuhayfith & Shaiti 2020), impacting their ability to effectively leverage BA functionalities. This disparity in BA maturity affects their capability to realise the full potential of BA in ERP systems for capturing business value. In rapidly changing business environments, a culture of change readiness is crucial, particularly for those using real-time BA technology, to address problems and seize opportunities efficiently (Anderson-Lehman et al. 2004; Cosic et al. 2012).

(4) **The Need for a Maturity Model for ERP BA Readiness and Capability**:

Existing BAMMs may not fully address the unique challenges and opportunities of ERP systems. A tailored model ensures that readiness and capability assessments are closely aligned with ERP-specific contexts (Cosic et al. 2012). Generic BAMMs often focus on an organisation's analytical capabilities but overlook readiness for advanced analytics implementation (Corallo et al. 2023). Readiness involves factors such as organisational culture, data infrastructure (technology), leadership support (governance), change management (people), and processes (operation), all crucial for successful analytics initiatives (Bozkus 2023; Hmoud et al. 2023; Leso et al. 2023). Due to variations in ERP readiness and BA capability across organisations, a structured framework and an ERP BA readiness and capability maturity model are needed to assess and benchmark an organisation's maturity levels. This assessment is essential for continuous improvement. With a clear understanding of their readiness and capability, organisations can strategise, invest wisely, and enhance their use of BA in ERP systems to capture business value.

1.5. Research Gaps

Three high-level main research gaps were identified: (RG1) Lack of research on CSFs for ERP BA readiness, (RG2) Limited understanding of how to apply CSFs with methodological rigour for BA capability measurement, and (RG3) Limited exploration and empirical application of CSFs underpinned by Item Response Theory for the assessment of ERP BA readiness and BA capability in organisations using ERP systems. These high-level gaps were further broken down into corresponding low-level sub-categories. These main and sub-categories of research gaps were then aligned with specific research questions (RQs) to provide a structured approach to addressing the identified gaps. High-level research gaps were identified, along with low-level research gaps related to the development of the BARCMM. The mapping of a research gap to corresponding RQs involves identifying specific areas within the gap, breaking them down into smaller, specific segments, and formulating RQs that are specific, measurable, achievable and relevant. This process helps researchers address and explore the identified gaps in a structured and effective manner. Figure 1.3 shows the mapping of high-level research gaps to research questions. Figure 1.4 shows the mapping of low-level research gaps to research questions.

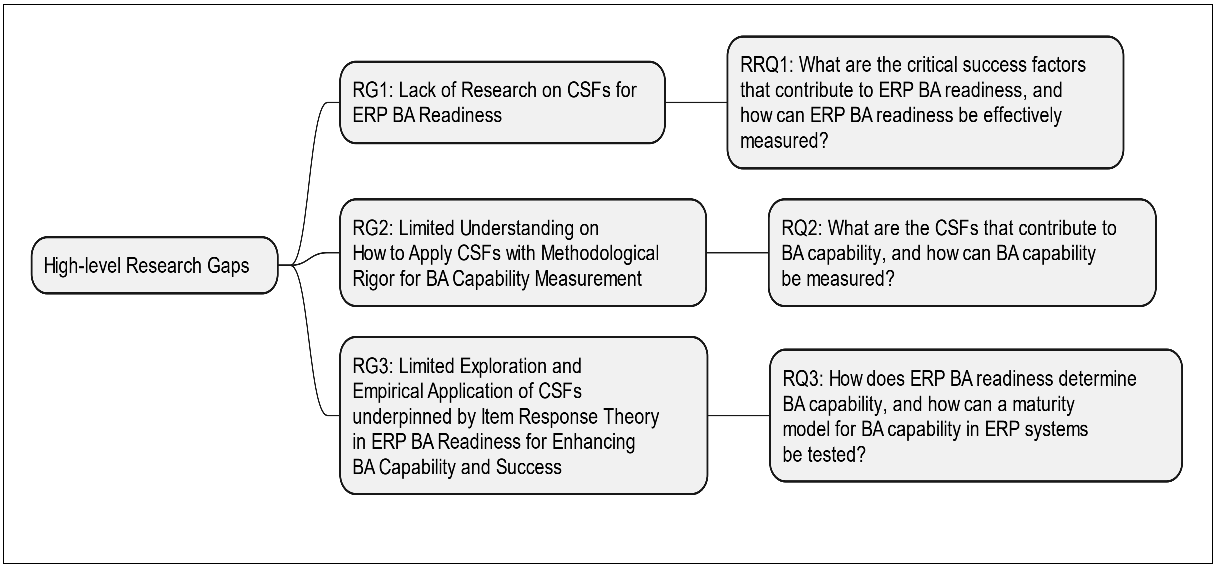

Figure 1.3 Mapping of High-level Research Gaps with Corresponding Research Questions

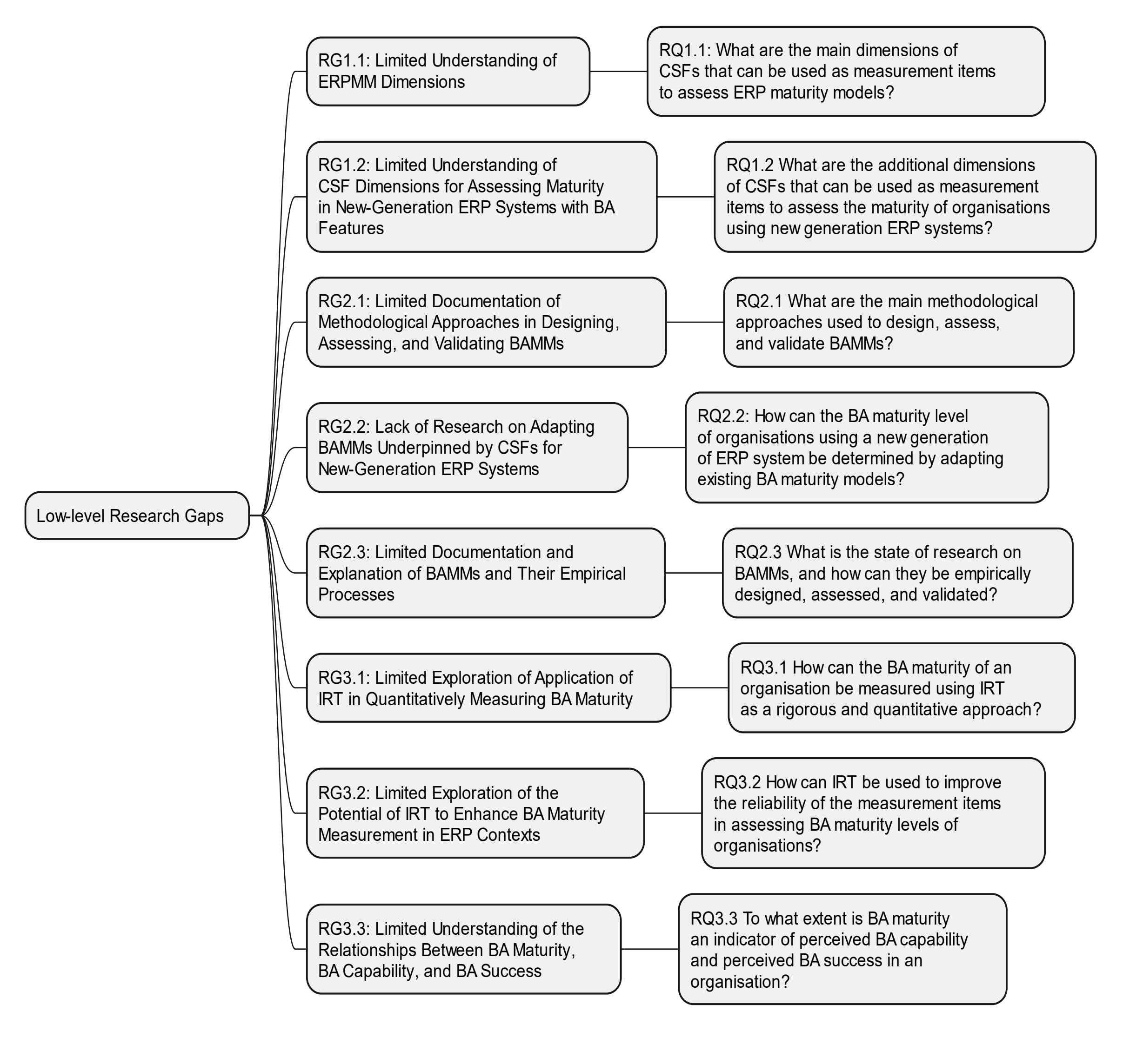

Figure 1.4 Mapping of Low-level Research Gaps with Corresponding Research Questions

Table 1.1 identifies the high-level research gaps and associated questions that focus on broader gaps pertinent to the initial search for existing maturity models related to BA readiness and capability in the design, development, and evaluation of the BARCMM. The high-level research questions focus on identifying the CSFs that contribute to ERP business analytics readiness and capability, developing measurement methods to assess them, and exploring the relationships between ERP BA readiness, BA capability, and BA success using Item Response Theory in the design, development, and evaluation of the BARCMM. These high-level research questions will be discussed in Chapter 4, Chapter 5, and Chapter 6 in the context of the design, development, and evaluation of the BARCMM.

In contrast, Table 1.2 outlines the low-level research gaps and specific questions that address the theoretical and practical aspects necessary to provide specific groundings to support the design, development, and evaluation of the BARCMM. The low-level research questions RQ1.1 and RQ1.2 focus on identifying the key dimensions of CSFs that can be used as measurement items to assess ERP maturity models, as well as additional dimensions to assess the maturity of organisations using new-generation ERP systems with BA functionalities (Wong & Lane 2023) (See SLR 1 in Chapter 2).

The low-level research questions RQ2.1 and RQ2.2 focus on adapting existing BA maturity models to assess the BA maturity level of organisations using new-generation ERP systems. These questions will be discussed in SLR 3 in Chapter 2.

The low-level research question RQ2.3 focuses on examining the state of research on BAMMs and how they can be empirically designed, assessed, and validated. RQ2.3 will be discussed in SLR 2 in Chapter 2.

The low-level research questions RQ3.1, RQ3.2, and RQ3.3 focus on investigating the use of IRT to quantitatively measure BA maturity, exploring how IRT can enhance the reliability of measuring BA maturity in ERP systems, and examining the relationships between BA maturity, perceived BA capability, and perceived ERP BA success to understand their implications for BA initiatives in organisations using ERP systems. RQ3.1, RQ3.2 and RQ3.3 will be discussed in in Chapter 4, Chapter 5, and Chapter 6.

Table 1.1 High-level Research Gaps and Associated Research Questions with Focus

Research Gap Category	**Research Gap Description**	**Research Question**	**Focus**
RG1: Lack of Research on CSFs for ERP BA Readiness	There is limited research specifically addressing the critical success factors contributing to ERP BA readiness, despite the existing literature offering insights into critical success factors for ERP implementation.	RQ1: What are the critical success factors that contribute to ERP BA readiness, and how can ERP BA readiness be effectively measured?	Identify CSFs that contribute to ERP BA readiness and develop effective measurement methods for assessing this readiness in the BARCMM.
RG2: Limited Understanding on How to Apply CSFs with Methodological Rigour for BA Capability Measurement	There is limited literature exploring the specific critical success factors that significantly contribute to BA capability and the development of standardised methods for measuring BA capability.	RQ2: What are the CSFs that contribute to BA capability, and how can BA capability be measured?	Identify specific CSFs that contribute to BA capability and develop rigorous measurement methods for assessing BA capability in the BARCMM.
RG3: Limited Exploration and Empirical Application of CSFs underpinned by Item Response Theory in ERP BA Readiness for Enhancing BA Capability and Success	Existing literature offers limited insight into identifying specific CSFs for ERP BA readiness that contribute most significantly to BA capability.	RQ3: How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?	Explore CSFs in ERP BA readiness and their impact on BA capability and success, using IRT to understand and empirically validate the relationship between ERP BA readiness, BA capability, and BA success in the BARCMM.

Table 1.2 Low-level Research Gaps and Associated Research Questions with Focus

Research Gap Category	**Research Gap Description**	**Research Question**	**Focus**
RG1.1: Limited Understanding of ERPMM Dimensions	Existing studies offer some insight into the dimensions of CSF for ERP implementation (Bhatti 2005; Huang et al. 2019), but there is a need for a more detailed exploration of dimensions of CSFs specifically tailored for assessing ERP maturity models.	RQ1.1: What are the main dimensions of critical success factors that can be used as measurement items to assess ERP maturity models?	Identify CSF dimensions for assessing ERP maturity models.
RG1.2: Limited Understanding of CSF Dimensions for Assessing Maturity in New-Generation ERP Systems with BA Features	While some research has addressed CSFs for ERP implementation (Saade & Nijher 2016), there is a specific gap in understanding the additional CSF dimensions that are relevant to assessing the maturity of organisations that use new-generation ERP systems that support BA functionalities.	RQ1.2: What are the additional dimensions of critical success factors that can be used as measurement items to assess the maturity of organisations using new generation ERP systems?	Identify additional dimensions for assessing maturity in new generation ERP systems with BA functionalities.
RG2.1: Limited Documentation of Methodological Approaches in Designing, Assessing, and Validating BAMMs	Existing literature often lacks a detailed documentation of the various methodological approaches employed for designing, assessing, and validating BA maturity models (Wong et al. 2021)	RQ2.1: What are the main methodological approaches used to design, assess, and validate BA maturity models?	Investigate methodological approaches in designing BAMMs.

Table 1.2 Low-level Research Gaps and Associated Research Questions with Focus

Research Gap Category	Research Gap Description	Research Question	Focus
RG2.2: Lack of Research on Adapting BAMMs Underpinned by CSFs for New-Generation ERP Systems	There is a scarcity of research specifically addressing the adaptation of existing BA maturity models for organisations implementing new-generation ERP systems, which is increasingly relevant in the context of evolving technology.	RQ2.2: How can the BA maturity level of organisations using a new generation of ERP system be determined by adapting existing BA maturity models?	Address adaptation of BA maturity models for new generation ERP systems.
RG2.3: Limited Documentation and Explanation of BAMMs and Their Empirical Processes	The current state of research on BAMMs and their empirical design, assessment, and validation is not well-documented, making it challenging for scholars and practitioners to navigate this specific field (Fedouaki et al. 2013).	RQ2.3: What is the state of research on BAMMs, and how can they be empirically designed, assessed, and validated?	Examine documentation of BAMMs and their empirical processes.
RG3.1: Limited Exploration of Application of IRT in Quantitatively Measuring BA Maturity	A research gap exists in applying Item Response Theory (IRT) to rigorously and quantitatively measure BA maturity, despite its common use in education and healthcare.	RQ3.1: How can the BA maturity of an organisation be measured using IRT as a rigorous and quantitative approach?	Investigate using IRT for quantitative BA maturity assessment.
RG3.2: Limited Exploration of the Potential of IRT to	There has been limited exploration of IRT to enhance the reliability	RQ3.2: How can IRT be used to improve the reliability of	Explore the potential of IRT to enhance the reliability of

Table 1.2 Low-level Research Gaps and Associated Research Questions with Focus

Research Gap Category	**Research Gap Description**	**Research Question**	**Focus**
Enhance BA Maturity Measurement in ERP Contexts	and validity of measurement items for evaluating BA maturity in organisational settings.	the measurement items in assessing BA maturity levels of organisations?	measuring BA maturity levels in ERP contexts.
RG3.3: Limited Understanding of the Relationships Between BA Maturity, BA Capability, and BA Success	There is a lack of understanding of the relationships between BA maturity, BA capability and BA success for organisations using ERP systems.	RQ3.3: To what extent is BA maturity an indicator of perceived BA capability and Perceived ERP BA success in an organisation?	Examine relationships between BA maturity, perceived BA capability, and ERP BA success to understand their correlations and implications for BA initiatives in organisations using ERP systems.

Prior empirical studies of BA maturity models (BAMMs) focus on technological and operational aspects (Muntean et al. 2019; Cosic 2020). Maturity models (MMs) are a widely accepted approach for systematically documenting and guiding the development and transformation of organisations based on best or common practices (Paulk et al. 1993). There is relatively little rigorous empirical research on the assessment and validation of maturity models (Wendler 2012; Monteiro & Maciel 2020), and on the assessment of BA maturity levels of organisations using ERP systems (Ariyarathna & Peter 2019; Wong et al. 2021). In this research, the identified research gaps are addressed. An instrument to measure the BA maturity of organisations using ERP systems is designed, developed, and evaluated. This is achieved using a rigorous methodological approach based on Rasch analysis and hierarchical clustering. The outcome of this research will enable the construction of an appropriate and methodologically rigorous approach for the design, assessment, and validation of BAMMs. The eleven research gaps (three high-level research gaps and eight low-level research gaps) in the existing literature on BA maturity models for organisations using ERP systems are identified as follows:

Research Gap 1 (RG1) identified in Chapter 2, Section 2.5: Lack of Research on CSFs for ERP BA Readiness (addressed by RQ1 in Chapter 4, Chapter 5 and Chapter 6): There is limited research specifically addressing the critical success factors contributing to ERP BA readiness, despite the existing literature offering insights into critical success factors for ERP implementation. Marchand & Peppard (2013) argued that deploying analytical IT tools is relatively easy, but understanding how they might be used is much less clear. There has been limited research conducted on the issues associated with the use of business analytics in global implementations of ERP systems, particularly in the GCR. Furthermore, a comprehensive examination of measurement methods for ERP BA readiness is essential. This research gap is significant because ERP BA is becoming increasingly important for organisations that want to gain a competitive advantage in the global market. ERP BA allows organisations to extract valuable insights from their data, which can be used to improve decision-making and operations. However, many organisations are not adequately prepared for ERP BA, which can lead to costly failures (Ariyarathna & Peter 2019).

Research Gap 1.1 (RG1.1) identified in Chapter 2, SLR 1: Limited Understanding of ERPMM Dimensions (addressed by RQ1.1 in SLR 1): Existing studies offer some insight into the dimensions of critical success factors (CSF) for ERP implementation (Bhatti 2005; Huang et al. 2019), but there is a need for a more detailed exploration of dimensions of CSFs specifically tailored for assessing ERP maturity models. This research gap is significant because ERP systems are complex and multifaceted, and a one-size-fits-all approach to maturity assessment is not sufficient. Existing ERP maturity models are often too generic and do not adequately account for the specific needs of different industries and organisations (Rauch et al. 2020).

Research Gap 1.2 (RG1.2) identified in Chapter 2, SLR 1: Limited Understanding of CSF Dimensions for Assessing Maturity in New-Generation ERP Systems with BA Features (addressed by RQ1.2 in SLR 1): While some research has addressed critical success factors (CSF) for ERP implementation (Saade & Nijher 2016), there is a specific gap in understanding the additional CSF dimensions that are relevant to assessing the maturity of organisations that use new-generation ERP systems that support BA functionalities. To address this gap, future research may focus on developing a framework or model that identifies and assesses these unique CSF dimensions contributing to organisational maturity within the context of new-generation ERP systems supporting BA functionalities. This can help businesses make more informed decisions and derive greater value from their ERP investments in a rapidly evolving technological landscape.

Research Gap 2 (RG2) identified in Chapter 2, Section 2.5: Limited Understanding on How to Apply CSFs with Methodological Rigour for BA Capability Measurement (addressed by RQ2 in Chapter 4, Chapter 5 and Chapter 6): There is limited literature exploring the specific critical success factors that significantly contribute to BA capability and the development of standardised methods for measuring BA capability (Wong et al. 2021).

Research Gap 2.1 (RG2.1) identified in Chapter 2, SLR 3: Limited Documentation of Methodological Approaches in Designing, Assessing, and Validating BAMMs (addressed by RQ2.1 in SLR 3 in Chapter 2): Existing literature often lacks a detailed documentation of the various methodological approaches employed for designing, assessing, and validating BA maturity models (Wong et al. 2021). Methodological approaches play a crucial role in understanding CSFs and developing standardised measurement methods for CSFs. Without robust methodologies for designing, assessing, and validating BA maturity models, it becomes challenging to identify and measure the CSFs accurately. Therefore, addressing Gap 2.1 is essential for effectively addressing Gap 2, as it provides the necessary groundwork for developing standardised measurement methods and understanding CSFs in BA capability. This gap highlights the need for a more in-depth exploration of the methodologies employed in this domain.

Research Gap 2.2 (RG2.2) identified in Chapter 2, SLR 3: Lack of Research on Adapting BAMMs Underpinned by CSFs for New-Generation ERP Systems (addressed by RQ2.2 in SLR 3 in Chapter 2): There is a scarcity of research specifically addressing the adaptation of existing BA maturity models for organisations implementing new-generation ERP systems, which is increasingly relevant in the context of evolving technology. While studies exist on both BA maturity models and ERP maturity models, research that directly addresses the adaptation of BA maturity models underpinned by CSFs to new-generation ERP systems is limited, indicating a notable gap in the literature. This gap is significant because it reflects the evolving technology landscape where modern ERP systems are becoming increasingly integrated and advanced. As organisations adopt these new-generation ERP systems, there is a need for tailored BA maturity models that are underpinned by relevant CSFs to effectively assess and optimise their performance.

Research Gap 2.3 (RG2.3) identified in Chapter 2, SLR 2: Limited Documentation and Explanation of BAMMs and Their Empirical Processes (addressed by RQ2.3 in SLR 2 in Chapter 2): The current state of research on BAMMs and their empirical design, assessment, and validation is not well-documented, making it challenging for scholars and practitioners to navigate this specific field (Fedouaki et al. 2013). Research on BAMMs is an emerging area, and there is a need for a comprehensive review of the state of the literature on BAMMs, including empirical design and validation approaches. This would provide valuable insights into the evolution and best practices within this domain.

Research Gap 3 (RG3) identified in Chapter 2, Section 2.5: Limited Exploration and Empirical Application of CSFs underpinned by Item Response Theory in ERP BA Readiness for Enhancing BA Capability and Success (addressed by RQ3 in Chapter 4, Chapter 5 and Chapter 6): Existing literature offers limited insight into identifying specific CSFs for ERP BA readiness that contribute most significantly to BA capability. This should involve a more granular analysis of the CSFs and their relative importance in the context of ERP systems. Most existing BA maturity models are practitioner-based and are not rigorously developed and documented with a theoretical foundation. This suggests that there is a need for more research on the theoretical underpinnings of BA success (Cosic et al. 2012).

Research Gap 3.1 (RG3.1) identified in Chapter 2, Section 2.5: Limited Exploration of Application of IRT in Quantitatively Measuring BA Maturity (addressed by RQ3.1 in Chapter 4, Chapter 5 and Chapter 6): A research gap exists in applying IRT to rigorously and quantitatively measure BA maturity, despite its common use in education and healthcare. Research Gap 3.1 focuses on the limited exploration of applying IRT to quantitatively measure BA maturity. This gap is intricately related to Research Gap 3 because both aim to enhance the understanding of BA success within ERP systems. While Research Gap 3 emphasises the need for a detailed exploration and identification of CSFs contributing to BA capability, Research Gap 3.1 introduces IRT as a rigorous theoretical and repeatable quantitative method to assess BA maturity. By incorporating IRT into BA maturity assessment, Gap 3.1 addresses the inadequacy of existing BA maturity models, which often lack theoretical foundations and do not offer comprehensive insights (Cosic 2020). Therefore, Gap 3.1 complements Gap 3 by providing a quantitative approach to assessing BA maturity. However, the current literature lacks comprehensive studies on the adaptation of IRT for BA maturity assessment, necessitating further research. To address this gap, scholars should develop IRT-based measurement tools tailored to the multidimensional nature of BA maturity and conduct empirical studies to assess their effectiveness.

Research Gap 3.2 (RG3.2) identified in Chapter 2, Section 2.5: Limited Exploration of the Potential of IRT to Enhance BA Maturity Measurement in ERP Contexts (addressed by RQ3.2 in Chapter 4, Chapter 5 and Chapter 6): There has been limited exploration of IRT to enhance the reliability and validity of measurement items for evaluating BA maturity in organisational settings. Prior research on Rasch analysis has demonstrated its effectiveness in enhancing the reliability and validity of measurement items. Raber et al. (2013a) developed a BI maturity model and proposed a Rasch-based measurement instrument to assess BI maturity in organisational settings. This approach aligns with the use of Rasch analysis to improve the accuracy and precision of maturity assessments in the context of BI maturity within organisations. Rasch analysis is a type of IRT that is used to measure latent traits, such as knowledge, skills, and abilities. It is based on the principle that the probability of a person answering a question correctly depends on the trait level of the person and the difficulty of the question. This research gap underscores the necessity to explore how IRT can be effectively utilised to enhance the accuracy and precision of BA maturity assessments. This could require refining the methodologies and techniques employed in the application of IRT to ensure more robust and valid measurements in the context of ERP BA maturity.

Research Gap 3.3 (RG3.3) identified in Chapter 2, Section 2.5: Limited Understanding of the Relationships Between BA Maturity, BA Capability, and BA Success (addressed by RQ3.3 in Chapter 4, Chapter 5 and Chapter 6): There is a lack of understanding of the relationships between BA maturity, BA capability and BA success for organisations using ERP systems. Understanding the specific CSFs for ERP BA readiness (Research Gap 3) can inform the investigation of how BA maturity influences BA capability and success (Research Gap 3.3), providing a comprehensive understanding of the factors driving BA success in organisations. The relationship between BA maturity, perceived BA capability, and Perceived ERP BA success requires further examination. It is essential to determine to what extent the level of BA maturity of an organisation is indicative of its perceived capability and the actual success it achieves in the domain of BA.

By addressing these research gaps, scholars and practitioners can gain a deeper understanding of the importance and robustness of CSFs informing the measurement of BA readiness, maturity, and success within ERP systems, facilitating more effective decision-making and organisational performance improvement. Using rigorous methodological approaches such as Rasch analysis and hierarchical clustering can help address some of the identified gaps, particularly in enhancing the validity and reliability of BA maturity assessment. Continued research in these areas is crucial for advancing the understanding of BA readiness, maturity, and success within ERP systems. Rasch analysis is employed to measure the difficulty of survey items related to BA capabilities, while hierarchical clustering is used to categorise organisations into five maturity levels based on their responses. This approach aims to provide a more objective and reliable measure of BA maturity. Additionally, the reliability of the measurement instrument has been assessed through item-fit statistics and the person-item map, thereby reinforcing the validity and accuracy of the measurement instrument. The findings are strengthened by Research Phase III, which involves designing, assessing, and validating BARCMM. Empirical data collection and analysis using PLS-SEM aim to determine if the relationships between BA maturity, perceived ERP BA success, and perceived BA capability demonstrate a positive association. This confirmation is necessary to validate the basic assumption that organisations with higher maturity levels will have higher perceived ERP BA success and higher perceived BA capability.

1.6. Research Methodology

The research methodology used in this study is described and justified in detail in Chapter 3. The methodological approach for determining BA Readiness Maturity and BA Capability Maturity in organisations is based on a research framework that adapts previous work in Business Intelligence Maturity Models (BI MM) and the alignment of business and IS (Information Systems) strategies. This methodological approach utilises surveys to collect empirical data on BA readiness and capability maturity within organisations that have implemented ERP systems with BA tools.

Two surveys were conducted as part of the development and evaluation of the proposed BARCMM to assess the maturity levels of organisations using ERP systems with BA tools. Survey 1 consisted of 40 items that measured the nine dimensions of BA readiness and BA capability within the BARCMM. These dimensions represent increasingly difficult indicators of BA maturity. Respondents of each survey were requested to evaluate the items in ERP BA Readiness profile and BA Capability profile questions using a Likert scale consisting of seven points, enabling them to express their level of agreement from "(1) strongly disagree" to "(7) strongly agree." Survey 2 included a more extensive set of 58 items, also measuring the same nine dimensions of BA capability. Like Survey 1, respondents used a seven-point Likert scale to rate these items. The reason for conducting two surveys lies in the desire to achieve specific research objectives:

(1) Comparison and Validation: Using anchor items in Rasch analysis ensures consistency and comparability across survey versions, allowing for measuring the same constructs on a single scale, comparing results between surveys, and validating the measurement instrument's construct reliability and convergent validity (Boone 2016; Clark & Watson 2019). By using two surveys with a shared set of item anchors, the aim is to assess how the same item anchors could be used in subsequent versions of the survey to express the measure of an organisation on a single scale. This allowed for the comparison of results between the two surveys and provided a means to validate the measurement instrument construct reliability and convergent validity for the BARCMM.
(2) In-Depth Assessment: The second survey (Survey 2) with a larger number of measurement items provided a more comprehensive and detailed assessment of BA readiness and BA capability across the nine dimensions. This allowed for a deeper understanding of the organisation's maturity levels in each dimension.
(3) Robust Analysis: The use of two surveys allowed for a robust statistical analysis, which is crucial when developing and evaluating a maturity model like the BARCMM. It ensured that the measurements were accurate, reliable, and reflective of the diverse aspects of BA readiness and BA capability within organisations.

The maturity levels are assessed using ideal maturity profiles and the Euclidean metric. The approach follows a three-phase process: BARCMM Phase A involves developing the survey instruments based on essential characteristics of the BARCMM in Appendix C, BARCMM Phase B employs hierarchical clustering and Euclidean distances to determine maturity levels for dimensions and organisations, and Phase C uses Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the impact of BA maturity on perceived BA capability and success in organisations using ERP systems. This research applies a positivist paradigm and quantitative methods to provide a rigorous and repeatable methodological approach for constructing and evaluating the BARCMM.

1.7. Scope and Research Setting

The scope of this PhD thesis focuses on developing and evaluating a Business Analytics Readiness and Capability Maturity Model (BARCMM) for organisations using ERP Systems in the GCR. Prior research examined critical success factors specifically for ERP systems or only specifically for BA without the consideration of the impact of the various levels or stages of an ERP BA maturity model. Therefore, an empirical study of the critical success factors leading to the success of BA in ERP systems in the GCR will enable organisations to evaluate their ERP BA readiness and BA capability based on their levels or stages in the ERP BA maturity model. By conducting surveys and employing quantitative methods, the research aims to provide a systematic and empirically grounded framework for assessing and improving BA maturity levels within organisations utilising ERP systems. Through the exploration of eleven identified research gaps (three high-level research gaps and eight low-level research gaps), the thesis seeks to contribute to the advancement of knowledge in BA maturity modelling and facilitate informed decision-making for organisational performance enhancement in the context of Business Analytics capabilities for organisations using ERP systems in the GCR. The research methodology aligns with a positivist paradigm. It uses quantitative methods to ensure the robustness and repeatability of the developed BARCMM. This provides a solid foundation for advancing understanding and practice in this domain.

The research settings involve a two-stage survey approach (Survey 1 as a pilot study and Survey 2 as a full study) with robust questionnaire design and sampling strategies, targeting diverse organisations in the GCR to develop and validate the BARCMM. Sampling design details are in Section 3.5.2, and data-collection strategies are in Section 3.5.3.

1.8. Chapter Summary

This study focuses on developing and evaluating the BARCMM to assess the BA readiness and capability levels of organisations using ERP systems in the GCR. The research aims to offer a rigorous methodology for constructing the maturity model using Rasch analysis and hierarchical clustering. Validating the BARCMM involves using PLS-SEM to test whether BA maturity positively influences perceived ERP BA success and perceived BA capability.

The motivation for this study is to address the research gap in understanding and measuring BA readiness and capability within organisations using ERP systems in the GCR. The aim is to develop a model that provides a benchmark for continuous improvement. This model also seeks to enhance strategic alignment, thereby improving business value realisation.

The key research gaps were identified at both high and low levels. The high-level gaps focused on (RG1) Lack of Research on CSFs for ERP BA Readiness, (RG2) Limited Understanding of How to Apply CSFs with Methodological Rigour for BA Capability Measurement, and (RG3) Limited Exploration and Empirical Application of CSFs underpinned by Item Response Theory in ERP BA Readiness for Enhancing BA Capability and Success. These high-level gaps were then broken down into corresponding low-level sub-categories and mapped to specific research questions. The low-level gaps addressed the theoretical and practical aspects necessary to support the design, development, and evaluation of the BARCMM. This included identifying key CSF dimensions for ERP maturity models, adapting existing BA maturity models, and examining the state of BAMM research. The low-level questions also investigated using Item Response Theory to measure BA maturity, enhance reliability, and explore the relationships between BA maturity, perceived capability, and perceived ERP BA success. This structured approach, using high-level and low-level gaps mapped to corresponding research questions, helps address the identified gaps in a comprehensive and effective manner through the design, development, and evaluation of the BARCMM across the three research phases.

The research is divided into three phases, with the first two phases, Research Phases I and II, involving systematic literature reviews to inform the development and implementation of the BARCMM. Research Phase III focuses on the design, assessment, and validation of the BARCMM, and presents the empirical study results of applying the validated BARCMM model to organisations in the GCR.

The justification for this research is grounded in four key factors: (1) the pressing need to address the critical challenges in integrating ERP systems and Business Analytics, (2) the varied levels of ERP readiness and BA capability across organisations, (3) the significant impact of organisational maturity on BA readiness and capability within ERP systems, and (4) the requirement for a tailored maturity model to effectively assess ERP BA readiness and capability.

The three high-level research gaps identified in this study are: (RG1) Lack of research on CSFs for ERP BA readiness; (RG2) Limited understanding of how to apply CSFs with methodological rigour for BA capability measurement; (RG3) Limited exploration and empirical application of CSFs underpinned by Item Response Theory in ERP BA readiness for enhancing BA capability and success.

The research methodology is based on a framework that adapts previous work on Business Intelligence Maturity Model by Raber et al. (2013a) which can also be applied to BAMMs. The methodology utilises surveys to collect empirical data on BA readiness and capability maturity within organisations that have implemented ERP systems with BA tools. The maturity levels are assessed using ideal maturity profiles and the Euclidean metric, following a three-phase process. The research applies a positivist paradigm and quantitative methods to provide a rigorous and repeatable approach for constructing and evaluating the BARCMM.

The scope of this research focuses on developing and evaluating the BARCMM for organisations using ERP Systems in the GCR. This study employs a two-stage survey approach, with Survey 1 as a pilot and Survey 2 as a full study, targeting diverse organisations in different industry sectors in the GCR.

CHAPTER 2: LITERATURE REVIEW

Chapter 2 provides the foundation for developing the Business Analytics Readiness and Capability Model (BARCMM) for organisations using ERP systems. This chapter begins with a traditional review of the literature on Enterprise Resource Planning Systems, Business Analytics, and Capability Maturity Models. Key findings from the systematic reviews in Sections 2.2, 2.3, and 2.4 identify and discuss concepts that underpin the development and evaluation of the BARCMM in subsequent chapters of this research.

Section 2.1 outlines foundational concepts for the three systematic literature reviews (SLR 1, SLR 2, SLR 3) in later sections. It addresses the evolution of ERP systems, incorporating advanced BA capabilities with Industry 4.0 technologies to improve decision-making, inventory tracking, and workforce management. Followed by Sections 2.2, 2.3, and 2.4, which feature three systematic literature reviews. SLR 1 develops a classification framework for CSFs in assessing organisational maturity within ERP systems, defining concepts and exploring the roles of CSFs as measurement items in ERP maturity models (Wong & Lane 2023). SLR 2 reviews methods for designing, assessing, and validating Business Analytics Maturity Models (Wong et al. 2021). SLR 3 performs a systematic literature review on measuring Business Analytics Maturity in ERP Systems. The results of these three SLRs will guide the design and development of the proposed BARCMM and inform the creation of questionnaire survey instruments and methodologies for assessing BA readiness and capability maturity in organisations using ERP systems in the GCR. Section 2.5 identifies research gaps for developing the BARCMM, emphasising the need for context-specific CSFs and robust methodologies, such as Item Response Theory and Rasch analysis, to improve the assessment of BA readiness and capability maturity in organisations using ERP systems in the GCR. Finally, the chapter concludes with Section 2.6, providing a Chapter Summary and Conclusion. Figure 2.1 illustrates the structure of Chapter 2. The findings from SLRs 1, 2, and 3 will guide the methodological approach for designing, developing, and validating the BARCMM for ERP systems in Chapters 4, 5, and 6. Chapter 4 develops and evaluates the BARCMM for contemporary ERP systems in the GCR. Chapter 5 provides a rigorous quantitative assessment of BA maturity in organisations using modern ERP systems. Chapter 6 presents key empirical findings from the BARCMM assessment, emphasising its role in optimising BA capabilities within ERP systems.

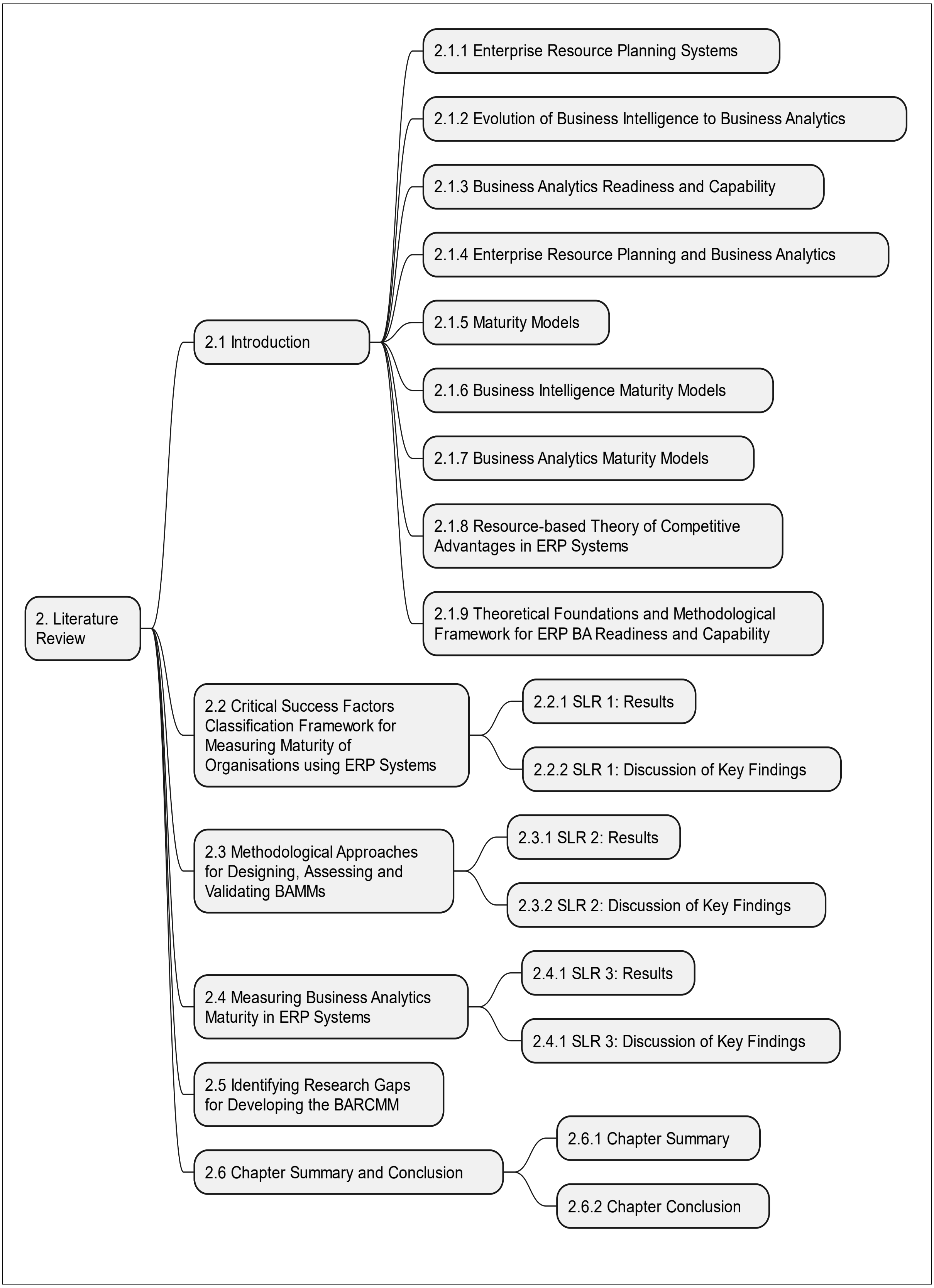

Figure 2.1 Structure of Chapter 2

2.1. Introduction

2.1.1. Enterprise Resource Planning Systems

Enterprise resource planning (ERP) systems integrate organisational processes using a common database and shared reporting tools, facilitating effective communication and data sharing across functional areas (Dredden & Bergdolt 2007).

ERP systems enhance operational efficiency, informed decision-making, collaboration, and organisational growth. Key factors for medium to large organisations include:

(1) **Streamlined Processes**: ERP systems integrate processes such as finance, human resources, manufacturing, supply chain, and customer relationship management into a unified platform, eliminating silos and redundancies (Hong & Kim 2002; Gupta & Kohli 2006; Laudon & Laudon 2019).

(2) **Data Visibility and Accuracy**: A common database ensures accurate, up-to-date information, enabling informed decision-making and a comprehensive view of organisational performance (Rajan & Baral 2015; Aziz et al. 2018; Laudon & Laudon 2019; Olaoye & Samon 2024).

(3) **Improved Reporting and Analysis**: Robust reporting and analytics tools generate insightful reports, identify trends, forecast performance, and support data-driven decisions (Nah et al. 2001; Fauzi 2022; Olaoye & Samon 2024).

(4) **Enhanced Collaboration and Communication**: Integrated processes and a centralised database facilitate seamless communication and collaboration, fostering teamwork and alignment towards goals (Butarbutar et al. 2023; Lara-Pérez et al. 2024).

(5) **Scalability and Adaptability**: ERP systems accommodate evolving business needs, regulations, and market conditions, supporting organisational growth and competitiveness (Salih et al. 2021; Olaoye & Samon 2024).

ERP systems have evolved to support the extended enterprise concept, driven by digital technologies, enabling collaboration across ecosystems (Davis & Spekman 2004). Enhanced business analytics features, such as dashboards and real-time data analytics, provide essential information and metrics (Srivastava et al. 2022). ERP systems offer a process-oriented view, increasing visibility of key business processes through real-time financial and production information (Nah & Delgado 2006).

Industry 4.0 involves digital networks of smart, self-optimising factories operating autonomously with minimal human intervention (Keskin et al. 2018). Technologies like the Internet of Things (IoT), cloud services, big data analytics, artificial intelligence (AI), machine learning (ML), and robotic process automation (RPA) significantly impact ERP system usage, improving decision-making, inventory tracking, and logistics (Frank et al. 2019; Ribeiro et al. 2021). Business analytics tools in ERP systems, extended to support Industry 4.0, enable predictive and prescriptive capabilities for customer behaviour, turnaround times, and production (Ghadge et al. 2020). Industry 4.0 enhances productivity and performance through IoT device intelligence and ML applications.

ERP systems serve as the digital backbone of medium to large organisations, integrating enhanced business analytics and Industry 4.0 technologies for improved decision-making, inventory tracking, and workforce management (Elragal & Hassanien 2019; Romero & Abad 2022). These intelligent ERP systems are crucial for digital transformation driven by technological innovations like AI, ML, business process automation, and cloud computing (Gašpar et al. 2023). Effective ERP implementation and use, assessed through maturity models, involve evaluating organisational resources, competencies, and abilities (Hairech & Lyhyaoui 2020).

Ptak and Schragenheim (2004, pp. 90-106) provide an organisational readiness assessment checklist with 25 questions, scoring each criterion from 0 (no evidence) to 4 (full compliance). A score of 90 or higher indicates readiness for successful ERP integration, while scores below 90 highlight areas needing improvement for better business results.

Organisations must assess and monitor ERP system impacts to realise benefits from Industry 4.0 integration. Adapting existing ERP maturity models (ERPMMs) to include Industry 4.0 dimensions is essential for measuring the maturity level and effectiveness of ERP systems (dos Santos-Neto & Costa 2019).

2.1.2. Evolution of Business Intelligence to Business Analytics

Business intelligence (BI) became popular in the 1990s, defined as processes and technologies converting data into meaningful information for business purposes (Chen et al. 2012). It encompasses analytics, business analytics, and information systems (Bartlett 2013) and focuses on collecting, storing, and exploring large databases for decision-making (Negash 2004).

In the late 2000s, business analytics (BA) emerged to represent the analytical component of BI. BA uses data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport & Harris 2007). It involves collecting business-related data and applying descriptive, predictive, and prescriptive analytics to support evidence-based decision-making and improve organisational performance (Schniederjans et al. 2014). Business analytics systems use capabilities like data warehousing, reporting, online analytical processing, dashboarding, data visualisation, predictive modelling, and forecasting to support decision-making (Cosic et al. 2012; Santiago Rivera & Shanks 2015). Debates exist on whether business analytics is a subset of business intelligence (Davenport & Harris 2007) or an advanced discipline within it (Laursen 2010). In this research, business analytics is seen as studying business data using statistical techniques and programming for decision support and insights to achieve business goals (Schniederjans et al. 2014). A comparison of BI and BA is shown in Table 2.1.

Table 2.1 Comparison of Business Intelligence and Business Analytics

Aspect	**Business Intelligence**	**Business Analytics**
Definition	A collection of theories, methodologies, processes, architectures, and technologies that convert raw data into valuable business information.	Study of business data using statistical techniques and programming for creating decision support and insights for achieving business goals.
Focus	BI includes analytics, business analytics, and information systems (Bartlett 2013, p.4). It focuses on gathering, storing, and analysing large datasets to aid decision-making and planning (Negash 2004).	A process that begins with data collection and sequentially applies descriptive, predictive, and prescriptive analytics to support and improve business decision-making and organisational performance (Schniederjans et al. 2014).

Chen et al. (2012) outline the evolution of business intelligence and analytics (BI&A) into three stages: BI&A 1.0, 2.0, and 3.0, as summarised in Table 2.2. These stages reflect increasing sophistication in handling diverse data and tasks, from structured data and reporting to real-time insights and actionable decisions.

Table 2.2 The Evolution of BI&A 1.0, 2.0, and 3.0 (adapted from Chen et al. 2012)

Key Characteristic	**BI&A 1.0**	**BI&A 2.0**	**BI&A 3.0**
Type of data	Structured	Structured and unstructured	Structured, unstructured, and sensor-based
Key technologies	RDBMS, data warehousing, ETL, OLAP, data mining, and statistical analysis	Data retrieval, opinion mining, question answering, web analytics, social media analytics, social network analysis, and spatial-temporal analysis.	Location-aware analysis, person-cantered analysis, context-relevant analysis, mobile visualisation, and HCI
Focus	Reporting and descriptive analytics	Predictive analytics and prescriptive analytics	Real-time analytics and actionable insights

BI transforms raw data into meaningful information for business purposes, encompassing analytics. BA, however, focuses on using statistical techniques and programming for decision-making and performance improvement through data analysis. The evolution from BI to BA reflects the demand for comprehensive data utilisation due to the big data phenomenon (LaValle et al. 2010; Chen et al. 2012; Pancić et al. 2023).

Initially, BI tools generated reports and dashboards for descriptive insights into past performance. The shift towards data-driven decision-making, prompted by the explosion of big data, necessitated tools for predicting future performance and offering prescriptive recommendations (Sarker 2021; Elgendy et al. 2022; Obaid & Abu-Naser 2023). BA tools provide advanced capabilities like sales forecasting, customer churn prediction, product promotion recommendations, and pricing optimisation. This evolution is driven by diverse data sources, big data technologies, and sophisticated analytics capabilities (Purcell 2012; Mikalef et al. 2019; Ciampi et al. 2021).

Integrating advanced data analytics through BA tools with modern ERP systems enables informed decision-making, optimises operations, and allows swift adaptation to market changes (Elragal & Hassanien 2019; Romero & Abad 2022). This synergy between BA and ERP systems not only streamlines processes but also drives innovation and competitive advantage, the focus of this research.

2.1.3. Business Analytics Readiness and Capability

Organisational readiness is the state an organisation achieves before starting an activity (Helfrich et al. 2011). Organisational capability refers to the knowledge, skills, and routines that enable an organisation to deliver competitive value to customers (Day 1994). In this research, BA readiness is the perceived degree of readiness and essential prerequisites needed to capture the full business value of BA in ERP systems. BA capability is the perceived ability to deliver competitive business value using BA. The BA Readiness and Capability Maturity Model (BARCMM) posits that BA cannot be realised without organisational readiness, and the maturity of BA readiness will influence BA capability to capture business value. Assessing an organisation's readiness and capability to utilise BA in ERP systems is crucial for:

(1) **Enhancing Organisational Performance:** BA can improve decision-making, resource optimisation, and risk mitigation. Evaluating readiness and capability identifies gaps and areas for improvement, leading to better performance (AlMuhayfith & Shaiti 2020; Balić et al. 2022; Nour 2023).

(2) **Maximising ERP System Potential:** ERP systems integrate various organisational operations. Incorporating BA functionalities can optimise and automate processes using data-driven insights. Assessing readiness ensures effective use of these functionalities, maximising ERP potential (Badi 2024).

(3) **Identifying CSFs:** Recognising CSFs for BA readiness and capability in ERP systems is essential for successful implementation. Identifying these CSFs helps organisations improve their BA readiness and capability (Ngai et al. 2008; Shaul & Tauber 2013).

(4) **Benchmarking and Continuous Improvement:** Assessing maturity levels provides a benchmark for current states and progress. This facilitates continuous improvement, helping organisations adapt to changing environments and maintain competitiveness (Backlund et al. 2015; Lameijer et al. 2023).

2.1.4. Enterprise Resource Planning and Business Analytics

ERP vendors are embedding more BA capabilities into their applications, with dashboards providing key information and metrics (Srivastava et al. 2022). Many are adding specific analytics features to their systems (Drobik & Rayner 2015). ERP systems with BA capabilities can improve decision-making and performance. BA can be integrated internally within the ERP system or deployed externally, extracting data from the ERP database (Elragal & Hassanien 2019). The new generation of these ERP systems, known as intelligent ERP systems, form the backbone of Industry 4.0, featuring in-memory technology, service-oriented architecture, cloud computing, and integration with manufacturing execution systems and programmable logic controllers (Zeba et al. 2019; Gašpar et al. 2023). New generations of ERP systems support BI and BA initiatives by integrating processes from suppliers to customers with shared data and visibility (Almajali et al. 2016). These ERP systems, with embedded BI and BA tools, enable a data-driven strategy to achieve business goals (Wang 2016). Previous studies on BA maturity models focus on technological and operational aspects, such as tool use, alignment with organisational functions, and performance measurement, but often overlook theoretical knowledge in developing these models (Ariyarathna & Peter 2019). Maturity models are essential for documenting and guiding organisational development based on best practices (Paulk et al. 1993). Researching BA maturity models in the context of ERP systems is crucial, as they are the digital backbone of medium to large organisations increasingly integrating new technologies like distributed computing, flash memory, mobile devices, cloud computing, big data analytics, and in-memory applications as critical data capture points (Ajah & Nweke 2019).

2.1.5. Maturity Models

A maturity model assesses competence, establishes a roadmap for improvement, and evaluates development effects. It identifies an organisation’s strengths and weaknesses, producing quantitative values (Paulk et al. 1995). The Capability Maturity Model (CMM), developed at Carnegie Mellon University in 1991, aimed to improve software processes. Since then, maturity models have been used to enhance capabilities in areas such as project management, knowledge management, and information technology (IT) (Teah et al. 2006; Brookes & Clark 2009; Becker et al. 2010).

The Capability Maturity Model Integration (CMMI) framework, evolving from the CMM for Software, includes best practices for product and service development. The latest version, CMMI for Development 1.3 (2010), integrates software development, systems engineering, and product development, with additional models for Acquisition and Services (Software Engineering Institute 2010). In 2014, the CMMI Institute introduced the Data Management Maturity (DMM) model to bridge business and IT perspectives (CMMI Institute 2014). Updates to CMMI, including CMMI 2.0 (2018) and CMMI 3.0 (2023), aim to enhance flexibility, adaptability, and regional adoption, adding new content in People Management, Data Management, and Virtual Delivery (Degerli 2020; CMMI Institute 2023; Fariz et al. 2023). Despite the increase in maturity models, there is a lack of structured development and perceived quality, necessitating the application of a maturity model to themselves (van Hillegersberg 2019). Maturity models may be level-based, following CMM's five levels: Initial, Repeatable, Defined, Managed, Optimising (Paulk et al. 1993), or focus area models outlining steps in various domains (Van Steenbergen et al. 2010). These models may cover broad organisational improvement (van Hillegersberg 2019). However, van Hillegersberg (2019) notes that research on maturity models lacks depth, highlighting the need for a rigorous design of BA readiness and maturity models tailored to organisational needs. Wendler (2012) found that while empirical studies dominate, there is a shortage of theoretical publications grounding maturity models in both theory and practice. Further comparisons are detailed in SLR 2, which examines methodological approaches for creating, evaluating, and validating maturity models. Most systematic literature reviews provide general overviews but lack detailed technical insights for effective implementation.

2.1.6. Business Intelligence Maturity Models

Criticisms have been raised about the arbitrariness and fuzziness in the design and development of BIMMs (Becker et al. 2009). Generally, BIMMs lack strong theoretical grounding and overly focus on data warehousing aspect of BI (Becker et al. 2010). The American SAP User Group (ASUG) developed a BIMM with four stages involving four categories of BI practices (Hawking et al. 2011). This model is useful for evaluating BI maturity and identifying areas needing attention. For accurate assessment, companies should use multiple models to cover more key areas, offering a broader view of their maturity and potential challenges. However, results from different models are not directly comparable due to non-standardised metrics, areas, levels, and criteria (Rajterič 2010). Raber et al. (2013a) investigated the relationship between BI maturity and the business benefits of BI, and the results showed that mature organisations had significantly higher business benefits in BI compared to organisations with lower maturity levels. Literature on BIMMs often focuses on specific dimensions rather than providing a comprehensive view (Thamir & Theodoulidis 2013; Brooks et al. 2015). These models offer detailed insights into areas like technical processes or organisational capabilities, aiding in the assessment and improvement of BI readiness and maturity. Using multiple models can enhance the precision of maturity assessments, but differences in metrics and criteria can complicate comparisons (Rajterič 2010). Table 2.3 provides a summary and comparison of BIMMs by focus, design, assessment, validation, and source. It highlights differences in design approaches, survey scope, and validation processes. The BI Maturity Model developed by Raber et al. (2013a, 2013b) stands out due to its validation through expert consultation, potentially enhancing its reliability and comprehensiveness. The approach of the BI Maturity Model by Raber et al. (2013b, 2013a) can be adapted for BAMMs, providing a foundational framework for BAMMs.

Table 2.3 Comparison of BIMMs with Sources

Maturity Model	**Focus**	**Design**	**Assessment**	**Validation**	**Source**
Lahrmann et al.'s BIMM	Dimensions: Strategy, Organisation/ Process, IT support	Quantitative bottom-up approach (Rasch and cluster analysis)	Questionnaire results from 51 cross-industry companies	Not specified.	Lahrmann et al. (2011) [Academia]
Lukman et al.'s BIMM	BI in Slovenia	Quantitative bottom-up approach (K-Means algorithm)	Questionnaire results from 131 cross-industry companies	Not specified.	Lukman et al. (2011) [Academia]
Raber et al.'s BIMM	Dimensions: Strategy, Social System, Technical System, Quality, Use/Impact	Quantitative bottom-up approach (Rasch and cluster analysis)	Questionnaire results from 51 cross-industry companies	Discussion with three industry experts on comprehensiveness, self-assessment, and BI roadmap	Raber et al. (2013b, 2013a) [Academia]

2.1.7. Business Analytics Maturity Models

Davenport and Harris (2007) defined a staged, prescriptive BA maturity model with five stages. Cosic et al. (2012) defined the Business Analytics Capability Maturity Model (BACMM) that provides a holistic view of BA readiness of an organisation across technology, people, culture and governance. Cosic et al. (2012)'s BACMM comprises sixteen BA capabilities grouped into four capability areas: governance, culture, technology, and people. The governance capability involves managing BA resources and assigning decision rights to align initiatives with organisational objectives. The culture capability encompasses the organisational norms, values, and behaviours that shape data handling practices. The technology capability includes the development and utilisation of hardware, software, and data in BA activities. The people capability pertains to the skills and knowledge of individuals using BA in their roles (Cosic et al. 2012). Maturity models can also be used to analyse both strengths and weaknesses of organisations as a whole or within specific business functions (Mettler & Rohner 2009).

BAMMs are summarised in terms of focus, design, assessment and validation in Table 2.4. The majority of BAMMs were developed by practitioners who do not provide documentation on the foundations of the design of the BA maturity model. The model development process proposed by Cosic et al. (2012) is based on the construction approach by Becker et al. (2009) which shows that BAMMs can be adapted from maturity models developed for other IT domains such as IT Management. In Table 2.5, the four BAMMs from Table 2.4 are further compared in terms of purpose, origin, stages/levels, dimensions, and assessment. According to Becker et al. (2009), a maturity model is descriptive in purpose of use if it is applied for as-is assessments when the current capabilities of the organisation under investigation are assessed against given criteria. A maturity model is prescriptive in purpose of use, if it indicates how to identify desirable maturity levels and provides guidelines on improvement measures. Most practitioners' maturity models are prescriptive and use proprietary assessment methods and measurement items.

Table 2.4 Comparison of BAMMs with Sources

Maturity Model	Focus	Design	Assessment	Validation	Source
Business Analytics Capability Maturity Model (BACMM)	Assess BA initiatives within large-scale Australian organisations	The model development process is based on approach of Becker et al. (2009) IT Management Maturity Model	16 key capabilities aggregated to measure maturity across four high-level BA capabilities and overall BA capability	Delphi study with expert panel for validating and refining BA Capability Framework	Cosic et al. (2012); Cosic et al. (2015); Cosic (2020) [Academia] Adapted from Becker et al. (2009)
TDWI Analytics Maturity Model	Predictive, social media/text, cloud, and big data analytics	Not specified.	Assess enterprises' analytics capabilities	Not specified.	Halper and Stodder (2014) [Practitioner]
INFORMS Analytics Maturity Model	Benchmarking capabilities and identifying actions to improve the analytical maturity	Not specified.	Each dimension has a potential high score of 10 points.	Not specified.	The Institute for Operations Research and the Management Sciences (2017) [Practitioner]
International Institute for Analytics (IIA) Analytics Maturity Model	Optimising performance by improving analytics capabilities	Not specified.	Analytics Maturity assessed against 33 competencies across five DELTA model categories	Not specified.	International Institute for Analytics (n.d.) [Practitioner]

Table 2.5 Comparison of BAMMs: Academia and Practitioners

<table>
<tr><td>Maturity Model</td><td>Business Analytics Capability Maturity Model (BACMM)</td><td>TDWI Analytics Maturity Model</td><td>INFORMS Analytics Maturity Model</td><td>International Institute for Analytics (IIA) Analytics Maturity Model</td></tr>
<tr><td>Purpose</td><td>Descriptive</td><td>Prescriptive</td><td>Prescriptive</td><td>Prescriptive</td></tr>
<tr><td>Origin</td><td>Cosic et al. (2012); Cosic et al. (2015); Cosic (2020)
[Academia]</td><td>Halper and Stodder (2014)
[Practitioner]</td><td>The Institute for Operations Research and the Management Sciences (2017)
[Practitioner]</td><td>International Institute for Analytics (n.d.)
[Practitioner]</td></tr>
<tr><td>Stages/ Levels</td><td>5 levels:
Level 0 – Non-existent
Level 1 – Initial
Level 2 – Intermediate
Level 3 – Advanced
Level 4 – Optimised</td><td>5 stages: Nascent, Pre-adoption, Early Adoption, Corporate Adoption, Mature/ Visionary</td><td>3 levels:
Beginning, Developing, Advanced</td><td>5 stages:
Analytically impaired, Localised analytics, Analytical aspirations, Analytical companies, Analytical competitors</td></tr>
<tr><td>Dimensions</td><td>4 dimensions:
Technology, People, Culture and Governance</td><td>5 dimensions: Organisation, Infrastructure, Data Management, Analytics, Governance</td><td>3 dimensions: Organisational, Analytics Capability, Data & Infrastructure</td><td>5 dimensions: Data, Enterprise, Leadership, Targets, Analysts</td></tr>
<tr><td>Assessment</td><td>BACMM combines framework for BA capabilities with five level maturity scale (Paulk et al. 1993). The scale is applied to sixteen BA capabilities, which are then aggregated to determine maturity for four high-level BA capabilities and overall BA capability.</td><td>Each dimension potential high score of 20 points.
<table>
<tr><td>Score per Dimension</td><td>Stage</td></tr>
<tr><td>4–7.1</td><td>Nascent</td></tr>
<tr><td>7.2–10.1</td><td>Pre-Adoption</td></tr>
<tr><td>10.2–13.3</td><td>Early Adoption</td></tr>
<tr><td>13.4–16.6</td><td>Corporate Adoption</td></tr>
<tr><td>16.7–20</td><td>Mature/ Visionary</td></tr>
</table></td><td>Each dimension potential high score of 10 points.
<table>
<tr><td>Score per Dimension</td><td>Stage</td></tr>
<tr><td>1 – 3</td><td>Beginning</td></tr>
<tr><td>4 – 7</td><td>Developing</td></tr>
<tr><td>9 – 10</td><td>Advanced</td></tr>
</table></td><td>Analytics Maturity Assessment is evaluated against 33 competencies within five DELTA model categories. DELTA scores range from 1.00 to 5.99, with descriptive maturity stages assigned to each score range (1-1.99, 2-2.99, etc.) and aligned with five stages.</td></tr>
</table>

2.1.8. Resource-based Theory of Competitive Advantages in ERP Systems

Resource-based theory (RBT), also known as the Resource-Based View (RBV) of the Firm, posits that organisations develop internal capabilities to enhance their competitive advantage (Barney 1996). As a strategic management framework, RBT emphasises that a firm's internal resources, such as skills, knowledge, and assets, are crucial to outperforming competitors. RBT provides the theoretical and empirical basis for understanding how an organisation utilises information systems (IS), such as new-generation ERP systems and their BA capabilities, and links this to IS success. Peppard (2000) developed an IS success framework illustrating the link between IS capability and underpinning competencies, processes, roles, knowledge, skills, experience, and personal attributes. To gain a competitive advantage from ERP systems, organisations must utilise all available resources, often accelerated by competitive and regulatory pressures (Schniederjans & Yadav 2013). The Valuable, Rare, Imitability, and Organisation (VRIO) framework, part of resource-based theory, examines the link between an organisation's internal characteristics and its performance (Barney & Clark 2007, p. 57). An ERP system can provide a competitive advantage if it is valuable, uniquely implemented, imperfectly imitable, and if the business is organised to exploit its full potential (Beard & Sumner 2004).

Dynamic capabilities enable an organisation to adapt, integrate, and reconfigure resources in response to business environment changes (Augier & Teece 2007; Ambrosini et al. 2009). These capabilities sustain competitive advantage through continuous resource renewal and reshaping, via routines like sensing, seizing, and reconfiguration (Ridder 2012; Warner & Wäger 2019). Cosic et al. (2015) show that integrating dynamic capabilities with the resource-based view in a Business Analytics Capability Framework (BACF) enhances performance and competitive advantage by ensuring adaptability, continuous improvement, better decision-making, optimised resource allocation, and alignment of BA initiatives with strategic goals.

With new generations of ERP systems, organisations need the right resources and capabilities to succeed with embedded and extended BA functionalities. Each organisation's unique ERP implementation requires different staff capabilities. Competitive advantage and benefits are achieved by fully utilising and integrating ERP systems and BA capabilities with business partners across the supply chain.

Resource-based theory provides a theoretical lens for understanding BA capability maturity models in the context of new ERP systems. It suggests that organisations with higher BA maturity, having developed and leveraged unique and valuable resources such as advanced tools, skilled personnel, and robust data processes, gain more features and benefits from their analytics initiatives, thereby achieving a competitive advantage.

2.1.9. Theoretical Foundations and Methodological Framework for ERP BA Readiness and Capability

This section covers the foundational concepts of ERP systems and ERP BA readiness. It sets the stage for subsequent sections 2.2, 2.3, and 2.4 by covering the CSFs identified in SLR 1 and the methodological approaches discussed in SLR 2. Additionally, it addresses the methodological approach to assessing BA readiness and capability maturity from SLR 3. It explains how these findings will guide and inform the design, development, and evaluation of the BARCMM. It provides a comprehensive overview of how these elements collectively inform the theoretical underpinnings and methodological framework guiding the development of the BARCMM for assessing BA readiness and capability in ERP systems.

The findings of SLRs 1, 2, and 3 highlight their respective contributions to the design and development of the BA readiness and capability maturity model tailored for organisations utilising ERP systems. Table 2.6 shows how SLRs 1, 2, and 3 collectively influence the design, assessment, and validation of the BARCMM, providing frameworks, methodologies, and insights for assessing BA readiness and capability in organisations using ERP systems.

Table 2.6 Summary of SLR Contributions to BARCMM Development

SLRs	Focus	Contribution
1	Classification framework for CSFs in ERP systems' organisational maturity assessment (Wong & Lane 2023)	Identifies eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, Products & Services) as measurement items for ERP BA readiness in BARCMM. Aligns BA capabilities with Industry 4.0.
2	Methods for designing, assessing, and validating BAMMs (Wong et al. 2021)	Highlights Rasch analysis for BA maturity assessment and identifies gaps in applying these methods to BAMMs for ERP systems. Recommends combining Rasch analysis and clustering for comprehensive BA capability measurement and validation in BARCMM.
3	Examination of BAMMs for ERP systems	Notes the lack of specific models for ERP BA maturity and proposes adapting existing BAMMs using Rasch analysis and ERP-specific questions. Informs BARCMM by integrating BA items specific to modern ERP systems, aligning with Industry 4.0, and enhancing BA capabilities. Emphasises empirical validation and methodological rigour.

SLR 1 contributes significantly by developing a classification framework for CSFs in ERP systems' organisational maturity assessment (Wong & Lane 2023). It identifies eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services) that serve as measurement items for ERP BA readiness in the BARCMM. These dimensions are crucial for assessing how organisations using ERP systems integrate BA capabilities, aligning them with Industry 4.0 impacts. The findings of SLR 1 guide the inclusion of CSFs and dimensions relevant to ERP BA readiness and maturity assessment as measurement items in the questionnaire survey of the BARCMM measuring ERP BA readiness and capability of organisations using ERP systems.

SLR 2 reviews methods for designing, assessing, and validating BAMMs, highlighting Rasch analysis as a rigorous approach for BA maturity assessment (Wong et al. 2021). It identifies gaps in applying these methods specifically to BAMMs for ERP systems. The study recommends combining Rasch analysis and clustering, adopted in the BARCMM for comprehensive BA capability measurement and validation. The findings of SLR 2 influence the methodological rigour and validation techniques in developing the BARCMM.

SLR 3 examines BAMMs for ERP systems, highlighting the absence of models specifically tailored for assessing BA maturity in these environments. It proposes adapting existing BAMMs through Rasch analysis and incorporating ERP-specific profile questions to evaluate BA readiness and capability. The insights from SLR 3 guide the development of the BARCMM by suggesting integration of ERP-specific BA measurement items, ensuring alignment with Industry 4.0 trends and enhancing BA capabilities. Additionally, SLR 3 emphasises the need for empirical validation and methodological rigour, shaping the BARCMM's assessment and validation approach.

These SLRs 1, 2, and 3 collectively influence the design, development, and evaluation of the BARCMM by providing foundational frameworks, methodological approaches, and empirical insights necessary for assessing BA readiness and capability in organisations using ERP systems. They guide the selection of CSFs, define measurement items and dimensions, and recommend rigorous assessment methods like Rasch analysis and clustering. By addressing gaps in existing literature and advocating for systematic approaches, the SLRs ensure that the BARCMM is robust, empirically validated, and aligned with the evolving needs of organisations leveraging ERP systems for business analytics.

2.2. Critical Success Factors Classification Framework for Measuring Maturity of Organisations using ERP Systems

The first systematic literature review (SLR 1) was conducted on the classification framework of CSFs for measuring the maturity of organisations using ERP systems (Wong & Lane 2023). Details of SLR 1 are provided in Appendix H.

SLR 1 aimed to identify a CSF classification framework applicable to assessing ERP BA readiness and capability in organisations using ERP systems. Two research gaps were identified in SLR 1. The first, RG1.1, is a limited understanding of ERPMM dimensions. The second, RG1.2, is a limited understanding of CSF dimensions for assessing maturity in new-generation ERP systems with BA features. The dimensions of this CSF framework for measuring business analytics maturity for organisations using ERP systems are further explored in detail in SLR 3.

Given the emphasis of the research on BA maturity in organisations using ERP systems, it is believed that certain CSFs that lead to successful ERP systems will also contribute to successful BA capabilities. Therefore, understanding the CSFs and their classification in ERP systems is crucial. ERP systems often play a central role in organisations' data management and analysis processes. Analysing CSFs helps assess the maturity of an organisation in utilising ERP systems for analytics, which is directly related to the overarching goals of the research. Organisations with high ERP system maturity are likely to excel in using both embedded and add-on BA functionalities. By identifying CSFs specific to ERP systems, researchers can assess an organisation's maturity in utilising these systems for analytics. This aligns with research goals aiming to identify the dimensions of CSFs that measure the maturity of organisations using ERP systems, including their BA capability.

2.2.1. SLR 1: Results

The results of the first systematic literature review (SLR 1) are summarised below, with comprehensive details provided in Appendix H.

(1) Measurement Items for ERP Maturity Models

The three most common measurement items for determining maturity levels are CSFs, capabilities, and key process areas. CSFs are more versatile, as they can describe capabilities and key process areas generically or specifically. Many maturity models use questionnaires for management executives, making CSFs more widely used than capabilities and key process areas (Merkus et al. 2020). Executives might not be able to answer questions about specific capabilities or key processes beyond their management scope. CSFs used for ERP implementation success can also measure and assess maturity levels in an ERP maturity model, allowing for classification into dimensions and sub-dimensions to illustrate their use in assessing organisational maturity. They enable management executives to easily respond to assessment questionnaires, making them practical for evaluating ERP implementation and post-implementation success. Capabilities and key process areas are less commonly used due to the difficulty for executives to accurately assess these aspects in other departments or staff not under their direct management.

Table 2.7 summarises measurement items for ERP Maturity Models, including CSFs, capabilities, and key process areas, highlighting their versatility, applications, and practical usage.

Table 2.7 Types of Measurement Items for ERP Maturity Models

Types of Measurement Items	Description	Usage
CSFs (Critical Success Factors)	Versatile items that can be formulated in terms of generic or specific descriptions of capabilities and key process areas.	Widely used in maturity models as measurement items. Executives can easily respond to CSF-based questionnaires, making them more practical than capabilities or key process areas.
Capabilities	Specific abilities or proficiencies that an organisation or individual can develop.	Less commonly used in maturity models since executives may lack insight into specific capabilities of other staff or departments outside their management scope.
Key Process Areas	Specific processes that are critical to the success of an organisation's operations.	Less commonly used as executives may lack detailed knowledge of key processes in other departments.

(2) Dimensions for Classification of CSFs for ERP Implementation and Post-implementation Success

The CSFs identified in SLR 1 Phase 2 were categorised into seven dimensions: Governance, Culture, Technology, Operation, People, Project, and Performance. Table H.2 in Appendix H summarises the dimensions, sub-dimensions, and CSFs for ERP implementation and post-implementation success. Table 2.8 summarises these dimensions and specific CSF indicators, reproduced from Table H.2 with sources.

Table 2.8 Summary of CSF Dimensions and Indicators for ERP Implementation and Post-Implementation Success

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
Governance	Change management	Change agents & leadership; Management readiness for change; Scope for change; Management of change
	Strategic planning	Business plan/ vision/ goals/ justification; Clear goal/ objectives/ strategy; Acquisition strategy; Strategic IT plans & governance
	Top management support	Top management engagement/ involvement/ commitment/ awareness/ incentives; Dedicated resources; Funds support; Leaders support
Culture	Organisational culture	Learning & development; Participative decision making; Power sharing; Support & collaboration; Conflicts & risk tolerance culture

Table 2.8 Summary of CSF Dimensions and Indicators for ERP Implementation and Post-Implementation Success

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
	Employee morale	Employees' morale and motivation
Technology	Customisation	Customisation of ERP; Organisational fit of ERP; Minimal customisation; ERP adaptation
	Compatibility	ERP compatibility; Legacy systems; Data conversion; Fitness factors
	Quality	Implementation quality; Information, system & service quality; Data accuracy; Data migration; Vendor quality & support
	IT infrastructure	Technological complexity; IS resources; IS capabilities; System integration; System use
Operation	Business process management	Business process improvement; Business process re-engineering (BPR); Process formalisation
	Cooperation	Cross-functional/Inter-departmental cooperation; Network relationships; Connectedness with user departments
People	User satisfaction	Key user satisfaction; Employee satisfaction; Ease of use; User expectations
	Perceived usefulness	Shared belief in system benefits; Shared understanding of implemented technology; Behavioural intention; Individual impact
	Skills	Communication/ analytical/ leadership/ personal/ management/ technical skills; ERP experience/ expertise; Learning skills; User learning capacity; Users' absorptive capacity
	Social factors	Users attitude towards ERP system; Facilitating conditions; Near-term/ Long-term consequences; Affect; Competitive pressure
	Human resource management	Recruit, appraise, develop and preserve qualified employees
	Training and education	Training of personnel; Train IT staff in new skills; Training plan; Well-established education and training strategy; Effective training
Project	Project management	Project justification; Full-time project manager; Project champion; Proven implementation plan; Project planning; Cost benefit analysis; Leadership; Steering committee
	Project team competence	Project team empowerment; Teamwork participation/ composition; Team with multiple skills; Knowledge management competence; Group cohesion
	ERP selection	Feasibility of ERP project/ consulting services/ costing issues; ERP package selection; Use of consultants

Table 2.8 Summary of CSF Dimensions and Indicators for ERP Implementation and Post-Implementation Success

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
Performance	Organisational performance	Measurement of internal efficiency, competitiveness, profitability; Organisational objective consensus/ readiness/ impact; Performance evaluation & management/ auditing & control
	Overall efficiency	Coordination improvement; Task efficiency
	Usage performance	Utilisation performance/ metrics

The Governance dimension is classified into three sub-dimensions: Change management, Strategic planning, and Top management support. Change management includes the processes, tools, and techniques to manage the human side of change to achieve a required business outcome (Voehl & Harrington 2017, p. 5). Strategic planning is the process of defining an organisation's plans to achieve its mission (Baporikar 2015). Top management support refers to the extent to which senior management provides resources, direction, and authority before and after the implementation of ERP systems (Ifinedo 2008).

The Culture dimension is divided into two sub-dimensions: Organisational culture and Employee morale. Organisational culture comprises shared assumptions and understandings about how the organisation operates (Deshpande & Webster Jr 1989). Employee morale encompasses attitudes, emotions, satisfaction, and the overall view employees have of their organisation (Sania et al. 2015).

The Technology dimension consists of four sub-dimensions: Customisation, Compatibility, Quality, and IT infrastructure. Customisation involves modifying the ERP system's functionality, such as user interfaces, reports, and program codes, to meet specific business needs (Law et al. 2010). Compatibility is the extent to which a technological innovation aligns with users' values, needs, and past experiences (Rogers 2003). Quality encompasses system quality, information quality, and service quality (Bento & Costa 2013). IT infrastructure includes the physical devices and software needed to operate the business, along with enterprise-wide services covering human and technical capabilities (Laudon & Laudon 2020, p.165).

The Operation dimension is divided into two sub-dimensions: Business Process Management (BPM) and Cooperation. BPM is a holistic approach for evaluating, improving, and aligning business processes with organisational goals and strategy (Jarrar et al. 2000). This includes Business Process Improvement (BPI), Business Process Reengineering (BPR), and Business Process Optimisation (BPO). Cooperation involves collaboration among stakeholders, including vendors, managers, project leaders, users, and consultants, to monitor project progress and evaluate ERP system performance (Shatat & Dana 2016). It also covers cross-functional/inter-departmental cooperation, network relationships, and connections with user departments.

The People dimension comprises six sub-dimensions: User satisfaction, Perceived usefulness, Skills, Social factors, Human resource management, and Training and education. User satisfaction, including key user and employee satisfaction, ease of use, and user expectations, is crucial for effective ERP system use (Amoako-Gyampah & Salam 2004; Rouhani & Ravasan 2013). Perceived usefulness is the users' belief that the ERP system enhances organisational performance in routine and quality tasks (Putri et al. 2020). Skills encompass communication, analytical, leadership, personal, management, and technical skills (Al-Mashari et al. 2003; Park et al. 2007; Rouhani & Ravasan 2013). Social factors involve the internalisation of subjective culture and interpersonal agreements (Venkatesh et al. 2003). Human resource management covers recruitment, assessment, development, and retention of qualified employees (Rouhani & Ravasan 2013). Training and education involve activities for staff skill acquisition, including a training plan and strategy for effective training.

The Project dimension comprises three sub-dimensions: Project management, Project team competence, and ERP selection. Project management involves applying management principles, tools, and techniques to oversee large and complex ERP projects (Ghosh & Skibniewski 2010). Project team competence includes the emotional, managerial, and intellectual skills of the project manager and team members necessary to achieve project objectives (Oh & Choi 2020). ERP selection covers activities related to choosing an ERP package, including assessing feasibility, cost, and consulting services.

The Performance dimension includes three sub-dimensions: Organisational performance, Overall efficiency, and Usage performance. Organisational performance measures internal efficiency, competitiveness, and profitability (Chatzoglou et al. 2016). Overall efficiency refers to the improved coordination and task efficiency facilitated by the ERP system (Chou & Chang 2008). Usage performance pertains to the utilisation metrics generated by the ERP system (Park et al. 2007). SLR 1 indicates that successful ERP implementation and post-implementation are linked to numerous CSFs organised into seven dimensions and twenty-three sub-dimensions with specific focuses.

CSFs have been applied to assess the maturity levels of business processes in the post-implementation of an ERP system (Monkwe & Prinsloo 2016; Grube & Wynn 2018; dos Santos-Neto & Costa 2019). ERP systems feature tools to monitor key performance indicators (KPIs) from business data, aiding in the evaluation of BPM maturity levels specific to the organisation (Grube & Wynn 2018). During the post-implementation phase, the ERP system will be refined to better support and align with the business processes of the organisation (Monkwe & Prinsloo 2016).

In SLR 1 Phase 3, fourteen papers on ERP system maturity models were reviewed and summarised in Table H.3 in Appendix H, categorised by publication year, application area, measurement item, and maturity level. The table indicates that the CSF measurement items for ERP system maturity are derived from three types: High-level CSFs, CSFs for Specific Capabilities, and CSFs for Specific KPAs. Of the 14 papers, six employ a 5-level maturity model, three use a 4-level model, three use a 6-level model, and two use a 3-level model. CSFs for Specific Capabilities are the most common in nine of the papers, High-level CSFs appear in three, and CSFs for Specific KPAs are present in two.

(3) Selection of CSFs as Measurement Items for ERP Maturity Models

In maturity models, the selection of appropriate CSFs for measurement items depends on the design of the model. If maturity levels are defined by CSFs, then CSF-related measurement items are suitable. If defined by capabilities, then capability-related items are more appropriate. If defined by KPAs, then KPA-related items are suitable. Typically, the assessment of maturity levels involves a combination of generic and specific CSFs, capabilities, and KPAs, based on the domain-specific characteristics of the model.

In Appendix H, Table H.3, nine out of fourteen ERPMMs use CSFs for specific capabilities as measurement items, three models use high-level CSFs, and two use CSFs for specific KPAs. Despite most maturity models being defined by capabilities, it is feasible to utilise CSFs in capability-based definitions.

CSFs are stable, overarching factors critical to an organisation's success, representing its strategic objectives and long-term goals. They provide a high-level view and are less subject to short-term changes. Specific capabilities are more dynamic and evolve over time in response to changing technological environments and organisational needs. Formulating CSFs in terms of both generic and specific descriptions of capabilities allows a versatile and comprehensive approach to evaluating maturity levels. This approach enables both management and technical staff to contribute to the assessment process. CSFs provide a foundational framework, while specific capabilities can adapt to evolving circumstances, such as Industry 4.0 advancements.

(4) Examples of the Use of CSFs as Measurement Items for ERP Maturity Models

CSFs are more generic and generalisable than capabilities, making them useful for measuring organisational maturity in an ERP system. Capabilities, however, are specific to a particular organisation or industry and measure the organisation's ability to perform specific tasks or functions. Organisational capabilities arise from leveraging the combined competencies and abilities of individuals, though the organisation may not embody the same overall strengths (Ulrich & Smallwood 2004). Therefore, the connection between an organisation's operating environment and CSFs collectively makes CSFs a more reliable predictor of the organisation's capabilities to achieve its mission (Caralli et al. 2004).

The use of capabilities as measurement items often involves very specific descriptions, such as, “The company has the capability to collect, store, and manage big data effectively, captured from physical objects and external elements, to enhance plant productivity and minimise downtime through predictive analytics” (Wagire et al. 2021). In contrast, descriptions of CSFs are usually more generic and applicable across various organisations, for example, “Utilisation of machine-to-machine communication” (Schumacher et al. 2016). While a specific capability-related measurement item might be challenging for a non-technical employee to address, a more general CSF-related item can be answered by most employees and managers. CSFs are therefore more versatile and easier to apply and assess across different organisations.

(5) Adding Dimensions of CSFs for Industry 4.0 ERP Maturity Models

After reviewing the CSF dimensions of seven out of fourteen ERPMMs listed in Table H.3 in Appendix H that incorporate Industry 4.0, a new dimension, "Products & Services," has been introduced. This dimension includes two sub-dimensions: "Disruptive Business Models," which covers business model innovation and digital business models, and "Smart Products/Services," involving the digitalisation of offerings and data analytics for customisation. Additionally, two new sub-dimensions have been added under the existing "Technology" dimension: "Innovation," which includes smart factories, smart operations, and agile capabilities, and "Compliance & Security," addressing IT and digital security, as well as compliance within the organisation and with stakeholders. Assessing risks and managing cybersecurity threats have become crucial considerations for ERP systems.

Table 2.9 summarises additional CSF dimensions for ERP Maturity Models in Industry 4.0, reproduced from Table H.4 with sources.

Table 2.9 Summary of Additional CSF Dimensions and Measurement Items for Industry 4.0 in ERP Maturity Models

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
Technology	Innovation	Operations technology, Innovation management, Technological innovations
	Compliance & Security	Enterprise networks security policies, Data security & data privacy
Products & Services	Disruptive business models	Business model innovation, Digital business models
	Smart products/services	Smart manufacturing, Smart product/factory, Individualisation of products, Digitalisation of products, Product integration into other systems

2.2.2. SLR 1: Discussion of Key Findings

SLR 1 reviewed papers published from January 2000 to September 2021. In Phase 2, after applying inclusion and exclusion criteria, fifty-five of eighty papers were retained: forty-two on CSFs for ERP implementation success and thirteen on CSFs for ERP post-implementation success. These were categorised into seven dimensions of CSFs. Phase 3 identified fourteen papers on maturity models for ERP systems. The ERPMMs developed or adapted are classified according to specific dimensions and sub-dimensions from SLR 1, with various measurement items from CSFs.

The key contribution of this research is identifying a previously overlooked gap in the literature regarding the dual use of CSFs. CSFs have been used not only to predict ERP implementation and post-implementation success but also as measurement items in ERP maturity models over the past two decades. The research demonstrates that CSFs effectively measure organisational maturity with new ERP systems. Using fuzzy analytical approaches like Qualitative Comparative Analysis (QCA), researchers and practitioners can compare CSFs to determine their importance for ERP success. This has significant implications for board, senior management, project management practice, and academia. To better understand the importance of CSFs for Industry 4.0 capabilities in ERP systems, a further systematic literature review is recommended to identify current knowledge and gaps related to contingency effects and performance implications of Industry 4.0 technologies.

RQ1.1 aimed to identify and categorise CSFs into dimensions for use as measurement items in assessing ERP maturity models. This involved identifying CSFs related to both ERP implementation and post-implementation success and organising them into dimensions and sub-dimensions (see Table H.2).

RQ1.2 investigated additional dimensions of CSFs for measuring the maturity of organisations using new generation ERP systems. The original seven dimensions were revised to include eight dimensions with twenty-seven sub-dimensions to account for Industry 4.0 integration (see Table H.4). This extended framework provides a contemporary approach for assessing ERP maturity models and includes fourteen studies on ERP maturity, with seven focused on Industry 4.0.

CSF dimensions represent specific capability areas, process areas, design objects, or constructs for assessing maturity models (Rafael et al. 2020). Each dimension is described by various sub-dimensions or qualitative descriptions for maturity levels. This study found that the CSF dimensions and sub-dimensions used to evaluate ERP maturity models were tailored to the measurement focus of each model.

A comprehensive classification framework of CSFs for ERP system maturity assessment is shown in Table 2.10. This framework includes the addition of dimensions of CSFs for Industry 4.0 ERP maturity models. It highlights the specific indicators and sub-dimensions used for assessing ERP system maturity. This CSF framework is the main theoretical contribution of SLR 1, which can be used by researchers to classify the dimensions their maturity models are measuring. It also allows for expansion by adding sub-dimensions if new sub-dimensions are identified with advancements in ERP system technologies.

Table 2.10 Classification Framework of CSFs for ERP System Maturity Assessment

High Level Dimensions	**Sub-dimensions**	**Specific CSF Indicators**
Governance	Change management	Change agents & leadership; Management readiness for change; Scope for change; Management of change
	Strategic planning	Business plan/ vision/ goals/ justification; Clear goal/ objectives/ strategy; Acquisition strategy; Strategic IT plans & governance
	Top management support	Top management engagement/ involvement/ commitment/ awareness/ incentives; Dedicated resources; Funds support; Leaders support
Culture	Organisational culture	Learning & development; Participative decision making; Power sharing; Support & collaboration; Conflicts & risk tolerance culture
	Employee morale	Employees' morale and motivation
Technology	Customisation	Customisation of ERP; Organisational fit of ERP; Minimal customisation; ERP adaptation
	Compatibility	ERP compatibility; Legacy systems; Data conversion; Fitness factors
	Quality	Implementation quality; Information, system & service quality; Data accuracy; Data migration; Vendor quality & support
	IT infrastructure	Technological complexity; IS resources; IS capabilities; System integration; System use
	Innovation	Operations technology, Innovation management, Technological innovations
	Compliance & Security	Enterprise networks security policies, Data security & data privacy

Table 2.10 Classification Framework of CSFs for ERP System Maturity Assessment

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
Operation	Business process management	Business process improvement; Business process re-engineering (BPR); Process formalisation
	Cooperation	Cross-functional/Inter-departmental cooperation; Network relationships; Connectedness with user departments
People	User satisfaction	Key user satisfaction; Employee satisfaction; Ease of use; User expectations
	Perceived usefulness	Shared belief in system benefits; Shared understanding of implemented technology; Behavioural intention; Individual impact
	Skills	Communication/ analytical/ leadership/ personal/ management/ technical skills; ERP experience/ expertise; Learning skills; User learning capacity; Users' absorptive capacity
	Social factors	Users attitude towards ERP system; Facilitating conditions; Near-term/ Long-term consequences; Affect; Competitive pressure
	Human resource management	Recruit, appraise, develop and preserve qualified employees
	Training and education	Training of personnel; Train IT staff in new skills; Training plan; Well-established education and training strategy; Effective training
Project	Project management	Project justification; Full-time project manager; Project champion; Proven implementation plan; Project planning; Cost benefit analysis; Leadership; Steering committee
	Project team competence	Project team empowerment; Teamwork participation/ composition; Team with multiple skills; Knowledge management competence; Group cohesion
	ERP selection	Feasibility of ERP project/ consulting services/ costing issues; ERP package selection; Use of consultants
Performance	Organisational performance	Measurement of internal efficiency, competitiveness, profitability; Organisational objective consensus/ readiness/ impact; Performance evaluation & management/ auditing & control
	Overall efficiency	Coordination improvement; Task efficiency
	Usage performance	Utilisation performance/ metrics

Table 2.10 Classification Framework of CSFs for ERP System Maturity Assessment

High Level Dimensions	Sub-dimensions	Specific CSF Indicators
Products & Services	Disruptive business models	Business model innovation, Digital business models
	Smart products/services	Smart manufacturing, Smart product/factory, Individualisation of products, Digitalisation of products, Product integration into other systems

2.3. Methodological Approaches for Designing, Assessing and Validating Business Analytics Maturity Models

The second systematic literature review (SLR 2) addressed the research gap in the methodological approaches to designing, assessing, and validating BAMMs. It categorises existing research to build a rigorous approach, as detailed in Appendix I (Wong et al. 2021).

SLR 2 identified a research gap, RG2.3, concerning the limited documentation and explanation of BAMMs and their empirical processes. SLR 2 will guide the selection of a suitable methodological approach for designing, assessing, and validating the BARCMM in Chapters 4 to 6. Through reviewing, comparing, and analysing methodological approaches in existing BAMMs, the research aims to establish a robust foundation and framework for developing the BARCMM. This will ensure the use of an appropriate and rigorous methodological approach informed by existing research and practices for designing, assessing, and validating BAMMs.

2.3.1. SLR 2: Results

(1) BI/BA Maturity Models

In Appendix I, after SLR 2 Phase 3, the eight papers related to BI/BA maturity models, are summarised in Table I.2. This table shows that previous research evaluated BI/BA maturity models concerning their characteristics, methodological approaches for design, assessment, and validation, as well as key results and findings. This results in three BIMMs and five BAMMs offering some insights into the methodological approaches for the design, assessment, and validation of BI/BA maturity models.

Table I.3 summarises the properties, characteristics, and references of BI/BA maturity models. Wendler (2012) found in a systematic mapping study that while many publications focus on empirical development of maturity models, there is a shortage of theoretical reflective works demonstrating how these models can be grounded in both theory and practice.

(2) Business Intelligence Maturity Models

Three of the eight identified BI/BA maturity models are BIMMs. Table 2.11 compares BIMMs (design, assessment, and validation), as extracted from the original Table I.4 in Appendix I.

Table 2.11 Comparison of BIMMs (Design, Assessment, and Validation)

Author(s)	Design	Assessment	Validation
Lahrmann et al. (2011) [Academia]	Quantitative bottom-up approach (Rasch with cluster analysis)	Questionnaire results: 51 cross-industry companies	Not specified.
Lukman et al. (2011) [Academia]	Quantitative bottom-up approach (K-Means algorithm)	Questionnaire results: 131 cross-industry companies	Not specified.
Raber et al. (2013b, 2013a) [Academia]	Quantitative bottom-up approach (Rasch with cluster analysis)	Questionnaire results: 51 cross-industry companies	Discussion with three experts on model comprehensiveness, self-assessment, and BI roadmap

(3) Results of SLR 2: Business Analytics Maturity Models

In Appendix I, five of the eight identified BI/BA maturity models listed in Table I.2 are BAMMs. Table 2.12 provides a comparison of these BAMMs (design, assessment, and validation), as extracted from the original Table I.5.

The BAMMs include the Business Analytics Capability Maturity Model (BACMM) by Cosic et al. (2012); Cosic (2020), which is an academic BAMM, the TDWI Analytics Maturity Model by Halper and Stodder (2014), the INFORMS Analytics Maturity Model by The Institute for Operations The Institute for Operations Research and the Management Sciences (2017), and the International Institute for Analytics (IIA) Analytics Maturity Model by the International Institute for Analytics (n.d.) International Institute for Analytics (n.d.). Most BAMMs developed by practitioners lack documentation on the foundations of their design. Cosic et al. (2012) based their model development process on Becker et al.'s (2009) construction approach. This demonstrates that BA maturity models can be adapted from those developed for other IT domains such as IT Management.

Table 2.12 Comparison of BAMMs (Design, Assessment, and Validation)

Author(s)	**Design**	**Assessment**	**Validation**
Cosic et al. (2012); Cosic (2020) [Academia] based on Becker et al. (2009)	Model development based on Becker et al. (2009) approach	Sixteen key capabilities aggregated to assess maturity across four BA capabilities, resulting in an overall BA capability measure	Delphi study with expert panel to validate and refine BA Capability Framework
Halper and Stodder (2014) [Practitioner]	Not specified.	Assess enterprises' analytics capabilities	Not specified.
The Institute for Operations Research and the Management Sciences (2017) [Practitioner]	Not specified.	Each dimension has a maximum score of 10 points	Not specified.
Lasrado et al. (2017) [Academia]	Not specified.	Data set analysis and maturity scores using five methods: Additive Logic, Variance Techniques, Cluster, Minimum Constraints, Rasch Analysis	Compared measurement scale sensitivity and maturity stages; validated social media maturity-business value relationship using PLS-SEM
International Institute for Analytics (n.d.) [Practitioner]	Not specified.	Analytics Maturity Assessment evaluated against 33 competencies in five DELTA model categories	Not specified.

Table I.6 compares the Business Analytics Capability Maturity Model (BACMM) with three practitioners' BAMMs. It includes the BACMM, TDWI Analytics Maturity Model, INFORMS Analytics Maturity Model, and the International Institute for Analytics

(IIA) Analytics Maturity Model. The table details aspects such as purpose, origin, stages/levels, dimensions, and assessment.

This analysis highlights distinctions and similarities between BAMMs developed by academia and practitioners. It includes key details such as purpose, origin, stages/levels, dimensions, and assessment methods for models like the BACMM, TDWI Analytics Maturity Model, INFORMS Analytics Maturity Model, and International Institute for Analytics (IIA) Analytics Maturity Model. According to Becker et al. (2009), a maturity model is descriptive if used for as-is assessments of an organisation's current capabilities against given criteria. It is prescriptive if it identifies desirable maturity levels and provides guidelines on improvement measures. Most BAMMs developed by practitioners are prescriptive, using proprietary assessment methods and measurement items.

(4) Methodological Approaches used in Design, Assessment and Validation of Maturity Models

In Appendix I, Table I.7 presents a comprehensive comparison of three methods: Set Theoretic Approach (STA), Rasch Analysis, and Hierarchical Clustering, for developing and validating maturity models

Lasrado et al. (2017) explored the influence of different quantitative methods on the design and assessment of maturity models. Table 2.13 summarises the quantitative methods employed in the design, assessment, and validation of maturity models, adapted from Table I.8 with reference sources. The Set Theoretic Approach (STA) is a qualitative method for exploring complex relationships and identifying necessary and sufficient conditions, suitable for exploratory research. Rasch Analysis is a statistical method for measuring latent variables and validating maturity models, ideal for confirmatory research. Hierarchical Clustering groups cases based on similarity to identify characteristics. The choice of method depends on research goals and data nature. STA is best for exploring relationships, while Rasch Analysis and Hierarchical Clustering are better for confirming pre-existing models.

Table 2.13 Quantitative Methods in Maturity Models Research (Lasrado et al. 2017)

Phase	Method	Assumption	Application Summary
(1) Design	Rasch Analysis	Organisations with higher maturity have high probability of successfully implementing capabilities.	Rasch and cluster analysis used to describe software development process evolution with CMM questionnaire
			Initial MM derived in design phase from Rasch and cluster analysis results
	Set Theory: QCA and NCA applied together	Equifinality assumes multiple paths to maturation	QCA and NCA used to design social media maturity model with six-step procedure
(2) Assessment	Cluster: Two Step Clustering, Fuzzy Clustering	Groups of organisations are homogeneous in specific maturity capabilities	Cluster analysis categorised companies by organisational maturity and information system skill needs
			Clustering used to assess corporate collaboration maturity with mixed-scaled data
	Additive Logic: Summation or average of capabilities, with or without weights	A single linear path to higher maturity; higher maturity implies more capabilities implemented	Summation, simple average, and weighted average (with arbitrary or non-empirical weights) are common in maturity assessments
			Empirical weight calculation using methods like PLS-SEM is rare
	Minimum Constraints: (a) Statistical Squared Distance (SSD)	Single linear path to higher maturity based on the theory of constraints; overall maturity determined by lowest capability level	SSD for each maturity level is calculated using 21 items' characteristic values; organisation is categorised by lowest SSD, weighted by standard deviation at capability level
	(b) Euclidian Distance (EUC)		EUC is computed for a maturity dimension based on responses to specific items
(3) Validation	Variance Techniques: Regression, correlation coefficients, and significance tests	High maturity organisations achieve greater business benefits, performance, and value than lower maturity organisations	Validating maturity using regression and statistical significance tests
			Validating maturity with correlation coefficients against self-reported maturity, benefits, or performance
			Maturity level validated using PLS-SEM

In Appendix I, Figure I.2 shows the Methodological Framework for the Multi-Method Comparative Study of Maturity Models, adapted from Lasrado et al. (2017). This methodological framework can be applied to any maturity models. The figure illustrates: (1) the design and development of the maturity model survey instrument in Phase A, (2) the classification of each organisation into a maturity level in Phase B, and (3) the validation of maturity levels in Phase C.

Table 2.14 shows a comparative summary of methodological phases, descriptions, and techniques adapted from Lasrado et al. (2017).

Table 2.14 Comparative Summary of Methodological Phases and Techniques (Lasrado et al. 2017; Lasrado 2018)

Phase	**Description**	**Techniques**
Design Phase (1)	Development of maturity model survey instrument and classification of organisations.	Set theory, Rasch analysis, survey data, cluster analysis.
Assessment Phase (2)	Classification of organisations into maturity levels using statistical methods.	Clustering, additive logic, minimum constraints, statistical squared distances, Euclidean distances.
Validation Phase (3)	Validation of maturity levels and assessment of business value contribution.	Variance techniques, regression, correlation coefficients, statistical significance tests.

In the Design Phase (1), set theory reduces conditions by merging or dropping them, and Rasch analysis can develop the initial model and reduce measurement items. It can also calculate maturity scores and classify organisations using data from surveys and cluster analysis.

In the Assessment Phase (2), clustering, additive logic, and minimum constraints with statistical squared and Euclidean distances classify organisations into maturity levels.

In the Validation Phase (3), variance techniques such as regression and correlation coefficients with statistical significance tests determine how an organisation's use of BA, based on its assigned maturity level, contributes to business value.

Figure 2.2 provides a comparative view of Figure I.2, the Methodological Framework for the Multi-Method Comparative Study of Maturity Models (Lasrado et al., 2017), and Figure I.3, the Methodological Approach used in the Design, Assessment, and Validation of BI/BA Maturity Models (Raber et al., 2013b), as originally presented in Figures I.2 and I.3.

(5) Methodological Approaches used in Design, Assessment and Validation of BI/BA Maturity Models

In Appendix I, Figures I.2 and I.3 outline methodologies for studying and developing maturity models. Figure 2.3 compares Figure I.2, the Methodological Framework for the Multi-Method Comparative Study of Maturity Models (Lasrado et al., 2017), with Figure I.3, the Methodological Approach for BI/BA Maturity Models (Raber et al., 2013b).

Figure I.2 presents a comprehensive, multi-method approach for comparing maturity models as described by Lasrado et al. (2017). Figure I.3 focuses on the design, assessment, and validation of Business Intelligence/Business Analytics (BI/BA) Maturity Models by Raber et al. (2013a), detailing the specifics of BI/BA maturity modelling.

Figure I.2 highlights that the main design approaches for constructing maturity models are Rasch analysis and set theory (Lasrado et al., 2017). Rasch analysis is predominantly used for both design and assessment phases of BI/BA maturity models. Lahrmann et al. (2011) proposed a rigorous approach combining Rasch analysis and hierarchical cluster analysis to construct maturity models. Rasch analysis helps in the inductive allocation of organisational capacities to different maturity levels, supporting rigorous design and development (Cleven et al., 2014). Hierarchical clustering analysis offers a less subjective method for assigning organisational capabilities to maturity levels (Lahrmann et al., 2011).

Raber et al. (2013a) adapted Lahrmann et al.'s approach to develop an empirically grounded maturity model. They used Rasch analysis and hierarchical clustering to assess and classify BI maturity on a standardised scale, assigning measurement items to corresponding maturity levels. Their BI maturity instrument linked BI maturity to business benefits, assuming that higher BI maturity correlates with greater business benefits. This approach, detailed in Figure I.3, can be applied beyond BI to address methodological weaknesses in other BAMMs and includes: (1) design and development of a BIMM survey instrument in Phase A, (2) classification of organisations into BI maturity levels in Phase B, and (3) validation of BI maturity levels in Phase C.

Table 2.15 shows a comparative summary of methodological phases, descriptions, and techniques adapted from Raber et al. (2013b, 2013a).

Table 2.15 Comparative Summary of Methodological Phases and Techniques (Raber et al. 2013b, 2013a)

Phase	**Description**	**Techniques**
Phase A	Design and development of a Business Intelligence Maturity Model (BIMM) survey instrument.	Rasch analysis
Phase B	Classification of each organisation into a BI maturity level.	Hierarchical clustering analysis
Phase C	Validation of BI maturity levels.	Rasch analysis, Hierarchical clustering analysis, and PLS-SEM

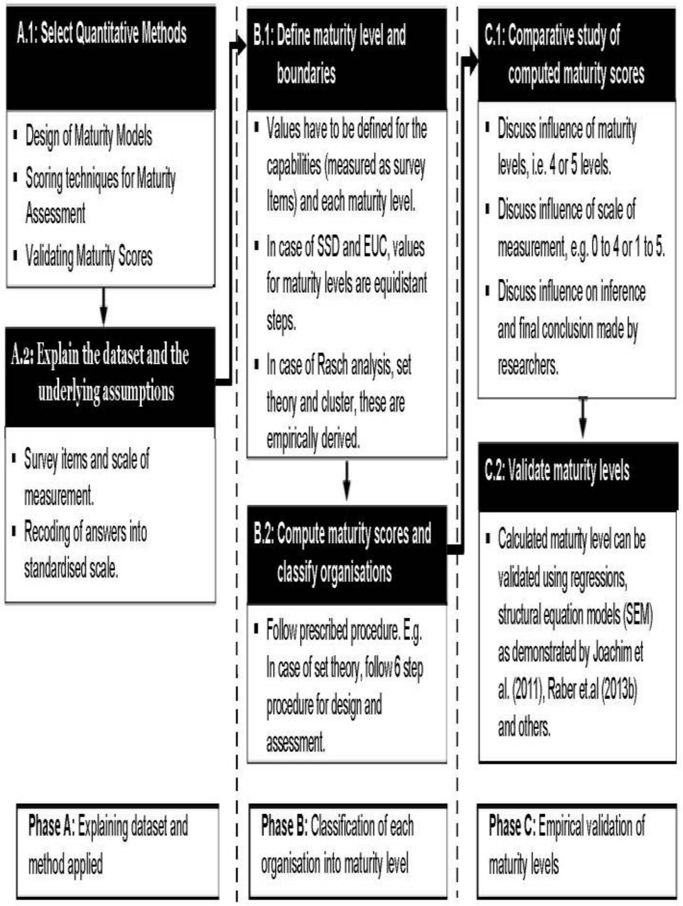

Figure I.2 Methodological Framework for the Multi-Method Comparative Study of Maturity Models (Lasrado et al. 2017)

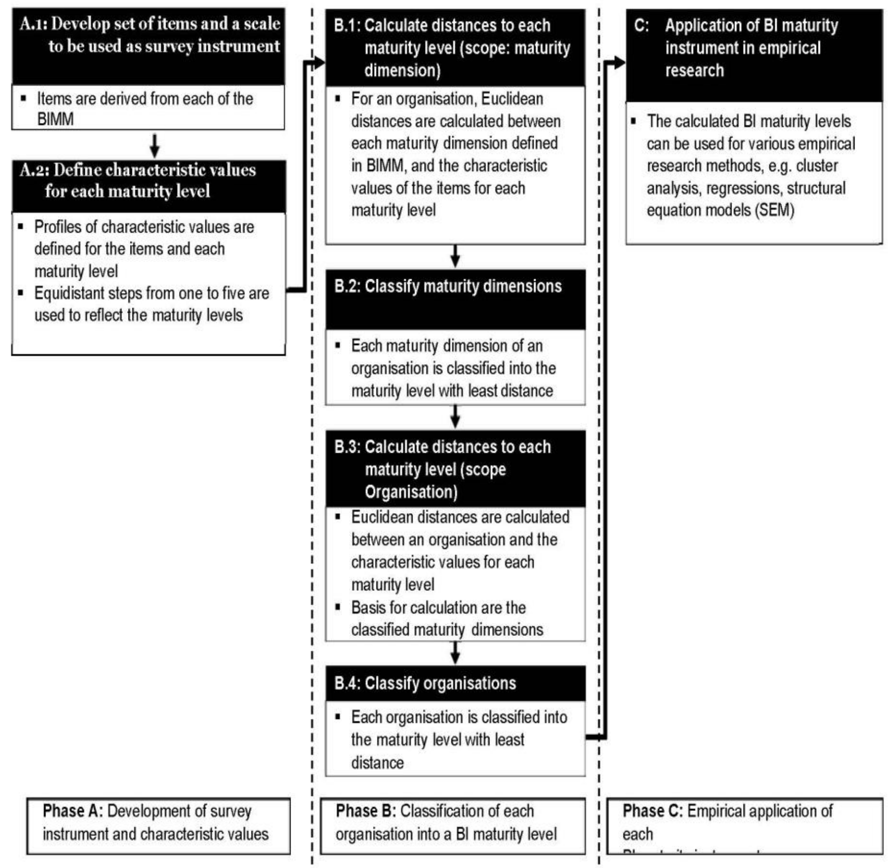

Figure I.3 Methodological Approach used in Design, Assessment and Validation of BI/BA Maturity Models (Raber et al. 2013b)

Figure 2.2 Comparative View of Maturity Model Methodologies (Lasrado et al., 2017; Raber et al., 2013b)

2.3.2. SLR 2: Discussion of Key Findings

SLR2 on methodological approaches for designing, assessing, and validating maturity models identified that: (1) key design methods include Rasch analysis and set theory; (2) main assessment methods are Cluster, Additive Logic, Minimum Constraints using Statistical Squared Distance, and Euclidean Distance; and (3) principal validation methods involve variance techniques, regression, correlation coefficients, and tests for significance against self-reported maturity, perceived benefits, or performance. Raber et al.'s (2013a) rigorous approach to developing a BIMM introduces a novel application of Rasch and cluster analysis for assessing maturity levels, which could be useful for constructing BAMMs. Academic BAMMs are predominantly descriptive, while practitioner-developed BAMMs are prescriptive. Practitioners aim to provide measurable outcomes for organisations, driven by financial incentives and the need to safeguard intellectual property, which limits detailed disclosure of design principles and assessment methods. In contrast, academic BAMMs are often not empirically validated in real-world settings, highlighting a gap between academic research and practical application. Thus, there is a need for more empirical studies to validate BAMMs both in design and assessment.

2.4. Measuring Business Analytics Maturity in ERP Systems

The third systematic literature review (SLR 3) was conducted on measuring BA maturity for organisations using ERP systems. Details of SLR 3 are provided in Appendix J.

Two research gaps were identified in SLR 3. RG2.1 is the limited documentation of methodological approaches in designing, assessing, and validating BAMMs. RG2.2 is the lack of research on adapting BAMMs underpinned by CSFs for new-generation ERP systems. The key findings of SLR 3 will guide and inform the development of the BARCMM for this research in Chapter 4.

2.4.1. SLR 3: Results

(1) Results of SLR 3: ERP Maturity Models

SLR 3 examines the design, assessment, and validation of BA maturity models for organisations using ERP systems. It posits that organisations with advanced ERP maturity are better equipped to utilise BA tools effectively. This, in turn, yields greater benefits. Literature on ERP Maturity Models is summarised in Table J.2 (Appendix J). The summary details their focus, maturity levels, measurement items, design, assessment, and validation.

There are three stage-based and twelve level-based ERP maturity models. Stage-based models define sequential maturity stages, each representing higher organisational capabilities and building upon the previous stage (Van Steenbergen et al. 2013; Lasrado et al. 2015). In contrast, level-based models define distinct maturity levels with specific criteria, allowing flexible progression (Van Steenbergen et al. 2013; Lasrado et al. 2015). Level-based models are more common and widely used due to their granularity, flexibility, ease of implementation, and broader industry adoption (Lasrado et al. 2015).

Ten of the fifteen ERPMMs use capabilities as measurement items, three use CSFs, and two use Key Process Areas (KPAs). The choice of measurement items depends on the maturity model design. If maturity levels are defined by capabilities, then capability-related items are suitable. CSFs, being more generic, can describe capabilities and KPAs. Many maturity models use questionnaires answered by management executives, making CSFs widely used instead of capabilities and KPAs (Merkus et al. 2020). Organisational capabilities emerge from leveraging individual competencies, although the organisation may not embody these strengths (Ulrich & Smallwood 2004). Thus, the link between an organisation's environment and CSFs makes them reliable predictors of organisational capabilities (Caralli et al. 2004).

An observation on using capabilities as measurement items is that they are usually very specific, for example, "The company has the capability to collect, store, and manage big data effectively, captured from physical objects and external elements, to improve plant productivity and minimise downtime through predictive analytics" (Wagire et al. 2021). In contrast, CSFs are more generic and generalisable, for example, "Utilisation of machine-to-machine communication" (Schumacher et al. 2016). Specific capability items may not be easily answered by non-technical employees. However, generic CSF items can be answered by most employees and managers and are more applicable across different organisations (Wong & Lane 2023). BPMMMs applied to ERP systems only measure the alignment of the business with ERP functionality and business process improvement. Other aspects of ERP systems are not measurable by BPM maturity models. Systematic literature reviews indicate extensive research on BPMMMs (Röglinger et al. 2012; Chaghooshi et al. 2016; Tarhan et al. 2016). A detailed analysis of BPMMMs is beyond the scope of this research.

Table J.3 in Appendix J compares fifteen ERP maturity models, covering their focus, research methodologies, and assessment methods. It provides information on aspects such as the number of models, types of measurement items, design, assessment, and validation. It also covers the evolution of models to incorporate Industry 4.0 technologies. The table also summarises authors, years, focus areas, research methodologies, and assessment methods. The focuses of these ERPMMs include Business Processes (Hammer 2007), ERP Usage (Holland & Light 2001; Parthasarathy & Ramachandran 2008; Gërvalla 2020), ERP Integration (Hwang & Grant 2014; Rockwell Automation 2014), Extended Enterprise (Deloitte 2017; Pulkkinen et al. 2019), Manufacturing Operations (Castor et al. 2016), and Industry 4.0 (Lichtblau et al. 2015; Geissbauer et al. 2016; Schumacher et al. 2016; Rafael et al. 2020; Wagire et al. 2021; Senna et al. 2023). Research methodologies in ERPMMs are either qualitative, quantitative, or a combination of both (Lasrado 2018; Menukhin et al. 2019). Common data collection methods for classifying maturity levels are self-assessment with surveys and third-party assessments evaluated by experts (Wendler 2012). Quantitative methods include cluster analysis, additive logic, and minimum constraints using statistical squared distances and Euclidean distances (Wong et al. 2021). Additive logic, which involves summing or averaging capabilities, is commonly used, assuming a linear path to higher maturity with more capabilities implemented (Chung et al. 2017). Clustering methods, such as conditional assessment logic, Two-Step Clustering, and

Fuzzy Clustering, assume homogeneity within groups of organisations across specific maturity capabilities (Benbasat et al. 1980).

(2) Results of SLR 3: Business Intelligence and Business Analytics Maturity Models

Table J.4 in Appendix J summarises eight papers in ascending order of publication year, illustrating how previous research assessed BI/BA maturity models in terms of focus, design, assessment, and validation. Five academic BI/BA maturity models include documentation on their design, whereas three practitioner models do not. Cosic et al. (2012) propose a model development process based on Becker et al.'s (2009) construction approach, demonstrating that BA maturity models can be adapted from IT Management models. All four BAMMs use capabilities as measurement items, vary in the number of maturity levels (3 to 5), and employ quantitative methods like Rasch analysis or K-Means algorithm. Design processes generally involve Rasch analysis and cluster analysis to derive maturity levels. Assessment methods include additive logic in BACMM and TDWI Analytics Maturity Model, and K-means clustering in BIMMs, with some incorporating qualitative evaluations by domain experts. While some models lack validation, Cosic (2020) used a Delphi study to refine the BA Capability Framework, and Raber et al. (2013b) discussed their model with industry experts to ensure comprehensiveness.

Table 2.16 summarises how previous research evaluated BI/BA maturity models in terms of design, assessment, and validation. This summary is adapted from Table J.4 in Appendix J. Five academic BI/BA maturity models include design documentation, while three practitioner models do not. Cosic et al. (2012) propose a development process based on Becker et al.'s (2009) approach, showing that BA maturity models can be adapted from other IT domain models. All four BAMMs use capabilities as measurement items, with maturity levels ranging from 3 to 5 and employing techniques like Rasch analysis or K-Means algorithm. The design process typically involves Rasch analysis and cluster analysis. Assessment methods include additive logic in models such as BACMM and TDWI Analytics Maturity Model, and K-means clustering in BIMMs, with some models including qualitative evaluations by domain experts. While some models lack validation, Cosic (2020) used a Delphi study to refine the BA Capability Framework, and Raber et al. (2013b) consulted industry experts to confirm their model's comprehensiveness.

Table 2.17 compares three BIMMs and five BAMMs based on their focus and assessment methods. This summary is adapted from Table J.5 in Appendix J. It provides general observations on various BI/BA maturity models. The research methodologies include qualitative and quantitative approaches, self-assessment tools, and empirical models, with a predominant emphasis on quantitative assessments for evaluating maturity levels. Assessment methods vary, employing additive logic, cluster analysis, and partial least squares, while engaging organisations through self-assessment questionnaires or interviews to encourage active participation in the evaluation process. According to Becker et al. (2009), a maturity model is descriptive if it assesses the current capabilities of an organisation against given criteria, and prescriptive if it outlines how to achieve desirable maturity levels and provides improvement guidelines. Most maturity models developed by practitioners are prescriptive and use proprietary assessment methods and measurement items. Unlike ERPMMs, none of the BA/BI MMs considered Industry 4.0 technologies. This absence of Industry 4.0 considerations in BA/BI MMs supports the rationale for integrating ERPMMs with BAMMs for organisations using ERP systems.

Table 2.16 Comparison of BIMMs/BAMMs: Maturity Models, Focus, Design, Assessment, and Validation

Maturity Model and Focus	**Design of BIMM/BAMM**	**Assessment of BIMM/BAMM**	**Validation of BIMM/BAMM**	**Source**
BIMM design and assessment	Quantitative bottom-up approach (Rasch and cluster analysis)	Rasch analysis with clustering	Not specified	Lahrmann et al. (2011) [Academia]
BIMM design, assessment and validation	Quantitative bottom-up approach (K-Means algorithm)	K-means clustering	Qualitative evaluation experts interpreted results to check consistency and integrity	Lukman et al. (2011) [Academia]
BAMM design, assessment and validation (BACMM)	Model development based on approach of Becker et al. (2009)	Additive logic	A Delphi study with an expert panel used to validate and refine BA Capability Framework constructs	Cosic et al. (2012); Cosic (2020) [Academia]
BIMM design, assessment and validation	Quantitative bottom-up approach (Rasch and cluster analysis)	Rasch analysis with clustering	Discuss final model with three industry experts on self-assessment, and BI roadmap.	Raber et al. (2013b) [Academia]
BAMM assessment (TDWI Analytics Maturity Model)	Not specified	Additive logic	Not specified	Halper and Stodder (2014) [Practitioner]
BAMM assessment (INFORMS Analytics Maturity Model)	Not specified	Additive logic	Not specified	The Institute for Operations Research and the Management Sciences (2017) [Practitioner]
BAMM comparison (Social media analytics)	Set theory	5 methods: Additive Logic, Variance Techniques, Cluster, Minimum Constraints, Rasch Analysis	Relationship between social media maturity and business value validated using PLS-SEM technique.	Lasrado et al. (2017); Lasrado (2018) [Academia]
BAMM assessment (Analytics Maturity Model)	Not specified	Additive logic	Not specified	International Institute for Analytics (n.d.) [Practitioner]

Table 2.17 Focus and Assessment Methods in BIMMs/BAMMs

Author(s), Year,	Focus	Assessment Method
Lahrmann et al. (2011) [Academia]	BIMM design and assessment: BI dimensions derived from existing literature, Dimensions: Strategy, Organisation/ Process, IT support	Rasch analysis with clustering: Calculates distances to maturity levels within maturity dimensions. Classifies maturity dimensions. Calculates distances to maturity levels for organisations. Classifies organisations into the maturity level with least distance.
Lukman et al. (2011) [Academia]	BIMM design, assessment and validation: Development and validation of a BIMM for organisations in Slovenia	K-means clustering: Uses the algorithm to minimise sum of squared errors (SSE). Determines optimal cluster number by plotting SSE values. Classifies organisations into maturity levels by clustering.
Cosic et al. (2012); Cosic (2020) [Academia]	BAMM design, assessment and validation: Assess BA initiatives within large-scale Australian organisations	Additive Logic: Applies maturity scale to 16 BA capabilities. Aggregates levels to measure maturity across four high-level capabilities and overall BA capability.
Raber et al. (2013b) [Academia]	BIMM design, assessment and validation: Dimensions: Strategy, Social System, Technical System, Quality, Use/Impact	Rasch analysis with clustering: Calculates distances to maturity levels within maturity dimensions. Classifies maturity dimensions. Calculates distances to maturity levels for organisations. Classifies organisations into the maturity level with least distance.
Halper and Stodder (2014) [Practitioner]	BAMM assessment: Predictive analytics, social media/ text analytics, cloud computing, and big data analytics approaches	Additive Logic: Questions are presented individually or in matrices, possibly weighted by importance. Each dimension can score up to 20 points, with sections scored separately and averaged across dimensions.
The Institute for Operations Research and the Management Sciences (2017) [Practitioner]	BAMM assessment: Benchmarking capabilities and identifying actions to improve the analytical maturity	Additive Logic: Assesses 12 questions on a 1-10 scale, allowing goal setting with target dates. Offers detailed maturity level summaries per factor with visualised charts.
Lasrado et al. (2017); Lasrado (2018) [Academia]	BAMM comparison: Influence of quantitative methods on maturity models using social media analytics dataset	Additive Logic, Variance Techniques, Cluster, Minimum Constraints, and Rasch Analysis.
International Institute for Analytics (n.d.) [Practitioner]	BAMM assessment: Optimising performance by improving analytics capabilities	Additive Logic: Maturity Assessment includes 33 competencies across five DELTA model categories. Scores range from 1.00 to 5.99, aligning with five descriptive maturity stages.

2.4.2. SLR 3: Discussion of Key Findings

The third systematic literature review (SLR3) examined ERPMMs and BIMMs/BAMMs in papers published from January 2000 to December 2023. It retained twenty-two papers: eight on BIMMs/BAMMs and fifteen on ERPMMs. No papers specifically addressed BAMMs for organisations using ERP systems. However, eight papers focused on the design, assessment, and validation of BIMMs/BAMMs, and fifteen on ERPMMs. The review highlights a gap in literature regarding BAMMs for assessing BA maturity in ERP systems. Existing research lacks integration of BA maturity assessment in ERP contexts. To fill this gap, a dedicated BAMM framework for ERP could be developed by adapting existing BIMMs/BAMMs and ERPMMs.

Some BAMMs, including BIMMs, evolved from MMs for IT management. These models focus on an organisation's analytics capability to manage data and inform business decisions. BAMMs evaluate how effectively organisations use resources to derive value from data. The three BIMMs and five BAMMs identified in this research use capabilities as measurement items rather than CSFs and KPAs. ERPMMs, which evolved from MMs for BPM, focus more on process and business alignment. They assess how organisations use ERP systems for performance improvement. In this research, 64% of ERPMMs use capabilities as measurement items, 22% use CSFs, and 14% use KPAs.

A systematic review of methods for designing, assessing, and validating maturity models revealed that: (1) key design methods include Rasch analysis and set theory; (2) primary assessment methods are Cluster, Additive Logic, Minimum Constraints using Statistical Squared Distance, and Euclidean Distance; and (3) major validation methods involve variance techniques using regression and correlation coefficients with significance tests to confirm self-reported maturity, perceived benefits, or performance. The approach of using Rasch and cluster analysis for developing a BIMM, as adopted by Raber et al. (2013a, 2013b), is applicable to BAMMs. Academic BAMMs are generally descriptive, detailing business analytics maturity but lacking improvement guidance, whereas practitioner-developed BAMMs are prescriptive, assessing current maturity and recommending specific actions. This distinction highlights a gap between academic research and practical application, underscoring the need for more empirical studies to design, assess, and validate BAMMs.

To address RQ2.1 "What are the main methodological approaches used to design, assess, and validate BAMMs?", ERPMMs (see Table J.2) and BIMMs/BAMMs (see Table J.4) in Appendix J were identified and categorised for application in determining BA maturity of organisations using ERP systems. The three BIMMs developed by academia used a quantitative bottom-up approach, employing (1) Rasch analysis supported by cluster analysis to derive maturity levels (Lahrmann et al. 2011; Raber et al. 2013b) or (2) K-Means algorithm (Lukman et al. 2011). Rasch analysis with cluster analysis is a rigorous method for designing and assessing maturity models. A new BAMM for ERP systems can use these methods to classify BA maturity levels, but reliability and convergent validity need confirmation through further empirical studies. Practitioners may use focus groups to qualitatively evaluate maturity levels after initial online surveys. Academic models are often validated by testing the hypothesis that higher maturity levels correlate with higher perceived success, using PLS-SEM.

To answer RQ2.2, "How can the BA maturity level of an organisation using a new generation of ERP system be determined by adapting existing ERP and BA maturity models?", this study found that additive logic is the most widely used method for assessing maturity levels, involving weighted scores defined by experts or pre-set criteria. However, this method is prone to bias. A more rigorous approach, such as conditional assessment logic to map scores to maturity levels, is needed to overcome subjective biases. Practitioner-developed models are often more used than academic ones but lack transparency in methodology and tools (Dikhanbayeva et al. 2020). A key research gap is the limited access to and scrutiny of the theory and methodology behind practitioners' models. Most practitioner models use simple additive or conditional logic and online self-assessment tools but lack methodological rigour. For new-generation ERP systems, particularly those supporting Industry 4.0, maturity models must integrate CSFs and adapt to technological advancements by incorporating CSFs into measurement items and assessing readiness across dimensions such as technological capability, organisational alignment, and strategic integration.

2.5. Identifying Research Gaps for Developing the BARCMM

The development and evaluation of the BARCMM are aimed at assessing the BA readiness and capability maturity of organisations using ERP systems in the GCR. The objectives include: (1) identifying CSFs for ERP BA readiness, developing effective measurement methods, and determining dimensions for assessing ERP maturity models; (2) focusing on identifying CSFs for BA capability, exploring measurement methodologies, and reviewing existing research for the empirical design and validation of the BARCMM; and (3) investigating the relationship between ERP BA readiness and BA capability, developing a maturity model, measuring the BA maturity of organisations using ERP systems by applying IRT, and examining the correlation between BA maturity, perceived capability, and perceived ERP BA success.

The findings of SLR 1 emphasise the significance of CSFs organised into eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services) as a basis for evaluating ERP system success and maturity levels. It suggests that future research should focus on the selection of context-specific CSFs to further enhance the assessment framework. The implications of the findings of SLR 1 for the development of BARCMM are summarised in Table 2.18. SLR 1 highlights the importance of CSFs across various dimensions for assessing ERP success and maturity, revealing a research gap (RG1) in CSFs for ERP BA readiness. Future studies should focus on context-specific CSFs to enhance assessment frameworks. These insights are crucial for developing the BARCMM.

Table 2.18 Findings of SLR 1 and Implications for BARCMM Development

Aspect	Findings of SLR 1	Implications for BARCMM Development
Focus on CSFs	Emphasises the significance of CSFs organised into eight dimensions.	Highlights the need to identify context-specific CSFs for assessing BA readiness and capability specifically for organisations using ERP systems.
Dimensions Identified	Identifies eight dimensions: Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services.	These dimensions can guide the development of the BARCMM framework and measurement methods.
Research Recommendations	Suggests future research should focus on the selection of context-specific CSFs.	Encourages empirical studies to validate the identified CSFs and their relevance to BA readiness.
Assessment Framework	Proposes CSFs as a basis for evaluating ERP system success and maturity levels.	Supports the creation of an assessment framework within BARCMM to evaluate BA readiness and maturity.
Implications for Future Research	Calls for enhanced focus on context-specific CSFs to refine assessment tools.	Stresses the importance of continuous research to adapt and improve the BARCMM based on industry-specific needs.

The findings of SLR 2 identify a notable gap in research regarding BAMMs tailored for organisations using ERP systems. It proposes the methodology by Raber et al. (2013b, 2013a), which effectively integrates Rasch analysis and clustering techniques to provide a comprehensive assessment of maturity levels, linking these levels to business success. The implications of the findings of SLR 2 for the development of BARCMM are summarised in Table 2.19. SLR 2 identifies a significant research gap concerning BAMMs tailored for ERP systems (RG2). It proposes a methodology integrating Rasch analysis and clustering to comprehensively assess maturity levels, linking them to business success. This gap highlights the need for a more methodologically rigorous approach in applying CSFs for BA capability measurement within ERP contexts, aligning with the objectives of the BARCMM.

Table 2.19 Findings of SLR 2 and Implications for BARCMM Development

Aspect	Findings of SLR 2	Implications for BARCMM Development
Focus on BA Maturity Models	Identifies a gap in BA maturity models specific to organisations using ERP systems.	Highlights the need to develop a tailored BA maturity model within BARCMM for organisations in the GCR.
Methodology Proposal	Proposes the Raber et al. (2013b, 2013a) methodology, which integrates Rasch analysis and clustering techniques.	Recommends adopting this methodology within BARCMM to assess BA maturity levels effectively and comprehensively.
Comprehensive Assessment	Provides a method for linking maturity levels to tangible business success.	Supports BARCMM in measuring the contribution of BA capability to business success in organisations using ERP systems.
Research and Validation Focus	Emphasises empirical design and validation of BA maturity models for BARCMM.	Advocates for rigorous empirical testing and validation of the proposed BA maturity model to ensure its reliability and validity.

The findings of SLR 3 highlight the lack of specific BAMMs for organisations using ERP systems. It suggests that existing models can be adapted by incorporating ERP profile measurement items and recommends the use of rigorous methods such as Rasch analysis and cluster analysis for evaluating maturity levels (Raber et al. 2013b, 2013a). Additionally, it calls for improved documentation and empirical validation of BAMMs to strengthen research in this area. The implications of the findings of SLR 3 for the development of BARCMM are summarised in Table 2.20.

Table 2.20 Findings of SLR 3 and Implications for BARCMM Development

Aspect	Findings of SLR 3	Implications for BARCMM Development
Lack of Specific Models	Highlights the absence of specific BA maturity models for organisations using ERP systems.	BARCMM must address this gap by developing tailored maturity models for BA in ERP contexts.
Adaptation of Existing Models	Suggests existing models can be adapted by incorporating ERP profile measurement items.	BARCMM should integrate ERP profile items to enhance relevance and applicability in assessments.
Methodological Recommendations	Recommends using rigorous methods such as Rasch analysis and cluster analysis for evaluating maturity levels.	BARCMM should incorporate these methodologies to ensure a robust assessment framework.
Need for Documentation	Calls for improved documentation and empirical validation of BAMMs.	BARCMM development should include comprehensive documentation and empirical testing to validate findings.

SLR 1, SLR 2, and SLR 3 collectively identify high-level research gaps (RG1, RG2, and RG3) crucial for developing the BARCMM to assess BA readiness and capability in organisations using ERP systems in the GCR. SLR 1 reveals RG1, highlighting a lack of research on context-specific CSFs for ERP BA readiness, emphasising the need for tailored assessment frameworks. SLR 2 identifies RG2, noting the absence of BAMMs specifically for ERP systems and proposing a robust methodology integrating Rasch analysis and clustering to assess maturity levels linked to business success. Finally, SLR 3 highlights RG3, pointing out the lack of specific BAMMs for ERP contexts and recommending adaptations of existing models alongside rigorous methods for evaluating maturity. These findings underscore the necessity of empirical validation and the integration of CSFs based on Item Response Theory, guiding the objectives of the BARCMM to enhance BA maturity assessment in organisations. A summary of findings from SLRs 1, 2, and 3 and corresponding research gaps for BARCMM development is given in Figure 2.3.

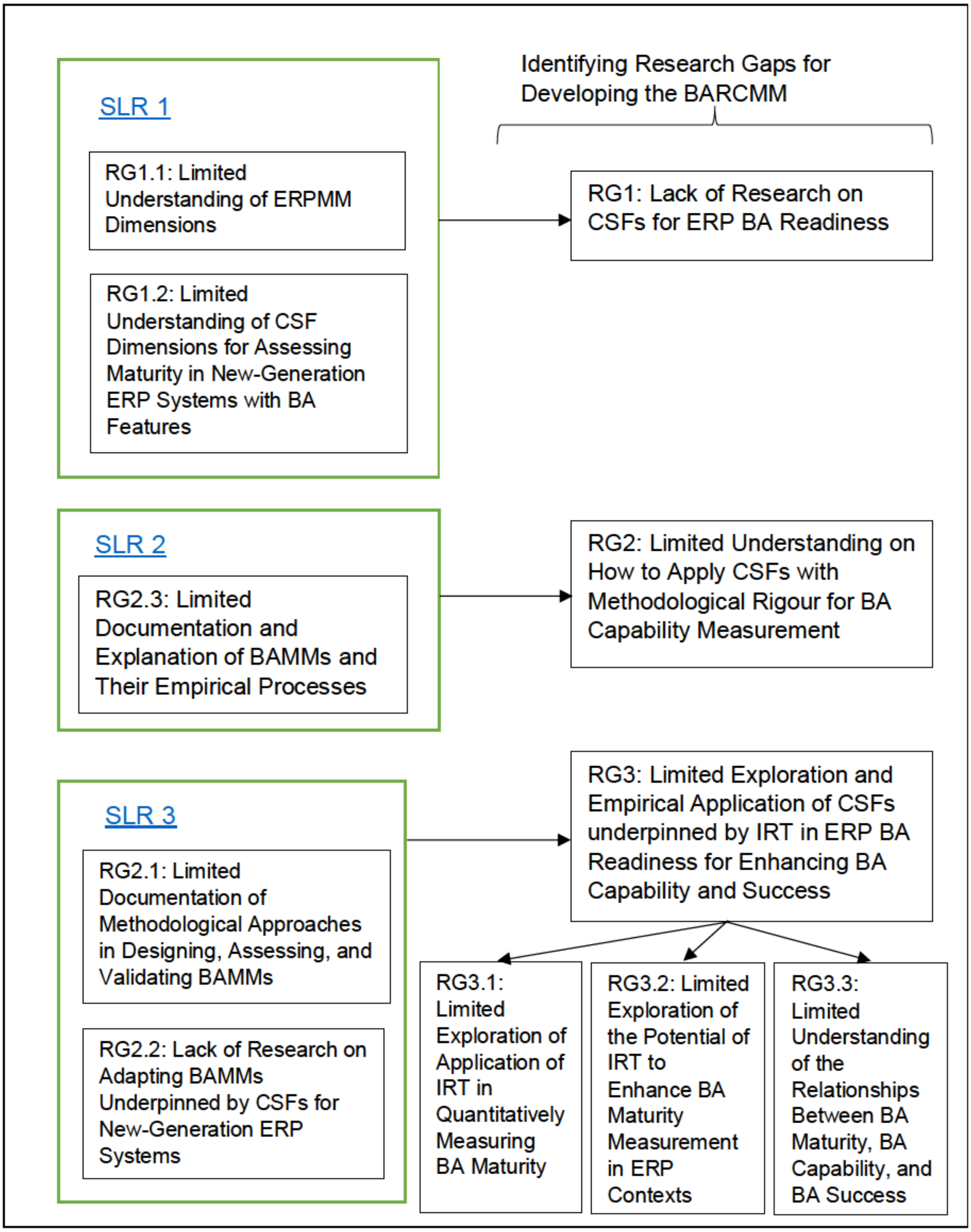

Figure 2.3 Summary of Findings from SLRs 1, 2, and 3 and Corresponding Research Gaps for BARCMM Development

The three high-level research gaps identified were: (RG1) a lack of research on CSFs for ERP BA readiness; (RG2) a limited understanding of applying CSFs with methodological rigour for BA capability measurement; and (RG3) a limited exploration and empirical application of CSFs underpinned by item response theory in ERP BA readiness. These gaps were addressed through the development of the BARCMM and Surveys 1 and 2, which aligned with research questions RQ1, RQ2, and RQ3.

High-level research gap (RG3) highlights the limited exploration and empirical application of CSFs underpinned by IRT in ERP BA readiness, which is essential for enhancing BA capability and success. This overarching gap connects closely with three low-level research gaps: RG3.1, RG3.2, and RG3.3.

RG3.1 focuses on the limited application of IRT for quantitatively measuring BA maturity, emphasising the need for a rigorous approach that existing models often lack. While RG3 identifies the need for detailed exploration of CSFs related to BA capability, RG3.1 introduces IRT as a robust method to address the inadequacies in current maturity models. By incorporating IRT, RG3.1 enhances the understanding of BA success within ERP systems, complementing RG3's emphasis on identifying impactful CSFs.

RG3.2 addresses the need for better reliability and validity in BA maturity measurement items through IRT, specifically in organisational contexts. Building on RG3, this gap underscores how IRT can refine measurement approaches, drawing on prior research like that of Raber et al. (2013a) to improve assessment accuracy. By exploring IRT's application, RG3.2 aims to bolster the methodologies used to evaluate BA maturity, further supporting RG3's objective of enhancing understanding of BA readiness.

RG3.3 concerns the relationships between BA maturity, capability, and success, which are crucial for understanding the factors that drive BA success in ERP systems. This gap ties back to RG3 by using insights from identified CSFs to investigate how BA maturity influences capability and success. Addressing RG3.3 allows for a more comprehensive examination of how these elements interrelate, providing a clearer picture of the dynamics at play in BA success.

The high-level research gap (RG3) and three low-level research gaps (RG3.1, RG3.2 and RG3.3) were addressed through the design of the BARCMM and the implementation of measurement instruments in Surveys 1 and 2. The empirical results will be analysed in Chapter 5 to provide insights into RQ3.1, RQ3.2, and RQ3.3.

2.6. Chapter Summary and Conclusion

2.6.1. Chapter Summary

Chapter 2 is structured to provide the groundwork for the detailed discussions in SLR 1, SLR 2, and SLR 3. It introduces key concepts and terminology essential for understanding the subsequent chapters. SLR 1 conducts a systematic literature review to develop the classification framework for CSFs in measuring organisational maturity using ERP systems. This includes aspects such as conceptual definitions, the use of CSFs in ERP maturity models, and the selection and application of CSFs as measurement items. SLR 2 conducts a systematic review of methodological approaches for designing, assessing, and validating BAMMs. It explores various methodological approaches that are used in the design, assessment, and validation of BIMMs/BAMMs. SLR 3 conducts a systematic literature review that focuses on measuring Business Analytics Maturity in ERP Systems, examining topics such as Business Intelligence/Business Analytics Maturity Models and the resource-based theory of competitive advantages in ERP systems.

The key findings from SLRs 1, 2, and 3 are foundational concepts about using CSFs as measurement items underpinning the development and evaluation of maturity models. These findings set the stage for Chapter 4, which is dedicated to the development and evaluation of the BA Readiness and Capability Maturity Model.

SLR 1 was conducted from 2000 to 2021 to investigate the implementation and post-implementation success of ERP systems, focusing on CSFs for categorising measurement items in ERP maturity models (ERPMMs). Most studies predate 2010, with later research from 2014 to 2021 examining newer ERP generations in the context of Extended Enterprise and Industry 4.0 maturity models. The SLR identifies that CSFs can be generic or specific, commonly used to assess organisational maturity levels. Notably, earlier studies did not consider Industry 4.0 technologies, prompting the inclusion of additional CSF dimensions such as Innovation, Compliance & Security, and Smart Products & Services in response to this gap. This research presents a CSF classification framework consisting of eight dimensions, accommodating Industry 4.0's impact on ERP systems, which serves as a guide for researchers and practitioners. Future studies should aim to refine the selection of

CSFs tailored to specific industry contexts and enhance the rigor in designing ERPMMs for maturity assessment. Limitations include potential oversight of relevant papers due to sourcing restrictions.

SLR 2 revealed that most papers on BI/BA maturity models provide general descriptions but lack technical detail on methodological applications. Many use Rasch analysis, assuming maturity increases in equidistant steps, for systematic and rigorous maturity level determination. Rasch analysis is widely used in maturity model construction, while Lasrado Lasrado et al. (2017) employ set theory with QCA and NCA to reduce measurement items. However, the validity and reliability of these instruments need larger sample testing. Future research should focus on empirical studies to validate the usefulness of BAMMs in quantifying business value from BA in organisations. Raber et al.'s (2013a) approach, integrating Rasch analysis and clustering, is considered superior for assessing BI/BA Maturity Models due to its methodological rigour, empirical grounding, comprehensive assessment, practical business outcome alignment, and applicability beyond BI. Therefore, the BARCMM will incorporate Rasch analysis and clustering for determining BA readiness and capability maturity in organisations using ERP systems. This approach is preferred for its rigorous methodology, empirical grounding, comprehensive assessment, business benefits linkage, broad applicability, validation techniques integration, and practical connectivity.

SLR 3 explored papers on ERPMMs and BAMMs, focusing on how BAMMs can be empirically designed, assessed, and validated for organisations using ERP systems. BA initiatives in new-generation ERP systems can be evaluated for business value using a BAMM. Dominant methodological design approaches include Rasch analysis and set theory. Assessment methods include Cluster, Additive Logic, and Minimum Constraints. Multivariate techniques validate the relationship between self-reported maturity and perceived benefits from BA initiatives. This research offers insights into the design, assessment, and validation of BAMMs for next-generation ERP systems, enabling rigorous measurement of BA maturity. Existing ERP and BAMMs can be adapted to assess BA maturity for leveraging advanced BA capability in ERP systems. Further empirical studies will confirm BAMM reliability for organisations using new-generation ERP systems, ensuring rigorous measurement of BA maturity.

2.6.2. Chapter Conclusion

In conclusion, this chapter has laid a strong foundation by extensively reviewing ERP systems in the context of BI and BA. Key concepts such as the integration of organisational processes through ERP systems, the transformation of data into actionable insights via BI, and the evolution towards BA for informed decision-making have been explored. Additionally, discussions on BA Readiness and Capability, ERP interactions with BA, and previous BI and BA maturity models have emphasised structured approaches for successful implementation within ERP systems. The chapter also introduced the BARCMM, highlighting the use of IRT models for item selection and Rasch analysis in evaluating measurement instrument quality. The conclusions of SLR 1, SLR 2, and SLR 3 provide insights that set the stage for the further development and evaluation of the BARCMM in Chapters 4 to 6.

SLR 1 contributes significantly to understanding how CSFs, organised across extended dimensions, can form the basis for measurement items to assess ERP system success and maturity levels. It also proposes strategies for incorporating Industry 4.0 impacts into ERPMM assessments using CSFs. Future studies are recommended to establish systematic approaches for selecting context-specific CSFs and to adopt rigorous methodologies for designing and assessing ERPMM maturity levels. The dimensions identified in this SLR, CSF classification framework consist of eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services), providing insights into the dimensions and questionnaires related to CSFs used in ERP BA Readiness of the BARCMM. The first five dimensions (Governance, Culture, Technology, Operation, People) selected in this SLR serve as measurement items for ERP BA readiness assessment in organisations using ERP systems. These dimensions are common to both CSFs in ERP implementation and BA readiness in ERP systems. It is assumed that companies making full use of ERP systems, integrating them with business partners upstream and downstream, will benefit from shared data among stakeholders, leading to improved business analytics capabilities and perceived BA success.

SLR 2 concludes that while there is considerable generic research on BI/BA maturity models, there is a lack of specific application to BAMMs for organisations using ERP systems. This gap highlights the need for targeted research in this area.

The commonly used Rasch analysis, which assumes equidistant steps in maturity levels, provides a systematic and rigorous basis for maturity assessment. Despite its widespread use, the validity and reliability of these measurement instruments require testing with larger sample sizes. To address RQ2.3, two methodological approaches were identified. Raber et al.'s (2013a) approach, combining Rasch analysis and clustering, significantly surpasses Lasrado et al.'s (2017) set-theoretical approach in BI/BA MMs. This methodology is distinguished by its rigorous and systematic incorporation of both Rasch analysis and hierarchical clustering in the design and assessment phases, providing a robust foundation for maturity model development. Empirical grounding enhances the model's validity and reliability, while comprehensive assessment via Rasch analysis and nuanced maturity level determination through hierarchical clustering further strengthen the approach. Additionally, the methodological approach by Raber et al. (2013b) links maturity levels to business benefits, extends its applicability beyond BI, and integrates thorough validation techniques. This connectivity between academic research and practical application, yielding measurable outcomes, establishes it as a superior approach for assessing BA maturity and organisational capability. The main contribution of SLR 2 is the finding that the method by Raber et al. (2013b, 2013a) can be adapted to design, assess, and validate BA maturity for organisations using ERP systems. This adaptation is detailed in Chapter 4, with empirical study results using the BARCMM presented in Chapter 5. These chapters illustrate the effective application of the method for a comprehensive evaluation of BA maturity levels in ERP systems.

SLR 3 concludes that there are no specific maturity models for assessing BA maturity in organisations using ERP systems. However, existing BAMMs can be adapted by adding ERP profile measurement items, including BA readiness and capability profiles. Many instruments use Rasch analysis, assuming maturity increases in equidistant steps, and set theory with QCA and NCA is used to reduce measurement items (Lasrado et al. 2017). To address RQ2.1, gaps in literature highlight the need for better documentation and empirical validation of BAMM methods. For RQ2.2, determining BA maturity in new-generation ERP systems involves identifying specific CSFs, integrating them as measurement items, and adapting existing frameworks. Rasch and Cluster Analysis provide a rigorous assessment method, ensuring organisations' capabilities are randomly selected for validity. Recommendations include enhancing BAMMs with profile questions aligned with Industry 4.0 and reinforcing BA capabilities in ERP systems, forming the BARCMM's basis. Future research should empirically validate BAMMs in real-world settings to quantify the business value of BA in organisations using new-generation ERP systems.

CHAPTER 3: RESEARCH METHODOLOGY

Chapter 3 outlines and justifies the research methodology used in the doctoral research. Section 3.1 provides an overview of the research aims and the chosen research framework. It outlines the rationale for selecting philosophical foundations, analytical methods, survey designs, analysis techniques, and research procedures. Section 3.2 outlines how each chapter aligns with the positivist research paradigm, emphasising systematic literature reviews and quantitative methods, and illustrates the relationship between each research phase, its corresponding chapter, and the relevant research questions. Section 3.3 outlines the methodological approach used in the research, detailing its suitability and significance for designing and evaluating the BARCMM. Section 3.4 outlines a structured research process that developed and validated a Business Analytics readiness and capability maturity model for organisations using ERP systems in the GCR. This process adhered to rigorous methodological principles, including problem formulation, literature review, theoretical framework development, research design, data collection, analysis, maturity profile definition, classification, validation through PLS-SEM, and drawing conclusions. The research maintained methodological integrity and ethical considerations throughout. Section 3.5 discusses the data collection strategies employed, covering the rationale, sampling design, and specifics of data collection across research phases. Section 3.6 outlines data-analysis strategies, deriving insights using Rasch analysis, hierarchical cluster analysis, and PLS-SEM to test hypotheses, addressing validity and inference quality. Section 3.7 discusses Rasch analysis, hierarchical cluster analysis, and PLS-SEM, alongside measures to ensure reliability. Section 3.8 outlines ethical considerations, emphasising adherence to human ethics principles and the guidelines of the University of Southern Queensland. Finally, Section 3.9 summarises the key elements, providing a clear understanding of the research methodology and setting the stage for the subsequent chapters. Figure 3.1 shows the structure of Chapter 3.

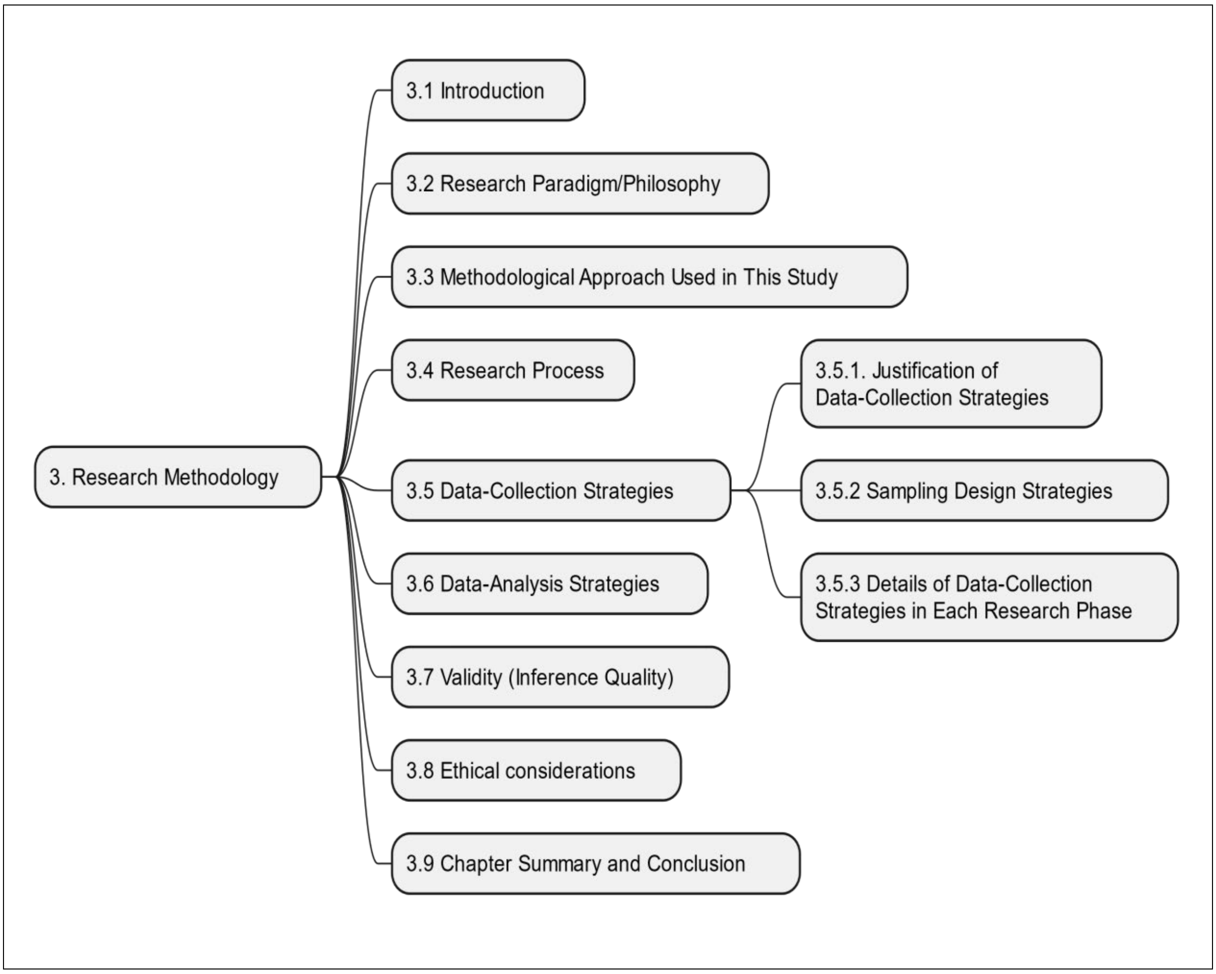

Figure 3.1 Structure of Chapter 3

3.1. Introduction

This chapter outlines the research methodology for designing, developing, and evaluating the Business Analytics Capability Readiness and Maturity Model (BARCMM). The BARCMM assesses BA readiness and capability of organisations using ERP systems in the GCR. The study, grounded in a positivist paradigm, employed quantitative methods to address research questions and test hypotheses, assuming reality is objective and measurable (Park, Konge & Artino Jr 2020; Dominion Dominic & Mahamed 2023). Questionnaires were used for data collection and analysis. The BARCMM development followed a rigorous approach guided by Rasch analysis, a 1-parameter logistic (1PL) IRT technique (Dekleva & Drehmer 1997; Lahrmann et al. 2011; Raber et al. 2013b), and included Rasch and hierarchical cluster analysis to design and evaluate maturity levels (Lahrmann et al. 2011; Raber et al. 2013b; Lasrado et al. 2015; Wong et al. 2021). Rasch analysis, based on item response theory, evaluates the probability of endorsing specific options, facilitating generalisability and assessing unidimensionality and item functioning (Hagquist et al. 2009; Combrinck 2020; Stemler & Naples 2021).

To develop and evaluate the BARCMM, two surveys were conducted, each measuring nine dimensions of Business Analytics Readiness and Capability Maturity (governance, culture, technology, people, operations, data source, analytics, collaboration capability, and sharing capability). Survey 1 consisted of 40 items, while Survey 2 included 58 items, both with a consistent set of item anchors. These surveys adapted measurement items from previous studies and were analysed using Rasch analysis and hierarchical clustering.

The research process is summarised in Figure 4.2, and involves three phases. In BARCMM Phase A, the survey instruments were developed based on the essential characteristics of the BARCMM. The measurement items were measured using a seven-point Likert scale. Ideal maturity profiles with characteristic values were defined for each level of maturity in BARCMM Phase B, and hierarchical clustering was applied to classify organisations into maturity levels based on the Euclidean distance metric. In Phase C, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to empirically assess the relationship between BA maturity, BA capability, and BA success in organisations using ERP systems.

3.2. Research Paradigm/Philosophy

The relationship between chapters and the research paradigm/philosophy is summarised in Table 3.1.

Table 3.1 Research Paradigms and Methods by Chapter

Chapter/Section	Research Paradigm/Philosophy	Description
Chapter 2, Section 2.2 (SLR 1)	Primarily positivist	Systematic literature review for ERP maturity assessment, rooted in empirical and objective methods (Wong & Lane 2023).
Chapter 2, Section 2.3 {SLR 2)	Positivist with methodological rigour	Systematic analysis and quantitative techniques for designing, assessing, and validating BAMMs (Wong et al. 2021).
Chapter 2, Section 2.4 (SLR 3)	Balanced positivism and interpretivism	Combines empirical research and methodological rigour with contextual understanding of organisational phenomena. Focuses on data-driven validation of BAMMs and their relevance to ERP systems.
Chapter 4	Positivist	Quantitative methodology for developing the BARCMM.
Chapter 5	Positivist	Uses quantitative methods, such as Rasch analysis and PLS-SEM, to evaluate BA maturity, assess relationships with ERP BA success, and analyse organisational capabilities.

Figure 3.2 shows the relationship between each research phase, its chapter, and the associated research questions.

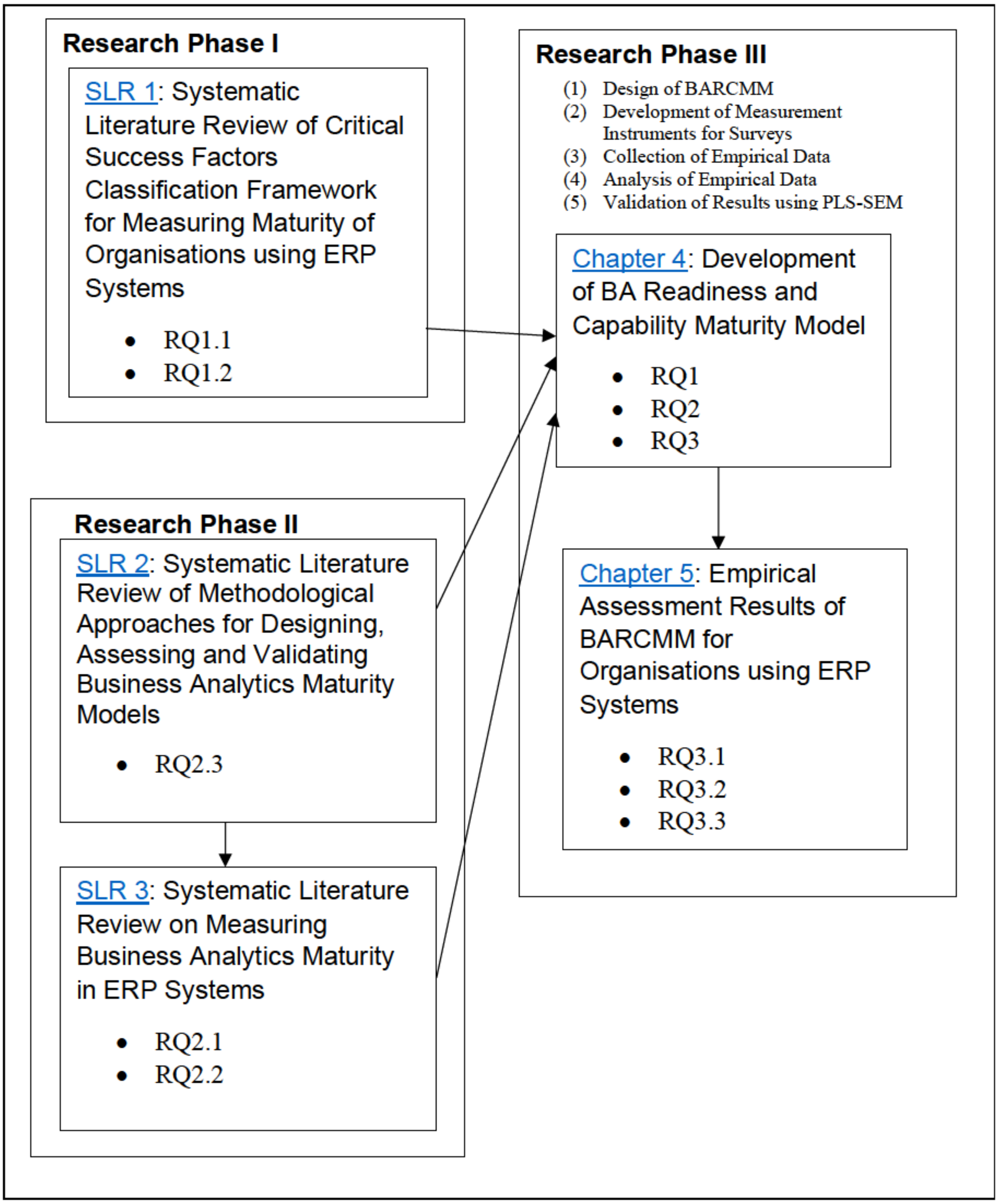

Figure 3.2 The Relationship Between Research Phases, Chapters, and Research Questions

In Chapter 2, SLR 1 primarily operates within a positivist research paradigm. The chapter details and explains the results and findings of a systematic literature review (SLR) aimed at identifying and categorising the CSFs necessary for assessing the maturity levels of organisations using ERP systems. This paradigm is rooted in empirical and objective methods of knowledge acquisition, employing a structured and rigorous approach to gather and analyse relevant literature, which aligns with the chapter's overarching goals of exploring the applicability of CSFs as measurement dimensions for ERP maturity models.

The research paradigm/philosophy in SLR 2 in Chapter 2 centres on achieving methodological rigour and systematic analysis for the design, assessment, and validation of BAMMs. The aim of SLR 2 is to identify the appropriate methodological approach for designing, assessing, and validating BAMMs. It is primarily dedicated to ensuring the robustness and credibility of the BARCMM developed within the study. The approach taken involves comprehensive investigations into BAMMs, commencing with clear objective definition and scope delineation. It then delves into the methodologies employed. This chapter aims to lay a solid foundation for comprehending maturity models, focusing specifically on BIMMs and Business Analytics Maturity Models, elucidating their distinctive attributes and applications. The research methodology dissects the methodological approaches employed in designing, assessing, and validating these models, with a specific emphasis on the BI and BA context. By focusing on leveraging quantitative techniques such as Rasch Analysis and cluster analysis, the paradigm exhibits characteristics of a positivist philosophy, prioritising empirical grounding for the development and evaluation of these models. These techniques can be applied to both BI and BA MMs. The overarching objective is to provide a robust and trustworthy framework for assessing and measuring organisational maturity in the domains of BA for organisations using ERP systems.

The research paradigm/philosophy in SLR 3 in Chapter 2 is a balanced combination of positivism and interpretivism. The positivist aspect emphasises empirical research, systematic documentation, and methodological rigour, with a focus on data-driven exploration and validation of concepts such as BAMMs. The interpretive component complements this by acknowledging the need for understanding and interpreting complex organisational phenomena, addressing knowledge gaps, and emphasising the relevance of these concepts to organisations using ERP systems. The Systematic Literature Review in this chapter aims to strike a balance between empirical rigour and a deeper understanding of the subject matter, particularly focusing on BA maturity within ERP Systems.

Chapter 4 is specific to the design and development of the Business Analytics Readiness and Capability Maturity Model (BARCMM) for organisations using modern ERP systems in the GCR. The research paradigm of this chapter is positivist, and the research method used in this chapter is quantitative. The central objective is to provide organisations with a robust framework to systematically assess and enhance their BA capabilities within ERP systems, acknowledging the transformative potential of BA in modern decision-making processes. The research's primary goals encompass discerning critical success factors for BA readiness, identifying BA capability drivers, and scrutinising the interplay between ERP BA readiness and BA capability. This research employs IRT methods, in particular, Rasch Analysis and hierarchical cluster analysis, to design and develop the BARCMM. The chapter's structured subsections offer a systematic approach to creating and validating the BARCMM, with the ultimate aim of aiding organisations in optimising their BA capabilities within ERP systems and gaining a competitive edge in the data-driven business landscape. For the construction and evaluation of the BARCMM in this research, a rigorous and repeatable methodological approach guided by item response theory was employed. Key analytical techniques, including Rasch analysis and hierarchical cluster analysis, were applied to design, develop, and evaluate the maturity levels of the BAMM (Fox & Jones 1998). Rasch analysis, a fundamental component of this research, is rooted in item response theory and evaluates the probability of endorsing different options on measurement items based on item endorsability and the organisation's agreeability. This approach allows for the generalisation of results between samples and items, facilitates the testing of unidimensionality for each survey item, and produces ordered sets of items based on difficulty. It identifies poorly functioning measurement items and unexpected item responses (Fox & Jones 1998).

Chapter 5 reports on how this study aims to provide a rigorous and quantitative assessment of BA maturity in organisations employing modern ERP systems. This approach is rooted in a positivist paradigm, which emphasises the collection and analysis of empirical data to discover objective, quantifiable insights. The use of quantitative methods, such as Rasch analysis and hierarchical cluster analysis, reflects this orientation. This research was conducted within a positivist paradigm, employing a quantitative research methodology to address the research questions (RQ3.1, RQ3.2, RQ3.3) and to test hypotheses H1 and H2. The positivist perspective assumes that reality is objective and can be measured using properties that are independent of the researcher and research instruments (Myers 2019). Quantitative research, a key component of this paradigm, involves the use of questionnaires, surveys, and experimental methods to collect data, which is subsequently analysed and transformed into numerical values for statistical analysis (Hittleman & Simon 1997). Furthermore, Rasch analysis provides a means to transform ordinal counts into linear measures, overcoming issues associated with imperfect unidimensionality in linear measurement of survey items (scales). The assumptions underpinning the use of Rasch analysis suggest that the more capable an organisation is, the more likely it is to succeed in achieving higher levels on relevant measurement items. Conversely, the more difficult the measurement item, the less likely an organisation will achieve success on that item. These fundamental characteristics of Rasch analysis prove highly effective in the design, development, and evaluation of maturity models.

In this research, two surveys (Survey 1 and Survey 2) were employed to collect empirical data for assessing BA maturity levels within organisations using ERP systems. These surveys focused on nine dimensions of BA readiness and BA capability, including governance, culture, technology, people, operations, data capability, analytics capability, collaboration tools capability, and sharing capability. Survey 1 consisted of forty items, while Survey 2 included fifty-eight items, with both surveys sharing the same set of item anchors (Table 3.4).

The development of the BARCMM in this research adopted a methodological approach similar to that used by Raber et al. (2013a) and Lahrmann et al. (2011) for the development of a Business Intelligence Maturity Model, originally developed by Dekleva and Drehmer (1997). The rigorous approach utilised in this model's development is not specific to Business Intelligence and can be applied to other related domains to address methodological weaknesses in the development of BAMMs.

The use of two surveys served a dual purpose: to ensure the reliability of the measurement items and to evaluate the construct reliability and convergent validity of the BARCMM. The surveys allowed for the measurement of BA maturity levels and to test relationship of BA readiness and capability with perceived BA success in organisations using ERP systems (Rouhani & Mehri 2016).

Information systems (IS) research is an applied field that is heavily oriented towards the application of information systems in business. This has meant IS research has tended to have a greater concentration on the practical or methodological issues, rather than the ontological and philosophical reasoning behind a particular research approach (Dobson 2001). It is suggested that if a researcher tests the hypothesis related to the research question, then the deductive research approach is useful; and if the researcher compares the existing theories with the collected data and information, then an inductive research approach is useful. The quantitative stage builds upon the understanding gained in the qualitative stage by collecting data from a large number of people thereby enabling some quantitative analysis (Creswell 2009). Easterby-Smith (2002, p28) argued that the key idea underpinning the positivism paradigm is that the world exists externally and that its properties should be measured through objective methods. This then brings together the epistemology of positivism with quantitative methods. Quantitative survey research design is adopted because it is cost effective and readily efficient way to collect the desired information to provide answers to the specific research questions investigated in this study. A conceptual framework for an ERP business analytics readiness and capability maturity model is formulated adapted from previous empirical models proposed by authors from the literature review (Lahrmann et al. 2011; Raber et al. 2013b) and data is collected using a quantitative survey instrument based on range of factors and dimensions.

The initial BA readiness and capability maturity model for this research was adapted from the measurement dimensions of the BA maturity model developed by Cosic et al. (2012), which itself was based on the BI maturity model by Hawking et al. (2011). The initial measurement instruments were adapted from the work of Rouhani and Ravasan (2013) for ERP profile questions. Additionally, it incorporated measurement items for BA capability based on dimensions used by Halo (2015). Both Hawking et al. (2011) and Halo (2015) provided questionnaire details of critical success factors used to collect and evaluate their BIMMs, which is a good starting point for the development of the survey questionnaire instrument for the initial proposed BARCMM. This model was further refined by adding relevant measurement items based on the essential characteristics of the BARCMM outlined in Appendix C, to assess BA readiness and capability in organisations using ERP systems in the GCR.

The approved questionnaire details are outlined in Appendix B-1 for Survey 1 and Appendix B-2 for Survey 2. Table 3.2 and Table 3.3 summarise the sections and questions for each survey. For exact questions, refer to Appendix B-1 for Survey 1 and Appendix B-2 for Survey 2.

In Survey 2, new questions are included in Part B, while the questions in Part A are identical to those in Survey 1. New measurement items are added after Survey 1 to address the unbalanced distribution of items across maturity levels, particularly the potential lack of measurement depth at the higher maturity levels 4 and 5. In Survey 2, eighteen new ERP BA profile measurement items (gov5, gov6, gov7, gov8, cul5, cul6, cul7, cul8, tec5, tec6, tec7, tec8, peo7, peo8, ope3, ope4, ope5, ope6) are added in Part B of Survey 2 to better assess and support progression towards these advanced levels of maturity, resulting in a total of 51 measurement items across the 5 maturity levels.

Survey 1 results are presented in Section 5.2. Section 5.7 explains the identification of new measurement items for Survey 2, with results in Section 5.9.

Table 3.2 Summary of Questionnaire Sections and Specific Questions in Survey 1

Section	**Specific Questions**
Demographics	Questions 1-3 related to organisation location, type, and industry.
About Yourself	Questions 4-5 concerning position within the organisation and involvement in BA.
General ERP Business Analytics	Questions 6-9 focusing on ERP BA usage, strategy, tools, and implementation duration.
Self-assessment of Critical Success Factors in ERP BA Readiness	Question 10 assessing critical success factors in ERP BAA Readiness in dimensions: Governance (gov1, gov2, gov3, gov4), Culture (cul1, cul2, cul3, cul4), Technology (tec1, tec2, tec3, tec4), People (peo1, peo2, peo3, peo4, peo5, peo6), Operation (ope1, ope2). (See Appendix D)
Perceived ERP BA success	Questions 11 evaluating ERP success levels in data accuracy (accu), ease of use (easy), integration (inte), efficiency (effi), and productivity (prod) (See Appendix E)
Self-assessment of capabilities in Business Analytics	Questions 12-15 about BA Data Capability (dat1, dat2, dat3, dat4, dat5), Analytics Capability (cap1, cap2, cap3, cap4, cap5), Collaboration Tools Capability (too1, too2, too3, too4, too5), and Sharing Capability (sha1, sha2, sha3, sha4, sha5). (See Appendix D)
Perceived BA success	Questions 16 evaluating BA success levels in data capabilities (bas1), analytics capabilities (bas2), collaboration capabilities (bas3), dissemination capabilities (bas4). (See Appendix E)
Concluding Questions	Questions 17-18 regarding additional success factors and interest in further survey participation.

Question 17 includes an open-ended inquiry asking whether there are any ERP/BA success factors that were not included in the Survey 1 questionnaire but are critical to their organisations. This question aims to capture valuable insights and nuances that may not be addressed by the predefined items, enabling respondents to share essential information about what contributes to the success of ERP and BA initiatives within their specific contexts.

Table 3.3 Summary of Questionnaire Sections and Specific Questions in Survey 2

Section	**Specific Questions**
Part A (same as Survey 1) is for new respondents. Participants who took part in Survey 1 only need to complete Part B.	
Demographics	Questions 1-3 related to organisation location, type, and industry.
About Yourself	Questions 4-5 concerning position within the organisation and involvement in BA.
General ERP Business Analytics	Questions 6-9 focusing on ERP BA usage, strategy, tools, and implementation duration.
Self-assessment of Critical Success Factors in ERP BA Readiness	Question 10 assessing critical success factors in ERP BAA Readiness in dimensions: Governance (gov1, gov2, gov3, gov4), Culture (cul1, cul2, cul3, cul4), Technology (tec1, tec2, tec3, tec4), People (peo1, peo2, peo3, peo4, peo5, peo6), Operation (ope1, ope2). (See Appendix D)
Perceived ERP BA success	Questions 11 evaluating ERP success levels in data accuracy (accu), ease of use (easy), integration (inte), efficiency (effi), and productivity (prod) (See Appendix E)
Self-assessment of capabilities in Business Analytics	Questions 12-15 about BA Data Capability (dat1, dat2, dat3, dat4, dat5), Analytics Capability (cap1, cap2, cap3, cap4, cap5), Collaboration Tools Capability (too1, too2, too3, too4, too5), and Sharing Capability (sha1, sha2, sha3, sha4, sha5). (See Appendix D)
Perceived BA success	Questions 16 evaluating BA success levels in data capabilities (bas1), analytics capabilities (bas2), collaboration capabilities (bas3), dissemination capabilities (bas4). (See Appendix E)
Concluding Questions	Questions 17-18 regarding additional success factors and interest in further survey participation.
Part B (new questions not included in Survey 1) is for all respondents in Survey 2. (See Appendix D)	
B1. Capabilities	From your perspective, please enter the percentage contribution of various capabilities to Business Analytics success.
B2. Governance	Rate your agreement on various governance aspects related to Business Analytics in your organisation (gov5, gov 6, gov 7, gov8).
B3. Culture	Rate your agreement on cultural aspects related to Business Analytics initiatives in your organisation (cul5, cul6, cul7, cul8).
B4. Technology	Rate your agreement on technological aspects related to Business Analytics adoption in your organisation (tec5, tec6, tec7, tec8).
B5. People & Operation	Rate your agreement on aspects related to the presence and involvement of staff with analytics skills (peo7, peo8). Rate your agreement on operational aspects and availability of analytics-related processes and tools (ope3, ope4, ope5, ope6).
B6. Interest in Results	Indicate if you would like to receive detailed survey results and provide contact information if interested.

3.3. Methodological Approach Used in This Study

The methodological approach used in the study is primarily positivist in orientation based on the quantitative method of research. Positivism is based on the premise that reality is factual in nature and problems or issues under investigation can be quantified irrespective of the researcher and the instruments used (Myers 2019). Quantitative research is characterised by the collection of data through questionnaires, surveys, and experiments, with the subsequent transformation of this data into numerical values for statistical analysis (Hittleman & Simon 1997). A quantitative survey was used to gather empirical data from organisations in order to develop the Business Analytics Readiness and Capability Maturity Model (BARCMM). This methodological approach provides a systematic and rigorous analysis of the data, facilitating the development of the BARCMM.

In this study, the methodological approach was guided by item response theory, specifically Rasch Analysis with hierarchical clustering, to rigorously and consistently construct the BARCMM (Lahrmann et al. 2011; Raber et al. 2013b; Wong et al. 2021). Rasch analysis and hierarchical cluster analysis were employed to design, develop, and evaluate the maturity levels of BARCMM. Rasch analysis (Fox & Jones 1998), is rooted in item response theory and assesses the likelihood of endorsing specific options for each measurement item based on their endorsability and the organisation's agreeability. Unlike classical test theory, Rasch analysis separates endorsability from agreeability, making it a powerful tool to generalise across different samples and items (Fox & Jones 1998; Boone, W. J. & Noltemeyer, A. 2017). It also helps test the unidimensionality of each survey item by acknowledging that response options for each measurement item may not be evenly spaced. Additionally, Rasch analysis organises items from easy to difficult and identifies poorly functioning measurement items as well as unexpected responses.

In the field of psychometric methodologies applied to the development of measurement instruments, Rasch analysis plays a fundamental role. This analytical approach serves as a systematic and methodological means of categorising the maturity of organisations based on survey results (Boone 2016). Rasch analysis generates both ordinal values and theta (θ) values, serving as a metric to evaluate the complexity of individual items and the competence of respondents along a unified continuum (Dabaghi et al. 2020). Additionally, Rasch analysis incorporates cluster analysis, which is instrumental in deriving five distinct maturity levels. These levels provide a framework for classifying organisations based on their diverse levels of competence (Peter et al. 2016). It is worth highlighting that Rasch analysis employs logit values for scoring responses, with each logit value indicating the relative difficulty of specific items. As a result, this process systematically assigns responses to ascending maturity levels, ranging from 1 to 5. This structured allocation facilitates a comprehensive assessment of organisational proficiency.

Rasch Analysis is a statistical method used for analysing responses to assesses the properties of measurement instruments such as surveys, tests, or questionnaires. Rasch Analysis involves calibrating items and persons, estimating θ values, using cluster analysis to create maturity levels, scoring responses with logit values, and then assigning responses to maturity levels based on the θ values and logit values (Boone et al. 2013; Bond 2015). This systematic approach helps in assessing and categorising individuals or organisations based on their abilities or maturity levels.

The following are the steps involved in Rasch Analysis, as used in this research:

(1) **Item and Person Calibration:** Rasch Analysis begins with calibrating both the items (questions or tasks) and the persons (individual respondents) on a common latent trait or ability scale. This calibration results in ordinal values for both items and persons. The calibration process aims to determine the difficulty of items and the ability of persons on the same measurement scale. The items' calibration is usually represented as item difficulty values, while the persons' calibration is represented as person ability values (Wright 1977).

(2) **Theta (θ) Estimation:** After calibration, Rasch Analysis estimates theta (θ) values for each person (respondent organisation). These θ values represent the person's position on the latent trait continuum. A higher θ value indicates a higher level of the trait (e.g., proficiency, competence), while a lower θ value indicates a lower level (Stemler & Naples 2021).

(3) **Cluster Analysis:** To derive maturity levels or categories, Rasch Analysis often incorporates cluster analysis. Cluster analysis is used to group persons with

similar θ values into clusters or categories. These clusters represent different levels of maturity or proficiency (Becker et al. 2010). The number of clusters is determined based on the research objectives, and it is common to have five distinct clusters, representing the five maturity levels. Since the BARCMM has five maturity levels, five clusters are used in the cluster analysis to determine the organisations into five maturity levels.

(4) **Scoring Responses:** In Rasch Analysis, responses to individual items are scored using logit values. Logit values represent the relative difficulty of each item. Items with higher logit values are considered more difficult, while those with lower logit values are easier (Boone 2016; Ekstrand et al. 2022). Respondents' responses to items are then assigned to specific maturity levels based on their θ values. For example, a respondent with a θ value within a certain range may be classified as belonging to maturity level 3.

(5) **Assignment to Maturity Levels:** Based on the logit values of the responses and the defined clusters from the cluster analysis, responses are systematically assigned to ascending maturity levels, usually ranging from 1 to 5 or as determined by the study. Since most BIMMs use five maturity levels (Becker et al. 2010; Lahrmann et al. 2011; Raber et al. 2013b, 2013a) and the BARCMM also uses five maturity levels, the number of clusters is set to five. Using cluster analysis overcomes subjective problems in defining maturity levels.

The fundamental assumptions applied to measurement items through the use of Rasch analysis are twofold: firstly, that more capable organisations are more likely to succeed on relevant measurement items, and secondly, that the more difficult a measurement item is, the less likely success with that measurement item will be achieved by any organisation. These characteristics of Rasch analysis make it effective for employment in designing, developing, and evaluating maturity models.

To collect data for the development and evaluation of the BARCMM, a quantitative survey instrument was adapted from previous studies (Cosic et al. 2012; Rouhani & Ravasan 2013; Halo 2015; Rouhani & Mehri 2016). Essential attributes of the five maturity levels of the BARCMM created for this research are detailed in Appendix C. The development of BARCMM in this research draws on the methodological approach used by Raber et al. (2013b) and Lahrmann et al. (2011) in creating a Business Intelligence Maturity Model, an approach originally developed by Dekleva and Drehmer (1997). The robust approach employed by Raber et al. (2013a) is adaptable and not limited to Business Intelligence, making it suitable for overcoming previous methodological shortcomings in the development of BAMMs in different industry sector domains.

Using anchor items in Rasch analysis guarantees uniformity and comparability across different survey versions. This approach enables the measurement of identical constructs on a unified scale, comparison of survey results, and validation of the instrument's construct reliability and convergent validity (Boone 2016; Clark & Watson 2019). The rationale for employing two quantitative surveys was two-fold: (1) to explore how the same set of item anchors could be used in subsequent versions of the survey to allow for person (organisation) measurements to be expressed on a single scale for comparison, and (2) to demonstrate how a rigorous approach can ascertain the construct reliability and convergent validity of BARCMM instrument. Two separate online surveys were administered to collect empirical data regarding the Business Analytics maturity levels attained by organisations using an ERP system with Business Analytics tools. These surveys measured nine dimensions: governance, culture, technology, people, operations, data source, analytics, collaboration capability, and sharing capability. Survey 1 comprised forty items, while Survey 2 contained fifty-eight items. Survey 2 is a superset of Survey 1, with both surveys sharing a common set of measurement items. Table 3.4 shows the full list of measurement items used in Surveys 1 and 2. Details of each measurement item can be found in Chapter 4, Table 4.8.

Table 3.4 Survey Items Used in Surveys 1 and 2

Profile	Dimension	Survey 1 Code	Survey 2 Code	Scale
ERP BA Readiness	Governance	gov1, gov2, gov3, gov4	gov1, gov2, gov3, gov4, gov5, gov6, gov7, gov8	1 - 7
	Culture	cul1, cul2, cul3, cul4	cul1, cul2, cul3, cul4, cul5, cul6, cul7, cul8	1 - 7
	Technology	tec1, tec2, tec3, tec4	tec1, tec2, tec3, tec4, tec5, tec6, tec7, tec8	1 - 7
	People	peo1, peo2, peo3, peo4, peo5, peo6	peo1, peo2, peo3, peo4, peo5, peo6, Peo7, peo8	1 - 7
	Operation	ope1, ope2	ope1, ope2, ope3, ope4, ope5, ope6	1 - 7
BA Capability	Data Capability	dat1, dat2, dat3, dat4, dat5	dat1, dat2, dat3, dat4, dat5	1 – 7
	Analytics Capability	cap1, cap2, cap3, cap4, cap5	cap1, cap2, cap3, cap4, cap5	1 - 7
	Collaboration Tools Capability	too1, too2, too3, too4, too5	too1, too2, too3, too4, too5	1 - 7
	Sharing Capability	sha1, sha2, sha3, sha4, sha5	sha1, sha2, sha3, sha4, sha5	1 - 7

Scale: (1) Strongly Disagree; (2) Disagree; (3) Somewhat Disagree; (4) Neutral; (5) Somewhat Agree; (6) Agree; (7) Strongly Agree

To determine the BA maturity level of each organisation, a hierarchical clustering approach was applied. This involved determining ideal maturity profiles and subsequently calculating the distance of an organisation to each maturity level using the Euclidean metric. The maturity level with the smallest Euclidean distance was considered the organisation's BA maturity level.

The BARCMM Phases A and B used for the development and evaluation of the BARCMM is illustrated in Figure 3.3. The complete three-phase approach used for the development and evaluation of the BARCMM is shown in Figure 4.2, and the following highlights the steps in BARCMM Phases A and B:

(1) **BARCMM Phase A:** Guided by the analytical approach of Raber et al. (2013a), a survey instrument was developed based on the essential characteristics of BARCMM. The nine dimensions of Business Analytics capability were measured using forty items in Survey 1 and fifty-eight items in Survey 2. These items were

rated on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). Ideal maturity profiles with typical characteristic values were defined for each maturity level, with the assumption that Business Analytics maturity increases linearly in equidistant steps and that items are measured using a seven-point Likert scale, akin to the approach used by Lahrmann et al. (2011).

(2) **BARCMM Phase B:** A two-stage hierarchical clustering approach, using the Euclidean metric, was employed to calculate the distances to each maturity level (scope: maturity dimension) and classify each maturity dimension of an organisation into the maturity level with the least distance. The Euclidean distance was calculated between the responses of an organisation to specific items belonging to the set of items of a dimension and their defined characteristic values for a specific maturity level. This process determined the maturity level for each dimension of maturity and, subsequently, for the organisation itself.

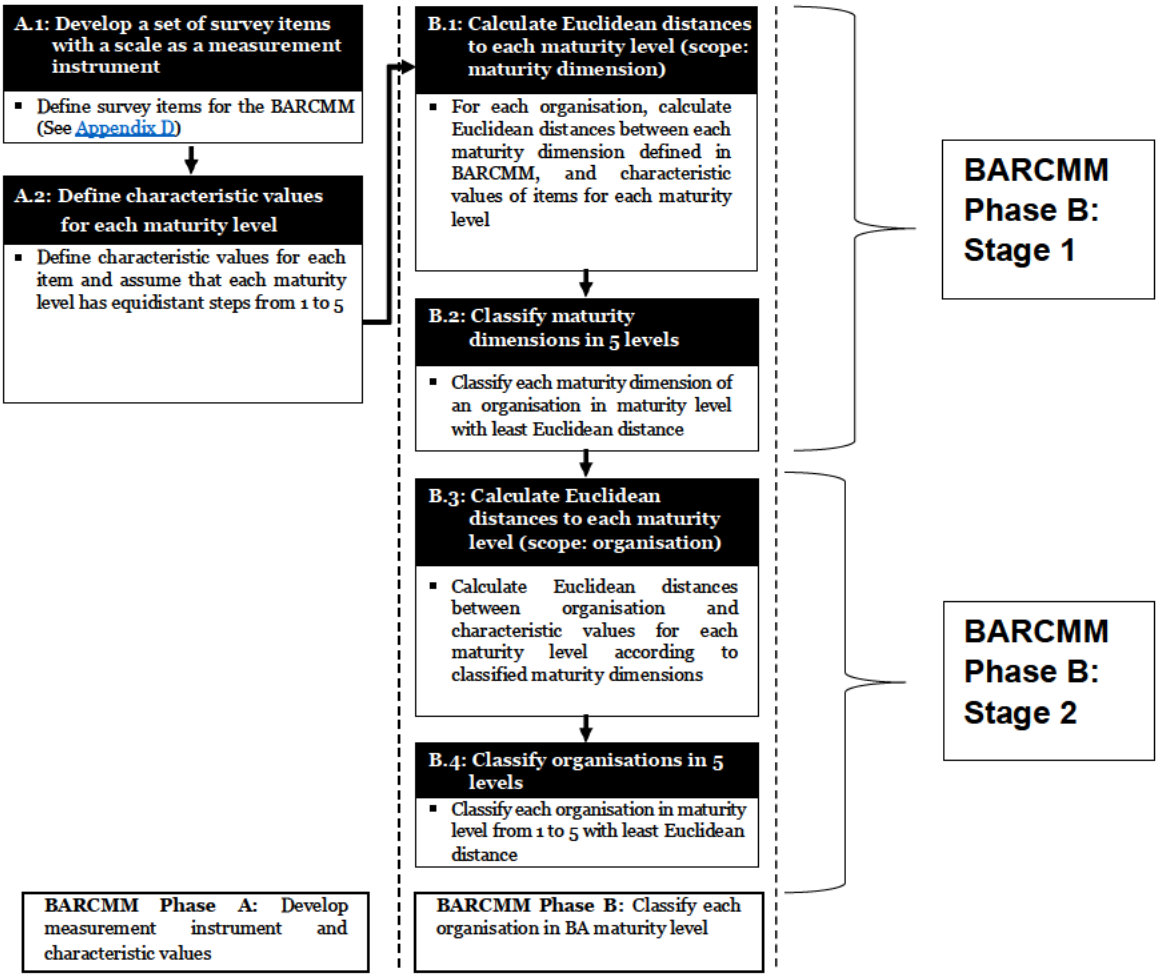

Figure 3.3 BARCMM Phases A and B of the Approach Used for the Development and Evaluation of BARCMM for Organisations Using ERP Systems

The rationale for employing two surveys was to determine if the measurement items from the pilot survey (Survey 1) constituted a reliable instrument for constructing BARCMM and assessing maturity levels. Should the Rasch analysis reveal insufficient coverage of each maturity level in Survey 1, the approach allowed for the inclusion of additional measurement items in Survey 2 to construct BARCMM to more reliably assess maturity levels.

For the calculation of Business Analytics readiness and capability maturity levels, a two-fold application of the Euclidean metric was employed in BARCMM Phase B. It assessed the distance to each maturity level within each dimension of maturity, subsequently determining the maturity level of each organisation. The least distant level was assigned to each dimension of maturity, characterising the organisation's BA readiness and capability maturity. This approach aimed to rigorously determine the maturity level of organisations using Rasch analysis and cluster analysis.

The detailed testing of hypotheses in BARCMM Phase C, where the BA maturity level of an organisation predicts the success of a BA initiative, is illustrated in Figure 3.4. The complete three-phase approach used for the development and evaluation of the BARCMM is shown in Chapter 4, Figure 4.2, and the following highlights the steps in BARCMM Phase C:

In BARCMM Phase C, the study empirically assessed Business Analytics maturity as a determinant of Business Analytics capability and success in organisations using ERP systems. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed for this purpose. SmartPLS, a software for path modelling in PLS-SEM, was used for the analysis. The PLS-SEM model was specified as a reflective measurement model, following the approach of Elbashir et al. (2008) and Raber et al. (2013a).

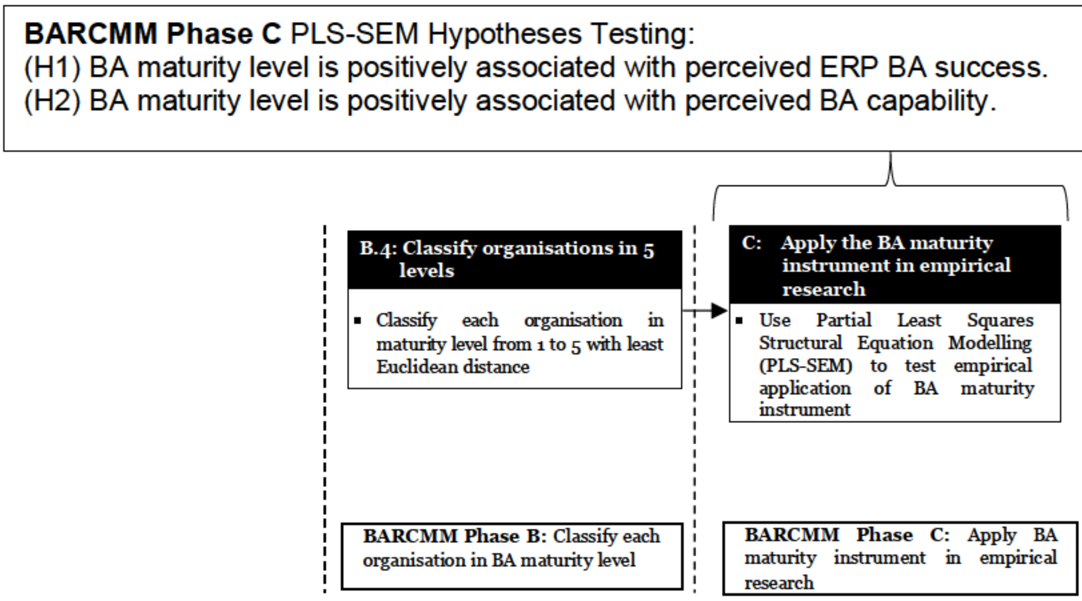

Figure 3.4 BARCMM Phase C PLS-SEM Hypotheses Testing, Showing How an Organisation's BA Maturity Predicts the Success of a BA Initiative

3.4. Research Process

The research process in this study was carefully structured and methodically executed, involving a series of well-defined stages from inception to result analysis. Guided by a rigorous methodological approach, it entailed a multifaceted process to efficiently accomplish the research objectives. A more detailed description of the research process followed in this study is presented below.

(6) **Problem Formulation:** The research process commenced with a clear problem statement and research questions. The research problem is the development and evaluation of a BA readiness and capability maturity model for ERP systems in the GCR.

(7) **Literature Review:** A comprehensive review of the existing literature in the fields of Business Analytics, Maturity Models, and Enterprise Resource Planning was conducted. This literature review served as the foundation for the theoretical framework and the identification of gaps in the current knowledge.

(8) **Theoretical Framework:** Building upon the literature review, a theoretical framework was constructed, drawing on concepts and theories from the field. This framework provided a solid basis for the development and evaluation of the BARCMM and the subsequent analysis of data. Previous literature reviews show that both positivist, interpretivist, and mixed approaches have been used in assessing maturity levels in maturity model assessments (Ghazal et al. 2013; Templier & Pare 2018; Ryan et al. 2020). In the positivist approach, quantitative methods are typically favoured for research. This involves using structured surveys or experiments to collect numerical data that can be statistically analysed to identify relationships between variables (Babones 2016; Park, Konge & Artino 2020). Positivism emphasises objectivity and aims to uncover universal laws governing social phenomena. Researchers employing positivism focus on observable facts and causal relationships, often employing large-scale surveys or experiments to test hypotheses (Gomm 2018). In the interpretivist approach, qualitative methods are preferred for research. This methodology emphasises understanding social phenomena through subjective experiences and meanings, focusing on the context and complexities of human behaviour (Chism et al. 2008; Thanh & Thanh 2015). Interpretivists believe that social reality is constructed by

individuals and can only be understood by exploring the perspectives of those involved (Chevrier 2024). This approach involves methods such as interviews, observations, and textual analysis to uncover deep insights and subjective meanings (Mezmir 2020). After reviewing other authors' research framework, a conceptual framework of an ERP business analytics maturity model is developed based on maturity models identified from the literature review and is evaluated using quantitative surveys with a variety of factors and dimensions. Both positivism and interpretivism can be employed in research; however, positivism is more suitable for this study due to the use of an anonymous survey where respondents will not be contacted for interviews.

(9) **Research Design:** The research process included the design of a rigorous and repeatable methodology for constructing and evaluating the BARCMM. This design was influenced by established models used in related domains and aimed to address the methodological weaknesses of previous BAMMs.

(10) **Data Collection:** The research involved the collection of empirical data to develop and validate the BARCMM. Two surveys were employed, Survey 1 and Survey 2, to measure Business Analytics maturity levels across nine dimensions. These surveys were based on previously validated instruments and designed to ensure that item anchors were consistent across versions.

(11) **Data Analysis:** The collected data was subjected to a detailed analysis using Rasch analysis and hierarchical cluster analysis. Rasch analysis was applied to evaluate the likelihood of endorsing specific options on each measurement item. It allowed the construction of the BARCMM by differentiating between endorsability and agreeability, contributing to the model's generalisability.

(12) **Ideal Maturity Profiles:** Ideal maturity profiles were defined for each level of maturity within the BARCMM, assuming linear progress across maturity levels and applying a seven-point Likert scale for measurements. These profiles served as reference points for categorising organisations into maturity levels.

(13) **Maturity Level Classification:** The hierarchical clustering approach, applying the Euclidean metric, was used to classify organisations into maturity levels. This process involved calculating distances between an organisation's responses to items and the defined characteristic values for each maturity level.

(14) **Data Validation:** The research process involved the empirical testing of Business Analytics maturity as an indicator of perceived Business Analytics capability and success in organisations using ERP systems. This validation was achieved through Partial Least Squares Structural Equation Modelling (PLS-SEM), which allowed for the assessment of the relationships between Business Analytics maturity and perceived capability and success.

(15) **Report and Conclusion:** The findings of the research were compiled into a comprehensive report, and conclusions were drawn based on the analysis of the data and the validation of the BARCMM. The research process provided insights into the impact of Business Analytics maturity on organisational capability and success.

Throughout the research process, careful attention was given to the integrity and validity of the methodology employed, as well as ethical considerations, ensuring that the research was conducted with the highest standards of professionalism and rigour. The detailed steps and methods applied in the research process allowed for the creation of a robust and repeatable framework for the development and evaluation of the BARCMM, contributing to the understanding of Business Analytics in organisations using ERP systems.

3.5. Data-Collection Strategies

The data-collection strategies applied in this research were carefully designed to align with the study's methodological approach and research objectives. A randomised selection process included organisations from various industry sectors to enhance the robustness of the results. Anonymous online surveys conducted in the GCR involved organisations with diverse capabilities, enriching the dataset.

3.5.1. Justification of Data-Collection Strategies

The chosen data-collection strategies were methodologically justified and aligned with the research's specific objectives and the nature of the Business Analytics maturity assessment. The following rationale supports the selection of these strategies:

Two surveys, 1 and 2, were used for the following reasons. First, these surveys were adapted from well-established instruments used in prior research (Cosic et al., 2012; Rouhani & Ravasan, 2013; Halo, 2015; Rouhani & Mehri, 2016). This adaptation ensured that the measurement items were grounded in validated and reliable sources, increasing the likelihood of robust and accurate data collection.

The rationale for employing two surveys in this empirical study is to ascertain whether the measurement items from the pilot survey (Survey 1) constitute a reliable instrument for constructing the BARCMM and assessing maturity levels. If the Rasch analysis identifies insufficient coverage of each maturity level in Survey 1, the approach using Rasch analysis allows the inclusion of additional measurement items in Survey 2 to reconstruct the BARCMM and provide a more reliable assessment of the maturity levels. The development and validation of Survey 1 and Survey 2 using Rasch analysis and clustering are summarised in Figure 3.5.

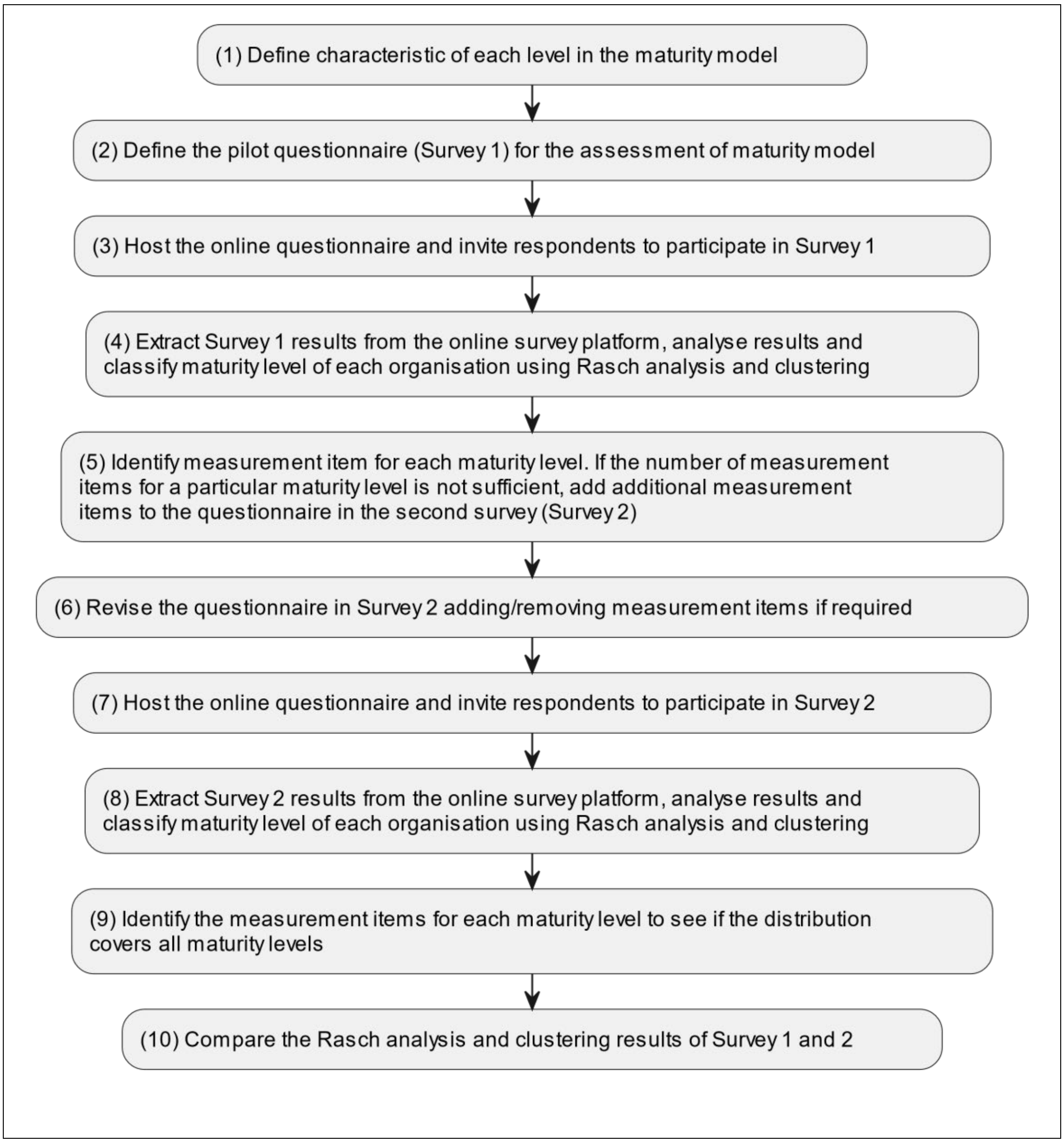

Figure 3.5 The Development and Validation of Survey 1 and Survey 2 Using Rasch Analysis and Hierarchical Cluster Analysis

Second, item anchors play a crucial role in survey design, as well as in psychological and educational assessment design, by providing reference points or standards that help respondents interpret and respond to survey or assessment questions consistently (Gehlbach & Brinkworth 2011; Boone 2016; Combrinck et al. 2017). Item anchors are also crucial in the development and validation of measurement instruments for maturity assessment (Laaber et al. 2023). They ensure that specific items accurately reflect the dimensions of maturity models and aid in assessing the validity and reliability of scales. Therefore, a consistent set of item anchors was employed in both Survey 1 and Survey 2. This consistency allows for the measurement of BA maturity levels across different dimensions while maintaining comparability between the two surveys. This approach of using item anchors was pivotal in achieving a clear and reliable assessment in educational settings (Gehlbach & Brinkworth 2011; Boone 2016). Capable students are more likely to answer difficult assessment items correctly compared to less capable students. Similarly, in the assessment of BA maturity, organisations with a high maturity level are more likely to give higher scores for challenging measurement items associated with high maturity levels. This approach allows for a uniform comparison of organisations' responses.

Furthermore, the use of a seven-point Likert scale in the surveys allowed for a nuanced measurement of responses, ranging from "strongly disagree" to "strongly agree." This granularity in data collection provided a comprehensive understanding of the organisations' positions on various items related to Business Analytics maturity. It facilitated the differentiation between organisations at different maturity levels, adding depth to the data collected.

The design of the surveys was justified based on their alignment with the research's objective of developing and evaluating the BARCMM. By incorporating items validated in previous studies, maintaining item anchor consistency, and utilising a Likert scale, the surveys served as a sound foundation for the research's data-collection phase.

3.5.2. Sampling Design Strategies

The sampling design for this research was thoughtfully planned to ensure the effective collection of data required to test the proposed research model. The following strategies were employed:

(1) Two-Stage Survey Approach: The research adopted a two-stage survey approach. The initial phase, Survey 1, involved the participation of 200 respondents representing a broad spectrum of large organisations in the GCR. These participants were the respondents from a pool of 1,200 invited participants for each survey. Survey 1 aimed to gather preliminary data for analysis, allowing for any necessary modifications before the subsequent stage, Survey 2 was conducted.

(2) Invitation Method: For both Survey 1 and Survey 2, participants were invited through a combination of email, LinkedIn peer invitations, and physical letters. To select organisations for participation in the study, several criteria were carefully considered. Firstly, organisations from diverse industry sectors were targeted to ensure a comprehensive representation of the business landscape in the GCR. Preference was given to large organisations due to their potentially greater impact and influence within their respective sectors. Geographical location was also a crucial factor, with priority given to organisations located within the GCR to maintain geographical relevance to the study's focus area. Moreover, organisations with operations or interests relevant to the research topic were identified as potential candidates for participation to ensure their insights were valuable. Lastly, efforts were made to select organisations with accessibility and willingness to participate, aiming for a higher response rate and ensuring data quality. To streamline the invitation process, a company database was established to store contact information categorised by industry sectors.

(3) Random Sampling: From the company database, an initial random sample of 200 participants was selected for each survey, ensuring representation from 100 different organisations. This sampling approach was designed to maintain diversity and minimise potential biases. Each organisation received two invitations for two main reasons: Firstly, to cover responses from both technical and management staff, ensuring a comprehensive understanding of organisational perspectives and experiences across various levels and departments. Secondly, the dual invitation strategy allowed for the collection of diverse viewpoints within each organisation, enriching the survey data and providing a holistic understanding of organisational dynamics. In addition to the invitations from the company database, invitations were sent via LinkedIn Peer Contacts to expand the sample size and ensure randomness, covering industry sectors such as Financial, Information Technology, Logistics, Manufacturing, Utilities, and Others.

(4) Participant Selection: The targeted respondents for this research were chosen from a range of roles within the participating organisations. IT managers, project managers, and system administrators were identified as the most appropriate informants capable of accurately completing the online survey for this study. Their involvement was instrumental in providing valuable insights into the implementation of Business Analytics in ERP systems.

(5) Hosting the Online Surveys: an online survey site was established to facilitate the collection of completed online surveys from participants. Staff members from organisations in the GCR were invited to participate in the online surveys. Survey 1 was conducted between April 2017 and September 2018, and Survey 2 was conducted between October 2018 and October 2021. The details of the survey period, number of respondents, number of completed responses, and response rate for Survey 1 and Survey 2 are presented in Chapter 5, Table 5.1 and Table 5.9.

These sampling design strategies ensured a diverse and representative pool of participants, encompassing organisations in the GCR and involving individuals with roles critical to the research's objectives. The two-stage survey approach allowed for the collection of data for both preliminary analysis and the comprehensive study, ensuring the reliability and robustness of the research findings.

3.5.3. Details of Data-Collection Strategies in Each Survey Phase

The data-collection strategies in this research were implemented with precision in each of the two research survey stages, Survey 1 and Survey 2, to ensure thorough collection of relevant data. Survey 1, a Pilot Study, aimed to gather initial insights and validate the research model, while Survey 2, the Full Study, aimed to collect comprehensive data for model development and validation. Careful participant selection and the use of validated questionnaires ensured robust and reliable data across both phases.

In the first stage, Survey 1 (Pilot Study), a sample of 1,200 participants was invited from organisations across various industries in the GCR. This diverse group of participants included IT managers, project managers, and system administrators. Participants with these roles were chosen as they were considered the most knowledgeable and appropriate informants to answer the survey in this study. The questionnaire used in Survey 1 (Pilot Study) was developed based on prior validated instruments and sources, such as the work of Rouhani and Ravasan (2013) for ERP profile questions and the critical success factors of the Halo Business Intelligence

Maturity Model (Halo, 2015) for BA profile questions. The survey included a comprehensive set of items to assess BA maturity and other pertinent factors.

In the second stage, Survey 2 (Full Study), the research extended invitations to another set of 1,200 participants from organisations in various industries in the GCR. Survey respondents were invited to participate in the online survey via email and personal peer invitations in LinkedIn user groups covering financial, information technology, logistics, manufacturing, utilities, and other industries. This stage aimed to collect a more extensive dataset for comprehensive analysis and validation. Since Rasch analysis and cluster analysis assume that respondent organisations participating in the survey vary in BA capability across the five maturity levels, invitations to participants were randomly selected to ensure organisations with varying BA capabilities covering five clusters of capabilities.

Both Survey 1 and Survey 2 were hosted on an online survey site to facilitate the collection of responses from participants in the GCR. This platform ensured efficiency and accessibility for respondents. Both surveys focused on collecting data related to variables pertinent to respondent organisations that had experience of using BA functionalities in their ERP systems. Only completed responses were used in the empirical study data analysis. This data was crucial for developing and evaluating the BARCMM.

3.6. Data-Analysis Strategies

The data-analysis strategies employed in this research were designed to rigorously process the collected data and derive meaningful insights. Given the complex nature of the research and the diverse variables under consideration, a multifaceted approach was adopted. Rasch analysis and hierarchical cluster analysis were used to classify organisations into maturity levels for the BARCMM. Partial Least Squares Structural Equation Modelling (PLS-SEM) was then used to confirm the hypothesis, testing whether there is a positive correlation between higher maturity levels and increased perceived BA success and capability.

3.6.1. Rasch Analysis

One of the central data-analysis methods used in this research was Rasch analysis. Rasch analysis, rooted in item response theory, was instrumental in evaluating the likelihood of endorsing specific options on each measurement item. This method enabled the research to assess the endorsability and agreeability of measurement items independently. Rasch analysis provided a valuable means of assessing the responses of organisations across different Business Analytics maturity levels. Notably, Rasch analysis offered the following advantages:

(1) **Generalisability:** Rasch analysis facilitated the generalisability of measurement items across various samples and items, ensuring that findings could be applied beyond the specific dataset (Sudweeks et al. 2004; Hopkins et al. 2021).

(2) **Unidimensionality Testing:** By analysing the response options for each measurement item, Rasch analysis allowed for the testing of unidimensionality (Davis & Boone 2021), a crucial consideration when assessing Business Analytics maturity (Raber et al. 2013a).

(3) **Ordered Set of Items:** Rasch analysis resulted in an ordered set of measurement items, arranged from easy to difficult. This order was instrumental in understanding the progression of maturity levels (Combrinck 2018; Fertig et al. 2023).

(4) **Identification of Poorly Functioning Items:** Rasch analysis also identified measurement items that were not functioning effectively and provided insights into unexpected item responses (Christensen et al. 2024; Valentin et al. 2024).

(5) **Transformation of Ordinal Counts:** The transformation of ordinal counts into linear measures using Rasch analysis, relying on logit transformation within the Rasch model, has been commonly used in various fields such as healthcare, education, and social sciences (De Battisti et al. 2005; Boone 2016; Balparda et al. 2021; Ekstrand et al. 2022). In healthcare, Rasch analysis converts ordinal item responses into interval-level measurements, enabling a more accurate evaluation of patient outcomes and health-related scales (Balparda et al. 2021; Ekstrand et al. 2022). In education, Rasch analysis enhances the precision of learning evaluations by converting ordinal assessments into logit scales to assess student performance effectively (Boone 2016). In the social sciences, Rasch analysis facilitates the transformation of ordinal data into linear measures, enabling clearer assessment of attitudes, perceptions, and psychosocial constructs (De Battisti et al. 2005). In maturity models, organisations with greater

capabilities tend to perform better on challenging assessment items, similar to students with greater capabilities achieving higher scores in educational assessments. The transformation of ordinal counts into linear measures using Rasch analysis facilitates the development of a precise interval-level scale that is essential for rigorously assessing and categorising organisations into their respective maturity levels based on their responses to challenging measurement items (Lahrmann et al. 2011; Raber et al. 2013b; Fertig et al. 2023).

3.6.2. Hierarchical Cluster Analysis

Hierarchical cluster analysis, also known as hierarchical clustering, is primarily used in data mining, statistics, and other fields to identify natural groupings within a dataset (Abonyi & Feil 2007). The main purpose of hierarchical clustering is to create a hierarchy of clusters where similar objects are grouped together based on their attributes or distances between them (Friesen et al. 2014; Couckuyt & Van Looy 2021). Hierarchical cluster analysis was used to classify organisations into five distinct levels of BA maturity, based on their capabilities and characteristics as indicated by their responses to each of the measurement items in the assessment survey (Raber et al. 2013b). The Euclidean metric was applied in a two-stage process in Figure 3.3.

In the first stage (BARCMM Phase B: Stage 1), Step B.1 involved calculating the distances to each maturity level (scope: maturity dimension). The delta (δ) value, which represents item difficulty, was computed between the "as-is" value of an item and the median of the "to-be" value for all organisations. A positive δ value indicated a difficult and desired item, whereas a negative δ value indicated an item that was relatively easy to achieve. Step B.2 involved classifying each maturity dimension of an organisation into the maturity level with the least distance. The maturity level that was least distant was assigned to each dimension of maturity, resulting in five integer values characterising each organisation's Business Analytics maturity levels.

In the second stage (BARCMM Phase B: Stage 2), Step B.3 involved calculating the distances to each maturity level (scope: organisation). The Euclidean distance was applied to calculate the distances of each Business Analytics maturity level for an organisation. Then, Step B.4 involved classifying each organisation into the maturity level with the least distance. The organisation's Business Analytics maturity level was determined based on the least distance among the five computed distance values.

3.6.3. Partial Least Squares Structural Equation Modelling (PLS-SEM)

For the final stage of data analysis, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the relationship between BA Maturity in terms of BA Readiness and BA Capability and perceived BA Success. PLS-SEM, known for its versatility and accuracy with smaller sample sizes and constructs with fewer items (Lowry & Gaskin 2014; Hair et al. 2019; Li & Lay 2024), was used to assess the impact of Business Analytics maturity on Business Analytics capability and success in organisations using ERP systems (AlMuhayfith & Shaiti 2020; Ahmed et al. 2024; Fosso Wamba et al. 2024). This analysis was crucial for the empirical testing of the research model and hypotheses. It involved:

(1) **Path Analysis:** PLS-SEM enabled the examination of hypothesised models with multiple dependent variables and the measurement of direct and indirect effects.

(2) **Confirmatory Factor Analysis (CFA):** PLS-SEM utilised CFA to examine relations among ordinal variables, particularly Likert-type items, to validate the research model.

(3) **Prediction Error and Resampling Methods:** Prediction error measures were used to assess prediction accuracy, and resampling methods were employed for inference purposes. These techniques aided in evaluating how closely the PLS model fit the data.

3.7. Validity (Inference Quality)

This research focused extensively on validity, ensuring that research findings were robust and inferences drawn from data were of high quality. Content validity was achieved through comprehensive review and adaptation of survey instruments, while construct validity was addressed using rigorous analytical techniques such as PLS-SEM and CFA. Criterion validity was established by comparing the research model against established measures, confirming its predictive capability regarding Business Analytics maturity, BA capability, and ERP BA success. Convergent and discriminant validity were assessed to enhance the measurement model's reliability, and external validity was ensured by including a diverse range of organisations from the GCR, allowing for broader applicability of findings.

3.7.1. Content Validity

Content validity refers to the extent to which elements within a measurement instrument are appropriate and comprehensive representations of the targeted construct for a specific assessment purpose, encompassing both relevance and representativeness of the measured content (Haynes et al. 1995; Rusticus 2014, p.1261). Content validity in the development of the BARCMM measurement instrument is ensured through rigorous pilot testing and refinement across two surveys. The questions and items in these surveys were selected and adapted from validated instruments and previous studies, such as Rouhani and Ravasan (2013) for ERP BA readiness profile questions and the critical success factors of the Halo Business Intelligence Maturity Model (Halo 2015) for BA capability profile questions. The utilisation of established instruments ensured that the content of the surveys accurately represented the constructs under investigation. Survey 1 initially acted as a pilot to assess clarity, relevance, and comprehensiveness of measurement items among a representative sample of organisations. Feedback from Survey 1 participants informed refinements to survey questions and response scales, like the Likert scale, ensuring effective measurement of intended constructs. Rasch analysis and cluster analysis assessed item distribution and coverage across maturity levels, identifying gaps and redundancies. These insights guided refinements in Survey 2, enhancing BARCMM's comprehensiveness and validity to effectively measure ERP business analytics maturity across diverse organisational contexts.

3.7.2. Construct Validity

Construct validity is the extent to which a test's scores relate to other measures and can be explained within a theoretical framework for the construct it aims to assess (Strauss & Smith 2009; Cohen & Swerdlik 2017, p.176). Construct validity is addressed through PLS-SEM in Research Phase III. The focus is on assessing the relationships between BA maturity (as an exogenous latent variable) and perceived ERP BA success/perceived BA capability (as endogenous variables) using reflective measurement. This approach ensures that the latent constructs of BA maturity, perceived ERP BA success, and perceived BA capability are evaluated based on their collective indicator performance, rather than assuming indicators define these constructs. The PLS-SEM model constructed (see Chapter 5, Figure 5.4) tests hypotheses H1 and H2, confirming positive associations between BA maturity and perceived ERP BA success, and between BA maturity and perceived BA capability, respectively.

3.7.3. Criterion Validity

Criterion validity evaluates how accurately a test measures the outcome it was designed to measure (Borneman 2010). To establish criterion validity, the research model and its constructs were compared against established measures of Business Analytics maturity of organisations using ERP systems, perceived BA capability and perceived ERP BA success. This comparison helped validate the research model's ability to predict outcomes and its alignment with existing criteria in the field.

3.7.4. Convergent and Discriminant Validity

Psychological construct measures are validated by examining their relationships with other constructs as theorised (Strauss & Smith 2009), assessed for convergent and discriminant validity through PLS-SEM and CFA (Cheung et al. 2023). Convergent and discriminant validity in the research is ensured through testing hypotheses H1 and H2, which explore the relationship between BA maturity and perceived ERP BA success/perceived BA capability. These hypotheses propose that higher levels of BA maturity are positively associated with increased ERP BA success and enhanced BA capability in organisations. By using PLS-SEM with reflective measurement models, the study accurately represents latent constructs such as BA maturity, perceived ERP BA success, and perceived BA capability through their respective indicators. These relationships are explored by the structural model (see Chapter 5, Figure 5.4).

3.7.5. Predictive Validity

Predictive validity refers to the extent to which a measurement instrument can accurately forecast future outcomes or behaviours, serving as a reliable indicator of its alignment with a criterion measure (Becker et al. 2013; Cohen & Swerdlik 2017, p.182). In Research Phase III, predictive validity is assessed by evaluating how well perceived ERP BA success and perceived BA capability are predicted by BA maturity through PLS-SEM. This is achieved by testing hypotheses H1 and H2, which posit positive associations between BA maturity and these two outcomes. The reflective measurement model ensures that BA maturity, perceived ERP BA success, and perceived BA capability are assessed based on how their indicators collectively represent these latent constructs. The structural model in PLS-SEM examines the strength of relationships between exogenous (BA maturity) and endogenous (perceived ERP BA success, perceived BA capability) latent variables. Key evaluation criteria include path coefficients and R-squared (R^2) values. Path coefficients for H1 and H2 indicate the strength and direction of these relationships, with statistical significance confirming their reliability. The R^2 values show the proportion of variance in perceived ERP BA success and perceived BA capability explained by BA maturity, demonstrating its predictive power in these contexts. The empirical testing of hypotheses helped establish the predictive power of the research model. It also confirmed that the assumption that organisations with a higher BA maturity level will have higher perceived BA capability and perceived ERP BA success.

3.7.6. External Validity

External validity refers to the extent to which the conclusions drawn from a study sample can be applied to a broader population or other target populations (Khorsan & Crawford 2014; Findley et al. 2021). External validity encompasses two main forms: generalisability and transportability. Generalisability involves making inferences from a sample drawn from a defined population, while transportability refers to inferences based on a sample but targeted at a different population (Findley et al. 2021). In this study, external validity was ensured by including a diverse range of organisations from the GCR in both Survey 1 and Survey 2. The aim was to ensure that the findings could apply not only to the specific dataset but also to organisations with similar characteristics and in comparable environments.

3.8. Ethical Considerations

This research program was conducted after Ethics Approval was obtained from the University of Southern Queensland Human Research Ethics Committee on 9 Dec 2016 with the approval number H16REA180 (Appendix A-1). The ethics approval was granted for three years initially and was extended until 18 March 2022. A requirement of the ethics approval granted is that participants are provided with a Participant Information Sheet (PIS) describing the nature and objectives of the research, as well as the process of data collection. The PIS used in this research program are included in Appendix A-5: Research Questionnaire (Survey 1) and

Appendix A-6: Research Questionnaire (Survey 2). Ethics Renewal Approval number H15REA144 (Appendix A-2, A-3, and A-4) was granted for the remainder of the study until 18 March 2022, confirming compliance with the Australian National Statement on Ethical Conduct in Human Research.

All participants acknowledged that they had reviewed the Participant Information Form for Survey 1 and Survey 2 (Appendix A-5 and A-6) before their participation in the online questionnaire survey could commence. As outlined in the participant information form, questionnaire surveys were entirely voluntary, and anonymous to protect privacy and ensure confidentiality. In the online surveys, participants confirmed their consent by submitting the 'Agree' button on the online consent form. The online survey data was anonymous.

The questions used in the Survey 1 questionnaire are provided in Appendix B-1, and the questions used in the Survey 2 questionnaire are provided in Appendix B-2. The initial survey questionnaire is adapted from the work of Rouhani and Ravasan (2013) for ERP profile questions and the critical success factors of the Halo Business Intelligence Maturity Model (Halo 2015) for BA profile questions. PLS-SEM is a multivariate technique that enables researchers in the measurement of direct and indirect effects and performing test models with multiple dependent variables and also using of several regression equations simultaneously (AmirAlavifar & Mohd 2012). Confirmatory factor analysis (CFA) is widely used in SEM for examining hypothesised relations among ordinal variables, such as Likert-type items (Flora & Curran 2004). Therefore, multivariate regression in the context of path analysis within a structured equation modelling framework will be adopted to test hypothesised models with multiple dependent variables. However, Partial Least Squares (PLS) path modelling enjoys rapidly increasing usage in various business disciplines, such as management information systems, marketing, operations management and strategic management (Cepeda Carrión et al. 2016). A prediction error is used as a measure of prediction accuracy, and resampling methods for inference purposes, in order to assess how closely a PLS model fits the data (Sanchez 2013). Sanchez (2013) argued that PLS Path Modelling is suitable as both a component-based alternative for estimating Structural Equation Models, and a method for analysing a system of linear relationships between multiple blocks of variables.

Using questionnaires in employed in Survey 1 (Pilot Study) and Survey 2 (the Full Study), data was gathered from organisations that have implemented Business Analytics in their ERP systems. This study develops and evaluates a maturity model to assess BA Readiness and Capability in organisations using ERP systems in the GCR. Survey instruments are provided in Appendix C and Appendix D, with one section focusing on BA Readiness and the other on BA Capability. Analysis is conducted on fully completed surveys for both BA Readiness and BA Capability.

3.9. Chapter Summary and Conclusion

3.9.1. Chapter Summary

The research methodology in Chapter 3 follows a rigorous and systematic approach to developing and evaluating the Business Analytics Readiness and Capability Maturity Model (BARCMM). This approach is guided by three key principles:

(1) **Use of a positivist paradigm:** The research is guided primarily by a positivist paradigm, which assumes that reality is objective and measurable. The positivist paradigm is appropriate for this study, as it enables the development of a quantitative model of BA readiness and capability maturity, and is suitable given the use of anonymous surveys from respondents with their organisations using ERP systems in the GCR, without conducting respondent interviews.

(2) **Grounding in theory:** The research is grounded in the existing literature on BA readiness and capability maturity. The design of the measurement instrument and design methods are informed by the work of previous researchers (Lahrmann et al. 2011; Raber et al. 2013b) to develop the survey instrument and interpret the results of the data analysis.

(3) **Quantitative data collection and rigorous analysis:** The research uses a quantitative survey instrument to collect data on BA readiness and capability maturity. The survey instrument was adapted from previous studies by Rouhani and Ravasan (2013) for ERP profiles and Halo (2015) for BA capability profiles, and was carefully designed to ensure validity and reliability. The data collected from the two surveys was analysed using a variety of statistical techniques, including Rasch analysis and hierarchical cluster analysis.

The research methodology is divided into three research phases:

(1) Research Phase I

A systematic literature review (SLR) was conducted to develop a CSF classification framework for measuring the maturity of organisations using ERP systems. The CSFs identified will be used as measurement items in the ERP BA profile questions in the BARCMM. SLR 1 addressed RQ1.1 by identifying and categorising CSFs into dimensions for assessing ERP maturity models, and RQ1.2 by extending the dimensions to accommodate Industry 4.0 integration.

(2) Research Phase II

Two SLRs were conducted - one on measuring business analytics maturity in ERP systems (SLR 3) and another on methodological approaches for designing, assessing and validating business analytics maturity models (SLR 2). SLR 3 addressed RQ2.1 and RQ2.2 by examining methodological approaches for designing, assessing, and validating BA maturity models for ERP systems. SLR 2 explored methodological approaches for developing, evaluating, and validating BAMMs in general.

Two SLRs were conducted - one on methodological approaches for developing, evaluating, and validating BAMMs in general (SLR 2), and another on measuring business analytics maturity for organisations using ERP systems (SLR 3). SLR 2 addressed RQ2.3 and explored methodological approaches for designing, assessing, and validating BA maturity models. SLR 3 addressed RQ2.1 and RQ2.2 by examining methodological approaches for BA maturity models specific to ERP systems.

(3) Research Phase III

Phase III, presented in Chapters 4 to 6, focused on the design, assessment, and validation of the BARCMM. Phase III comprised (1) the design of the BARCMM (See Chapter 4), (2) the development of measurement instruments for Surveys 1 and 2 (See Chapter 4), (3) the collection of empirical data through Surveys 1 and 2 (See Chapter 5), (4) the analysis of the empirical data through Surveys 1 and 2 (see Chapter 5), and (5) the validation of empirical results using PLS-SEM (see Chapter 6).

To address RQ3.1, an inductive approach using Rasch analysis and hierarchical cluster analysis was used to allocate survey items and organisations to a BA capability maturity continuum. To address RQ3.2, surveys were designed and revised to evaluate and improve the BARCMM measurement instruments. The instruments are based on the essential characteristics of the BARCMM outlined in Appendix C and are adapted from previous studies. Survey 1 was conducted using the initial survey instrument with a sample of organisations. The instruments were altered based on the findings of Survey 1, and the new instruments were deployed in Survey 2. To address RQ3.3, structural equation modelling was used to test two hypotheses:

(H1) "BA maturity level is positively associated with perceived ERP BA success"

(H2) "BA maturity level is positively associated with perceived BA capability"

This was to confirm the assumption that organisations with a higher level of BA maturity will be more capable of using BA to achieve greater benefits and success.

3.9.2. Chapter Conclusion

The Methodological Approach for Determining BA Readiness Maturity and BA Capability Maturity is summarised as follows:

This research in developing and evaluating a BA Readiness and Capability Maturity Model follows the methodological approach used by Raber et al. (2013a) for the development of BIMM which was originally developed by Sabherwal and Chan (2001) for alignment of business and IS strategies. The approach adopted by Raber et al. (2013a) is not specific to BI, it can be used for other domains in order to overcome methodological weaknesses of the MM.

Two surveys (Survey 1 and Survey 2) were used to collect empirical data from organisations in the GCR to measure BA readiness maturity and BA capability maturity to assess the maturity levels achieved by an organisation using an ERP system with BA tools implemented. For the survey there were 20 BA Readiness measurement items and 20 BA Capability measurement items. Only survey respondents using an ERP system and BA tools implemented were included in determining each organisation's BA readiness maturity level and the corresponding BA capability maturity level.

Using ideal maturity profiles, the distance of an organisation to each maturity level was calculated by applying the Euclidean metric in two steps. The maturity level with the smallest Euclidean distance represents BA readiness maturity, BA capability maturity and the overall BA readiness and capability maturity level of the organisation.

BARCMM Phase A of the analytical approach is to develop a survey instrument based on the essential characteristics of the existing MM (Raber et al. 2013a). The BA capabilities included in the proposed BA readiness and capability MM form several groups of increasingly difficult indicators of BA maturity. The assessment of the five dimensions of maturity in BA readiness (i.e. governance, culture, technology, people, and operation) were measured by a total of 20 BA readiness items. Similarly, the assessment of the four dimensions of maturity in BA capabilities (i.e. data source capability, analytics capability, collaboration tools capability, and sharing capability) were measured by a total of 20 BA capability items. The list of items was structured in the survey using a Likert scale in seven points from (1) "strongly disagree" to (7) "strongly agree". The survey instruments used in the survey of BA readiness and BA capability maturity measurement instruments are shown in Appendix D.

In order to measure the responses to the survey in relation to the maturity levels, ideal maturity profiles with typical characteristic values, were defined for each level of maturity.

The theoretical approach in this research adopted the same approach as that adopted by Raber et al. (2013a) originally developed by Sabherwal and Chan (2001) and then adapted by Joachim et al. (2011).

These characteristic values are based on the assumption that each of the BA readiness and BA capability maturity increases in a linear manner in equidistant steps and on the fact that items are measured using a seven-point Likert scale.

The overall approach used for the design, development, and evaluation of the BARCMM is summarised in Figure 4.2. The research methodology described in this chapter is a significant contribution to the field of methodological studies measuring BA maturity for organisations using ERP systems. It provides a rigorous and systematic approach to developing and evaluating BA maturity for organisations using ERP systems. Further details are explained in Chapter 4, which focuses on the Development and Evaluation of the BA Readiness and Capability Maturity Model.

CHAPTER 4: DEVELOPMENT OF BA READINESS AND CAPABILITY MATURITY MODEL

Chapter 4 describes the development of the BA Readiness and Capability Maturity Model (BARCMM). It applies Item Response Theory and Rasch Analysis for measurement. The chapter also outlines the rationale, objectives, design, validation, and significance in assessing the BA readiness and capability maturity of organisations using ERP systems within the BARCMM. Section 4.1 explores Item Response Theory (IRT) and Rasch Analysis in developing maturity models. It underscores their role in measuring BA capability, standardising measurement methods, and ensuring the validity and reliability of assessment tools. The discussion illustrates why BARCMM employs Rasch Analysis and cluster analysis, integral components of IRT, in its design and development. Section 4.2 outlines the development of the BARCMM for organisations using BA with modern ERP systems, employing Rasch analysis and hierarchical clustering to measure maturity levels. It uses two surveys to identify anchor items and assess BA maturity levels, covering the research philosophy, model inspiration, design, methodology, and relevance in the GCR. Section 4.3 describes the review of previous BIMMs and BAMMs, the development and justification of the BARCMM, the methodology for measuring BA maturity levels using ERP systems, and the validation of the model through Rasch Analysis and hierarchical clustering, focusing on organisations in the GCR. Section 4.4 shows the design and process of creating the BARCMM measurement instruments, covering relevant theoretical frameworks, component dimensions, development, validation, and factors related to reliability and validity. Finally, Section 4.5 summarises Chapter 4, emphasising the significance of assessing BA capability maturity, particularly in ERP systems, and highlighting its theoretical and practical contributions. It concludes by emphasising the importance of using BARCMM as a comprehensive framework and self-assessment questionnaire measurement instrument that can assess the BA readiness and capability maturity level of organisations using ERP systems. Figure 4.1 shows the structure of Chapter 4.

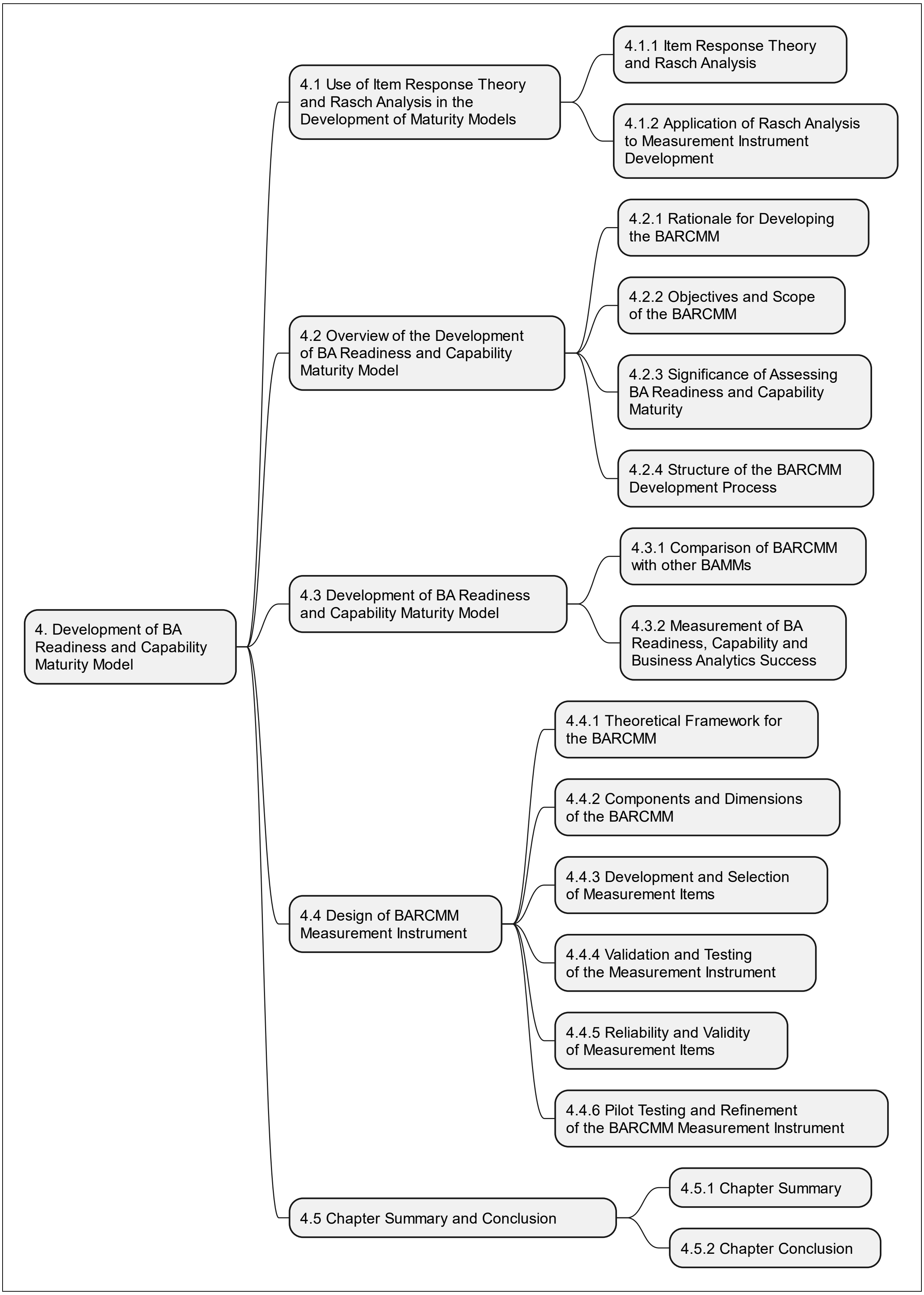

Figure 4.1 Structure of Chapter 4

4.1. Use of Item Response Theory and Rasch Analysis in the Development of Maturity Models

The findings from SLRs 2 and 3 guided the selection of Rasch analysis for assessing ERP and BA capability maturity in organisations using ERP systems. Rasch analysis offers a systematic and rigorous approach by assuming maturity progresses in equal steps, which helps quantify maturity levels. It is also widely used in constructing maturity models, providing a solid evaluation framework. Additionally, Rasch analysis allows for the integration of ERP profile measurement items into existing BAMMs, ensuring relevance for ERP-based organisations. This combination of rigour and adaptability makes Rasch analysis the optimal choice for evaluating organisational maturity in developing the BARCMM.

4.1.1. Item Response Theory and Rasch Analysis

IRT examines the relationship between an individual's response to a measurement item and their performance on an overall measure of the trait the item is intended to assess (Van der Linden & Hambleton 1997; Reise & Revicki 2014). It is widely applied in education, psychology, social science, medical research, and business (Raykov & Marcoulides 2011). This research extends IRT's applications to information systems research (Rusch et al. 2017) and maturity model development (Lahrmann et al. 2011; Raber et al. 2013a). IRT models include one-parameter logistic (1PL), two-parameter logistic (2PL), and three-parameter logistic (3PL) models (Rusch et al. 2017; Kean et al. 2018). The 1PL model, or Rasch analysis, uses the natural logarithm of the success probabilities on dichotomous items or endorsements on polytomous items. The 2PL model adds item discriminability and requires larger sample sizes (>1000), while the 3PL model includes a guessing parameter (Kean et al. 2018). The 1PL model, as a confirmatory model, requires data to fit the Rasch model for valid measurement, whereas the 2PL and 3PL models are exploratory and describe data variance (Rusch et al. 2017). Rasch analysis has been combined with cluster analysis for maturity models in information systems research (Dekleva & Drehmer 1997) and BI research (Lahrmann et al. 2011; Raber et al. 2013a).

4.1.2. Application of Rasch Analysis to Measurement Instrument Development

Rasch analysis measures variables like abilities, attitudes, and personal characteristics for psychological and educational assessments (Cleven et al. 2014). In CMM development, it allows for the inductive allocation of capabilities to maturity levels, supporting a rigorous CMM design. Cluster analysis helps avoid the arbitrariness in assigning capabilities to maturity levels, a criticism of other methods (Lahrmann et al. 2011). Rasch analysis has been used to allocate items to five maturity levels, supporting the design, construction, and evaluation of BA readiness and capability maturity models. Hierarchical cluster analysis provided a rigorous approach for assigning organisations to different maturity levels (Raber et al. 2013b).

Rasch analysis offers procedures for constructing and reviewing measurement instruments, documenting their reliability and construct validity (Boone 2016). The quality of an instrument can be assessed using item-fit and person-fit statistics. Item-fit statistics show how consistently responses to an item align with responses to other items (McCreary et al. 2013). Items should match the difficulty expected based on their position on the continuum, regardless of the respondent's ability. Items that do not fit the model may measure multiple variables and should be identified and possibly removed. This is done by examining infit and outfit statistics (Tavakol & Dennick 2013). Items that do not fit the model should be replaced. Misfit can occur if an item is unexpectedly answered correctly by less able individuals or incorrectly by more able ones (Zhang et al. 2020). Mean square values between 0.75 and 1.33 are acceptable (Wilson 2005, p.129). Items with infit and outfit mean square values greater than 1.33 may not fit the Rasch model and should be reviewed (Boone 2016), though this rule should be used as an indicator for further investigation rather than a strict criterion (Meyer 2014, p.89).

Another technique to evaluate the quality of a questionnaire survey is to examine person-fit statistics to identify response patterns that are unlikely to be observed based on the model (Felt et al. 2017). When a response pattern is deemed unlikely, it is assumed that responses to survey items are guided by a mechanism other than the specific construct of the survey (Meijer 2002). For example, a person randomly selecting item responses to finish the questionnaire more quickly would show a person-misfit, as the item selection is merely based on guesses (Felt et al. 2017). Person-fit indices, reported as infit and outfit mean square values, compare the actual scores with the expected scores, assessing the significance of a score at the individual level (Boone et al. 2014). These indices are based on the consistency of an individual's response pattern with valid item responses. As a rule of thumb, if the infit and outfit mean square values of a person are less than 0.5 or greater than 1.5, it may indicate poor person fit (Linacre 2002). If individuals show unusual response patterns, they may need to be excluded from the analysis, or further examination of their responses may be required (Boone 2016).

A person-item map evaluates an instrument's strengths and weaknesses by comparing person and item performance (Boone 2016). It displays respondent ability and item difficulty on the same scale, converting raw ordinal scores into probabilistic interval measures known as logits (Ismail et al. 2021). These logits enable comparisons between person measures and item measures on the same scale (Edelen & Reeve 2007). The map helps determine how well survey items match respondent abilities by assessing the proximity of mean item measures to mean person measures. If the means are close, it indicates good item targeting, meaning the items are appropriately challenging for respondents (Boone 2016).

Using Rasch analysis, researchers can create multiple versions of a survey with varying items, all expressed on the same scale. This involves using Item Anchors (Boone 2016), which are common items across different survey versions that serve as reference points, allowing person performance to be standardised on a single scale. By linking the measurement scale through these common items, differences in item difficulty across survey versions do not affect the interpretation of person results. For instance, after conducting Rasch analysis on Survey 1, common items in Survey 2 are anchored to the item difficulty values from Survey 1, ensuring that responses to Survey 2 align with Survey 1. The same process can be applied to link Survey 3 to Survey 2, thereby linking it back to Survey 1.

4.2. Overview of the Development of BA Readiness and Capability Maturity Model

This research sought to develop a BA readiness and capability maturity model (BARCMM) instrument for organisations using BA in the context of modern-day ERP systems. Previous Business Intelligence Maturity Models (BIMMs) (Lahrmann et al. 2011; Raber et al. 2013b, 2013a) and BACMMs (Cosic et al. 2012; Halo 2015) were reviewed and the BARCMM instrument is described and justified from existing literature. Then the approach used to measure BA capability maturity levels of organisations using ERP systems is described and justified. The measurement instrument was developed using the empirical approach proposed by Raber et al. (2013a). First, Rasch Analysis was used to determine the difficulty of each BA capability maturity measurement item and capability of each respondent organisation in relation to each of BA measurement items. Then hierarchical clustering analysis was used to determine the maturity level of each BA capability measurement item and the related capability for each respondent organisation on one standardised scale so that the measurement items and each respondent organisation could be assigned to corresponding maturity levels. This research provides a detailed example of how Rasch analysis together with hierarchical clustering analysis can be used to determine the difficulty of measurement items and classify organisations by their responses into BA maturity levels. The GCR was selected for this study as this region is considered to be the world factory (Zeng 2010p.184) and there are many organisations in this region using ERP systems with business analytics capability.

The three high-level research gaps (RG1: Lack of research on CSFs for ERP BA readiness, RG2: Limited understanding of applying CSFs with methodological rigour for BA capability measurement, and RG3: Limited exploration and empirical application of CSFs underpinned by item response theory in ERP BA readiness) were addressed through the design and development of the BARCMM and the conduct of Surveys 1 and 2, corresponding to high-level research questions RQ1, RQ2, and RQ3. This research was guided by a positivist paradigm and used a quantitative method to answer the high-level research questions RQ1, RQ2, RQ3, and low-level research questions RQ3.1, RQ3.2, and test hypotheses H1 and H2 in RQ3.3.

To address RQ1: "What are the critical success factors that contribute to ERP BA readiness, and how can ERP BA readiness be effectively measured?", based on the conclusion of SLR 1 in Chapter 2 related to RQ1.1 and RQ1.2, the five dimensions of ERP BA readiness were identified and used as measurement items in the BARCMM.

To address RQ2: “What are the CSFs that contribute to BA capability, and how can BA capability be measured?”, and based on the conclusions of SLR 3 for RQ2.1 and RQ2.2, and SLR 2 for RQ2.3: For RQ2.1, the study identifies gaps in the literature, highlighting the need for better documentation of BAMM development processes and empirical validation of assessment methods. For RQ2.2, a stepwise approach is proposed to assess the BA maturity level of organisations using new-generation ERP systems. This includes identifying CSFs, integrating them into measurement items and dimensions, and adapting existing BAMM and ERPMM frameworks using Rasch Analysis and Cluster Analysis for more rigorous and repeatable assessments. For RQ2.3, Raber et al.'s (2013a) approach, combining Rasch analysis and clustering, is found to significantly outperform Lasrado et al.'s (2017) set-theoretical approach in BI/BA Maturity Models. This approach offers a robust foundation for maturity model development through its systematic use of Rasch analysis and hierarchical clustering in design and assessment. Therefore, the BARCMM adopted Rasch analysis and hierarchical clustering for these phases.

To address RQ3: "How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?", the BARCMM is designed with measurement instruments in Survey 1 and 2, and the empirical results are to be addressed by RQ3.1, RQ3.2, and RQ3.3 in Chapter 5.

A positivist perspective assumes that reality is objective and measurable using properties which are independent of the researcher and instruments (Myers 2019). Quantitative research uses questionnaires, surveys and experiments to collect data which is examined and compiled into numbers for statistical analysis (Hittleman & Simon 1997). In this research, a rigorous and repeatable methodological approach guided by item response theory was employed for the construction of a BARCMM. This approach involved drawing from relevant previous literature, conducting Rasch analysis, and using hierarchical cluster analysis to design, develop, and determine maturity levels.

Fox and Jones (1998) discuss the application of Rasch analysis for measuring survey items using rating scales of varying difficulty, such as a 7-point Likert Scale. Rasch analysis, based on item response theory, evaluates the probability of endorsing each option based on item endorsability and respondent agreeability, unlike classical test theory which does not separate these factors. It enables generalisability between samples and items, tests for unidimensionality, and produces an ordered set of items from easy to difficult, identifying poorly functioning items and unexpected responses (Fox & Jones 1998). Rasch analysis transforms ordinal counts into linear measures and assesses unidimensionality problems with fit statistics (Wright & Linacre 1989). It assumes that more capable organisations are more likely to succeed on any given item, and that more difficult items are less likely to be successfully endorsed. These characteristics make Rasch analysis highly effective for designing, developing, and evaluating maturity models.

A quantitative survey instrument adapted from previous studies was used to collect data for developing and evaluating a BAMM (Cosic et al. 2012; Rouhani & Ravasan 2013; Halo 2015; Rouhani & Mehri 2016). Essential characteristics of the five BAMM maturity levels are detailed in Appendix C. The BAMM development adapted the methodological approach of Lahrmann et al. (2011) and Raber et al. (2013b, 2013a), originally based on Dekleva and Drehmer (1997). Raber et al.'s rigorous approach is generalisable beyond BI, addressing methodological weaknesses in BAMM development and the BARCMM used in this research.

The rationale for using two surveys is to (1) identify how the same set of item anchors can be used in subsequent survey versions to express a person (organisation) measure on a single scale for result comparison and (2) demonstrate how the rigorous approach can determine the construct reliability and convergent validity of the BAMM. Two separate online surveys collect empirical data to assess the BA maturity levels of organisations using ERP systems with BA tools. The nine dimensions (governance, culture, technology, people, operations, data source, analytics, collaboration capability, and sharing capability) are measured by forty items in Survey 1 and 58 items in Survey 2. Survey 2, which includes Survey 1, shares a common set of measurement items. Survey 2 aims to identify anchor items that consistently measure maturity levels. Details on identifying anchor items are provided in Chapter 5, Table 5.8, which compares the number of items for each maturity level in Surveys 1 and 2 (common and unique).

The complete list of measurement items used in both surveys is presented in Chapter 3, Table 3.4, with details of each measurement item provided in Table 4.8. In addition, Table 4.1 summarises the sources of the nine dimensions and measurement items adapted for this study.

Table 4.1 Sources for BARCMM Dimensions and Measurement Items

Dimension	**Source of construct and measurement items**
Governance	Cosic et al. (2012); Rouhani and Ravasan (2013); O'Neill and Brabazon (2019); Angreani et al. (2020)
Culture	Cosic et al. (2012); Rouhani and Ravasan (2013); O'Neill and Brabazon (2019); Angreani et al. (2020)
Technology	Cosic et al. (2012); Rouhani and Ravasan (2013); O'Neill and Brabazon (2019); Angreani et al. (2020)
People	Cosic et al. (2012); Rouhani and Ravasan (2013); O'Neill and Brabazon (2019); Angreani et al. (2020)
Operations	Rouhani and Ravasan (2013); Rouhani and Mehri (2016); Angreani et al. (2020)
Data Capability	Halo (2015); Hornick (2020)
Analytics Capability	Halo (2015); Hornick (2020)
Collaboration Tools Capability	Halo (2015); Hornick (2020)
Sharing Capability	Halo (2015); Hornick (2020)

The survey instrument, the forty items for Survey 1 and the fifty-eight items for Survey 2 measuring each of the nine dimensions of BARCMM Model are provided in Appendix D.

Using a hierarchical clustering approach (1) ideal maturity profiles and then (2) distance of an organisation to each maturity level was calculated by applying the Euclidean metric. The maturity level with the smallest Euclidean distance represents the BA maturity level of an organisation. The overall approach used for the design, development and evaluation of the BARCMM is summarised in Figure 4.2 (adapted from Raber et al. (2013a), see Figure I.3).

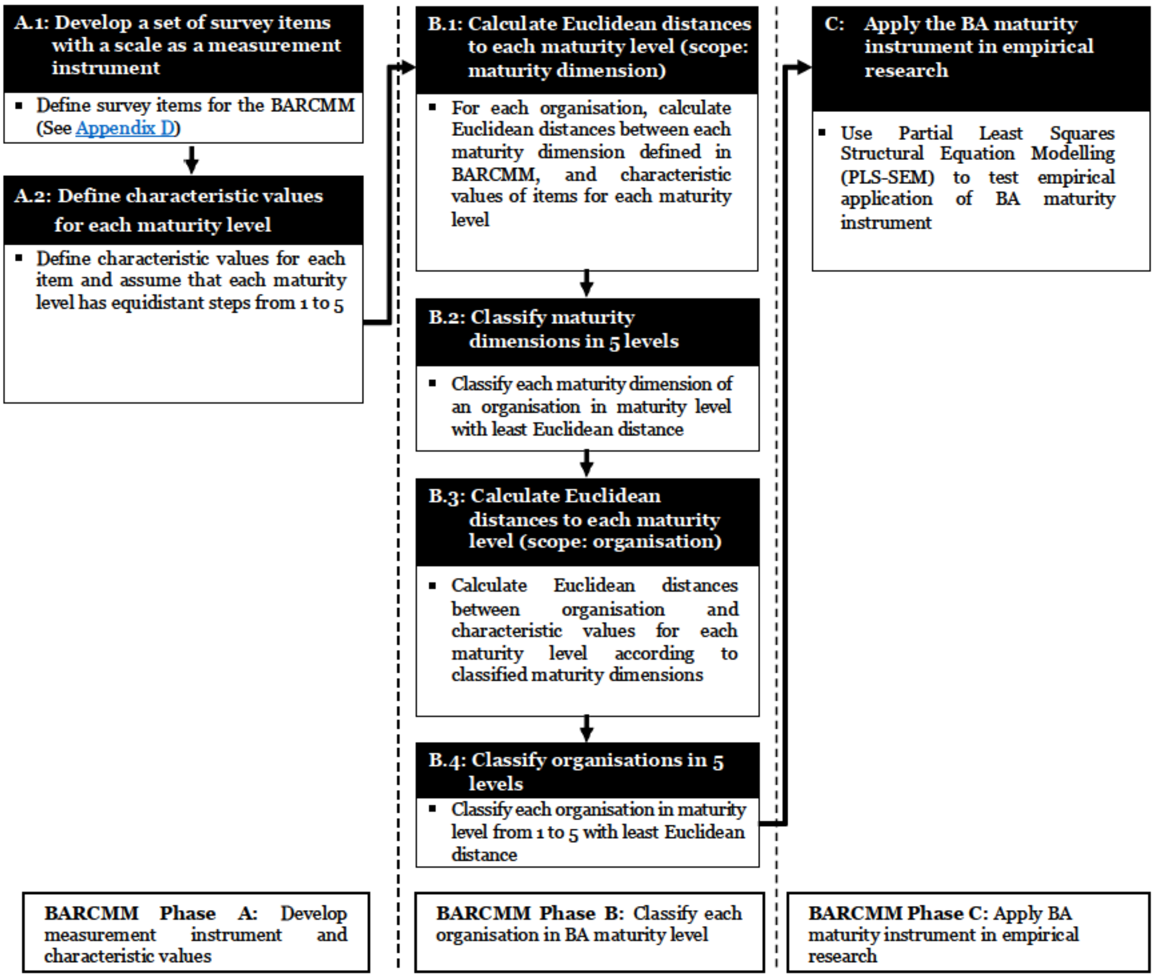

Figure 4.2 Approach used for Development and Evaluation of BARCMM for Organisations Using ERP Systems

Three phase approach used for the development and evaluation of the BARCMM is shown in Figure 4.2 and is now described in detail. BARCMM Phase A was guided by the analytical approach of Raber et al. (2013a), where a survey instrument was developed based on the essential characteristics of BARCMM (See Appendix C). The BA capabilities included in the BARCMM form groups of increasingly difficult indicators that measure BA maturity. The nine dimensions of BA capability in the BARCMM are measured by forty items in Survey 1 and fifty-eight items in Survey 2. The BA capability items were measured using a seven-point Likert scale ranging from (1) “strongly disagree” to (7) “strongly agree”. The measurement items for BA capability used in the online survey for both Survey 1 and 2 are provided in Appendix D. In order to assign the survey responses to the 40 BA capability items in Survey 1 and the 58 BA capability items in Survey 2 across five maturity levels, ideal maturity profiles with typical characteristic values, were initially defined for each level of maturity.

These characteristic values are based on the assumption that BA maturity increases linearly in equidistant steps and that items are measured using a seven-point Likert scale. The approach of using Rasch analysis follows similar steps documented by Lahrmann et al. (2011).

The characteristic values v_{li} for each item *i* and all levels *l* are defined as: v_{1i}=1 for Level 1, v_{2i}=2 for Level 2, v_{3i}=3 for Level 3, v_{4i}=4 for Level 4, v_{5i}=5 for Level 5. The ideal maturity profile for level *l* is represented by 40 items, with a rating of level *l* for each of the measurement items.

In BARCMM Phase B, a two-stage hierarchical clustering approach using Euclidean metric is used to (B.1) calculate the distances to each maturity level (scope: maturity dimension) and (B.2) classify each maturity dimension of an organisation into the maturity level with the least distance, then, (B.3) calculate the distances to each maturity level (scope: organisation) and (B.4) classify each organisation in the maturity level with the least distance.

In Step B.1, the delta (δ) value as an indicator of item difficulty was calculated between the "as-is" value of an item and the median of the "to-be" value of that item for all organisations. A positive δ value indicates a difficult and desired item while a negative δ value indicates an item that is easy to achieve. Rasch analysis produces an ordinal value that represents the logit measure of each item and organisation. A cluster analysis is then applied to the logit measure of the item by five clusters to derive five distinct maturity levels. The Euclidean distance is calculated for the specific dimension *d* of an organisation *o* between the responses x_{oi} given the specific items *i* belong to the set of items of the dimension I_d, and their defined characteristic values for a specific maturity level v_{li}. The distance value $DistD_{od}$ for each organisation *o* by maturity level *l* is:

$$DistD_{od}(l) = \sqrt{\sum_{i \epsilon I_d} (x_{oi} - v_{li})^2} \text{ for } 1 \leq d \leq n_d \text{ and } 1 \leq l \leq n_l$$

In Step B.2, the total number of dimensions is nine (n_d=9) and the total number of levels is five (n_l =5) for the BARCMM. Each BA maturity dimension of an organisation can be classified in a maturity level based on these distance values. The least distant level is assigned to each dimension of maturity, which gives five integer values for each organisation, which characterise the BA maturity levels of an organisation:

$$LevelD_{od} = m, \text{such that } DistD_{od}(m) = \min_{1 \le l \le n_l} \left(DistD_{od}(l)\right) \text{ for } 1 \le m \le n_l$$

In Step B.3, in order to calculate the distances of each BA maturity level $LevelO_o$ for an organisation o, the Euclidean distance is calculated between five maturity values $LevelD_{od}$ of each dimension, and the characteristic value of the specific maturity dimension d for each level l ($u_{ld} = l$).

In Step B.4, the least distance of the five computed distance values $DistO_o$ per organisation classifies an organisation's BA maturity level ($LevelO_o$):

$$DistO_o(l) = \sqrt{\sum_{d=1}^{n_d} (LevelD_{od} - u_{ld})^2} \text{ for } 1 \le l \le n_l, \text{then}$$

$$LevelO_o = m, \text{ such that } DistO_o(m) = \min_{1 \le l \le n_l} \left(DistO_o(l)\right) \text{ for } 1 \le m \le n_l$$

Once the maturity level of each organisation is classified in Step B.4, a set of measurement items for Perceived ERP BA Success and Perceived BA Capability (see Appendix E) is used to test RQ3: "How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?" It is assumed that organisations with higher BA maturity will show greater Perceived ERP BA Success and BA Capability than those with lower maturity. Following Elbashir et al. (2008) and Raber et al. (2013a), the proposed PLS-SEM model is specified as a reflective measurement model.

In BARCMM Phase C, the BA maturity level as a determinant of BA Capability and BA Success in organisations using ERP systems was empirically assessed using PLS-SEM. SmartPLS, a user-friendly software for path modelling in PLS-SEM (Ringle et al. 2015), was used for the analysis. PLS-SEM, which provides accurate estimates with small sample sizes and constructs with fewer items (Hair et al. 2016), validated the PLS-SEM model of BA maturity as an indicator of Perceived BA Capability and Perceived ERP BA Success in organisations using ERP systems.

4.2.1. Rationale for Developing the BARCMM

The development of the BARCMM addresses the need for organisations to systematically assess and enhance their BA capabilities within contemporary ERP systems. Organisations recognise the transformative potential of BA for optimising decision-making, gaining competitive advantages, and achieving strategic goals. However, the lack of a tailored maturity model for BA in ERP environments is a challenge. The BARCMM provides a structured framework for organisations to evaluate their current BA capability, identify improvement areas, and progress to higher maturity levels. It offers a roadmap to enhance BA capabilities within ERP systems, aligning business strategies with technological advancements and helping organisations stay competitive in a data-driven landscape.

4.2.2. Objectives and Scope of the BARCMM

This research aims to design, develop and evaluate the Business Analytics Readiness and Capability Maturity Model (BARCMM) using a rigorous and methodological approach. It seeks to assess the BA readiness and capability of organisations using ERP systems in the GCR using two questionnaire surveys: Survey 1 as the pilot study and Survey 2 as the full study. The use of two surveys also demonstrates that Rasch analysis and cluster analysis can identify measurement items based on item difficulty for each maturity level. Additionally, they can determine whether there are sufficient measurement items to measure a particular maturity level. Furthermore, these analyses can identify issues with measurement items using person-item maps and plots of average scores for each measurement item in radar charts.

The three main objectives are as follows:

(1) Objective 1 focuses on identifying CSFs for ERP BA readiness, developing effective measurement methods, defining dimensions for ERP maturity assessment, and exploring additional factors for the BARCMM.
(2) Objective 2 addresses CSFs for BA capability, methodologies for BA measurement, adaptation of BA maturity models to new-generation ERP systems, and empirical validation.
(3) Objective 3 investigates the relationship between ERP BA readiness and BA capability, tests a BA capability maturity model in ERP systems using IRT for

rigorous measurement, enhances measurement item reliability, and explores correlations between BA maturity, perceived BA capability, and perceived ERP BA success in Greater China Region organisations within the BARCMM framework.

The scope of the BARCMM encompasses the GCR, a region globally renowned as the factory of the world. Within this scope, the model is designed to capture the intricacies of organisations that have integrated ERP systems with BA capabilities. The rationale for using two surveys in this study is to verify whether the measurement items from Survey 1 reliably assess maturity levels for constructing the BARCMM. If Rasch analysis reveals gaps in Survey 1, Survey 2 revises and includes additional items to improve the BARCMM and enhance the accuracy of maturity level assessment. The development and validation of Surveys 1 and 2 through Rasch analysis and clustering are summarised in Figure 3.5 of Chapter 3.

This research undertakes a significant endeavour to develop a BA maturity model that encapsulates the holistic landscape of BA readiness and capability in organisations using ERP systems, with a specific focus on the GCR. By aligning objectives with this scope, the BARCMM aims to offer valuable insights and actionable guidance to organisations operating within this dynamic and influential region.

4.2.3. Significance of Assessing BA Readiness and Capability Maturity

This research highlights the importance of assessing BA readiness and capability maturity in organisations. It makes theoretical contributions by introducing the BARCMM, a framework for evaluating BA readiness and capability in organisations using ERP systems, helping them compare their current state with future prospects. Practically, it develops a self-assessment questionnaire based on the BARCMM, adaptable to new ERP systems supporting Industry 4.0. Using Rasch and cluster analysis, the research systematically determines maturity levels and predicts perceived BA capability and success. The BARCMM and questionnaire can be applied globally, allowing cross-regional comparisons and insights into industry maturity levels. Methodologically, the use of IRT and statistical techniques like Rasch analysis enhances measurement reliability and explores the relationships between BA maturity, capability, and success. While acknowledging limitations such as perception-based measures and regional focus, the research provides a foundation for future validation and expansion.

4.2.4. Structure of the BARCMM Development Process

The structure of the BARCMM development process involves several key phases and steps, as outlined below.

(1) BARCMM Phase A: Dimension Identification

In this phase, the research identified nine key dimensions of BA Maturity: Governance, Culture, Technology, People, Operation, Data Capability, Analytics Capability, Collaboration Tools Capability, and Sharing Capability. These dimensions were sourced from existing literature and previous studies, including works by Cosic et al. (2012), Rouhani and Ravasan (2013) , Rouhani and Mehri (2016), Angreani et al. (2020), Halo (2015), and Hornick (2020). Each dimension was associated with a set of measurement items to assess its maturity.

(2) BARCMM Phase B: Maturity Level Calculation

This phase involved the calculation of maturity levels for organisations based on their responses to the measurement items within each dimension. A hierarchical clustering approach was used to determine the ideal maturity profiles, followed by the calculation of the Euclidean distance of each organisation to each maturity level. The maturity level with the smallest Euclidean distance was assigned to each organisation, representing their BA maturity level. This process was repeated for each of the nine dimensions.

(3) BARCMM Phase C: Empirical Application

In this phase, the developed instrument for BA readiness and capability maturity was empirically applied to assess BA maturity as a determinant of BA capability and success in organisations using ERP systems.

4.3. Development of BA Readiness and Capability Maturity Model

Previous BIMMs (Lahrmann et al. 2011; Raber et al. 2013b, 2013a) and BAMMs (Cosic et al. 2012; Halo 2015) were reviewed to describe and justify the proposed BARCMM. The approach to measuring BA maturity levels in organisations using ERP systems is detailed and justified, following the empirical methods of Raber et al. (2013b, 2013a). Rasch Analysis assesses item difficulty and organisational capability, while hierarchical clustering analysis classifies items and organisations into maturity levels on a standardised scale. This research illustrates how Rasch and clustering analyses determine item difficulty and classify organisations into BA maturity levels. The GCR is selected for this study due to the high number of organisations using ERP systems with business analytics in the region.

Cosic et al. (2012) define a Business Analytics Capability Maturity Model (BACMM) that provides a comprehensive view of an organisation's BA capability across four domains: governance, culture, technology, and people. The Governance domain involves managing BA resources and aligning initiatives with organisational goals. The Culture domain covers organisational norms, values, and behaviours. The Technology domain addresses hardware, software, and data use in BA activities. The People domain focuses on employees' skills and knowledge in BA (Cosic et al. 2012). Cosic et al.'s BACMM was adapted from the maturity model for IT Management developed by Becker et al. (2009). Cosic et al. (2012) used a Delphi study to validate their framework with experts.

A systematic review by Angreani et al. (2020) identifies nine dimensions used in Industry 4.0 maturity models: Strategy, Leadership, Customers, Products, Operations, Culture, People, Governance, and Technology, with technology and operations receiving significant attention. BA technology is crucial for decision-making in an organisation's operations (Bayrak 2015). It can transform how organisations utilise internal and external data from various channels, including social networks, mobile devices, websites, and IoT sensors. By providing a comprehensive view of business operations and supply chain partners, BA technology enhances operational efficiency and supports a data-driven decision-making environment.

The Manufacturing Operation Management (MOM) capability maturity model by the Manufacturing Enterprise Solutions Association (MESA) outlines levels of efficiency in manufacturing, suggesting that higher maturity indicates fewer systemic problems and errors (Castor et al. 2016). In this research, the Operation dimension pertains to the use of BA within ERP systems to enhance operational and financial outcomes, such as improving information access, driving innovation, and increasing operational efficiency. Adding an Operations dimension to the BARCMM is appropriate as it incorporates the operational measurement of ERP systems, including whether they are customised to organisational needs and if processes are regularly audited for efficiency.

This research extends Cosic et al.'s work by quantitatively designing, developing, and evaluating the BARCMM for organisations using ERP systems, adapting four dimensions from their model (Governance, Culture, Technology, People) and incorporating the Operations dimension from Bayrak (2015) and Castor et al. (2016) for ERP BA readiness measurement. The inclusion of the Operations (Operation) dimension in the BARCMM is justified by its central role in ERP systems, alignment with industry trends, enhancement of model relevance, and provision of a holistic assessment of how BA capabilities support operational processes.

BA tools are now commonly integrated into ERP systems from major vendors, enabling data analysis and visualisation within operational applications or other software (Gessa et al. 2023; Bandara et al. 2024). The integration of big-data ERP systems with BA poses significant challenges, emphasising the trend of incorporating analytics within ERP environments (Shi & Wang 2018). Although two organisations may use the same ERP systems, their ability to leverage BA functionality depends on their capability to utilise the available functionalities and the extent to which they integrate and share data, collaborate, and disseminate information using the BA tools. Therefore, four additional dimensions (Data, Analytics, Collaboration, and Dissemination) are adapted from Halo's (2015) BI maturity model. Based on an extensive literature review, nine dimensions are proposed for the BARCMM: Governance, Culture, Technology, People, Operation, Data Capability, Analytics Capability, Collaboration Tools Capability, and Sharing Capability.

Table 4.2 compares the BI Maturity Model of Raber et al. (2013b) with the BARCMM developed and evaluated in this research.

Table 4.2 Comparison of Raber et al.'s (2013b) BI Maturity Model and BARCMM from Surveys 1 and 2

Comparison Criteria	**BI Maturity Model (Raber et al. 2013b)**	**BARCMM (Survey 1)**	**BARCMM (Survey 2)**
Number of Dimensions	5 dimensions (Strategy, Organisation, IT, Quality, and Use)	5 dimensions for ERP BA readiness (Governance, Culture, Technology, People, and Operation) and 4 dimensions for BA capability (Data Source Capability, Analytics Capability, Collaboration Tools Capability, Sharing Capability)	
Measurement Scale	Five-point Likert scale from (1) “strongly disagree” to (5) “strongly agree”)	Seven-point Likert scale from (1) “strongly disagree” to (7) “strongly agree”)	
Usable Sample Size	92	112	89
Focus	Business Intelligence Maturity for Business Benefits of BI	BA readiness and capability maturity for organisations using ERP systems	
No. of indicators in the questionnaire	25	49 (20 ERP BA readiness + 20 BA capability + 5 perceived ERP BA success + 4 perceived BA capability)	68 (38 ERP BA readiness + 20 BA capability + 5 perceived ERP BA success + 4 perceived BA capability)
Tools to validate the model	PLS-SEM analysis using the SmartPLS software (version 2)	PLS-SEM analysis using the SmartPLS software (version 3)	
Adopted bootstrapping sampling method	Generate 500 samples to estimate path coefficient significance	Generate 500 samples to estimate path coefficient significance	

An overview of the literature on business intelligence maturity models reveals that most of these models often concentrate on specific dimensions or domains of BI maturity, rather than providing a comprehensive view of the entire domain (Thamir & Theodoulidis 2013; Brooks et al. 2015). These models offer detailed insights into particular areas such as technical processes or organisational capabilities, enabling organisations to assess and improve specific aspects of their BI readiness and maturity. The maturity model is valuable for assessing a company's business intelligence maturity because it helps identify which areas require special attention. To obtain a more precise maturity level assessment, a company should employ multiple maturity models, expanding their coverage of key areas and gaining insights into the current state and potential challenges that need to be addressed to achieve a higher level of maturity and enhance business value. However, when using multiple models, it is important to note that results from different models may not be directly comparable. This discrepancy arises from the lack of standardisation in metrics, areas, levels, and criteria (Rajterič 2010).

In Chapter 2, Table 2.3 presents a comprehensive summary and comparison of BIMMs by focus, design, assessment, validation, and source. The models are analysed in terms of these key aspects to provide a holistic view of their characteristics and contributions to the field. These BIMMs differ in their design approaches, the number of companies surveyed, and the presence or absence of validation processes. The BI Maturity Model developed by Raber et al. (2013b, 2013a) stands out due to its validation through expert consultation, potentially enhancing its reliability and comprehensiveness.

4.3.1. Comparison of BARCMM with other BAMMs

The BARCMM is compared with the TDWI Analytics Maturity Model, Gartner BI and Analytics Maturity Model (Howson & Duncan 2015), model proposed by INFORMS (The Institute for Operations Research and the Management Sciences) (The Institute for Operations Research and the Management Sciences 2017a), and the International Institute for Analytics (IIA) Analytics Maturity Model (International Institute for Analytics n.d.). A detailed comparison of the proposed Business Analytics Readiness and Capability Maturity Model (BARCMM) with similar analytics maturity models is presented in Table 4.3.

Most maturity models are generic BAMMs, assessing analytics maturity across industries (Ariyarathna & Peter 2019) . However, they often neglect the specific requirements of Business Analytics in ERP systems, which possess distinct functionalities tailored to integrated business operations within the organisation, as well as the integration of ERP systems with their business partners in the supply chain (Nofal & Yusof 2013).

The BARCMM is designed as a level-based maturity model with five levels, adapted from the CMM. It aims to assess ERP BA readiness and BA capability of organisations using ERP systems in the GCR. When comparing the BARCMM to generic BAMMs, these models exhibit both similarities and differences, as outlined in Table 4.3.

These models primarily share a focus on enhancing analytics maturity within organisations. They employ a multi-level structure to assess the progression of analytics capabilities, featuring stages such as "Initial," "Repeatable," "Defined," "Managed," and "Optimising." Typically, this structure incorporates dimensions such as culture, technology, governance, and data management to assess analytics maturity. Furthermore, the BARCMM, as well as some other models, has an academic basis, drawing from academic research for its foundation.

These models diverge in their specific focus, with the BARCMM concentrating on "ERP BA readiness and BA capability," while others target different aspects like predictive analytics, social media analysis, or organisational analytics capabilities. The origin of these models varies: the BARCMM is academically rooted, while others may originate from organisations or practitioners such as TDWI, INFORMS, Gartner, or the International Institute for Analytics. Additionally, the number and nature of dimensions used for assessment differ among models. For instance, the BARCMM employs specific dimensions for ERP BA readiness and BA capability, while the TDWI model evaluates various dimensions related to organisation, infrastructure, data management, analytics, and governance. Moreover, each model defines its unique set of maturity levels, with definitions that cater to their intended purposes and industries. For instance, the BARCMM employs five levels from "Initial" to "Optimising," whereas the INFORMS Analytics Maturity Model adopts three levels: "Beginning," "Developing," and "Advanced."

Maturity models are primarily declarative and rely on self-assessment, providing a snapshot of a situation and a framework for defining and prioritising improvement measures. Their key strengths include ease of use, applicability from functional and cross-functional perspectives, opportunities for consensus and team building, and the ability to be performed by external auditors or through self-assessment (Boughzala & de Vreede 2011).

The BARCMM developed in this study is informed by previous BA analytics maturity models, as shown in Table 4.4. Appendix F provides an overview of the five ERP BA readiness dimensions, including definitions and contributions from existing literature. Appendix G provides an overview of the four BA capability dimensions, including definitions and literature contributions.

The BARCMM is designed for organisations using an ERP system with implemented Business Analytics. It shares a focus on improving analytics capabilities with the TDWI, INFORMS, and IIA Analytics Maturity Models. However, they differ in origins, stages/levels, and dimensions. The BARCMM, academic in origin, has five maturity levels based on the CMM/CMMI framework. The TDWI model has five stages, focusing on various analytics approaches. The INFORMS model has three levels, emphasising benchmarking and improvement actions. The IIA model has five stages and evaluates across five dimensions. Each model interprets analytics maturity differently but aims to enhance organisations' analytical capabilities.

Table 4.3 Comparison of BARCMM with Other BAMMs

<table>
<tr><th>Maturity Model</th><th>Focus</th><th>Origin</th><th>Stages/Levels</th><th>Dimensions</th><th>Interpretation</th></tr>
<tr><td>BARCMM</td><td>ERP BA readiness and BA capability</td><td>Academic Based on Cosic et al. (2012), Hawking et al. (2011), Halo (2015)</td><td>5 levels (adapted from CMM/ CMMI): Initial, Repeatable, Defined, Managed, Optimising</td><td>5 ERP BA readiness dimensions: Governance, Culture, Technology, People, Operation
4 BA capability dimensions: Data Source Capability, Analytics Capability, Collaboration Tools Capability, Sharing Capability</td><td>ERP BA Readiness Dimensions:
<table>
<tr><td>Dimension</td><td>Survey 1</td><td>Survey 2</td></tr>
<tr><td>Governance</td><td>gov1-gov4</td><td>gov1-gov8</td></tr>
<tr><td>Culture</td><td>cul1-cul4</td><td>cul1-cul8</td></tr>
<tr><td>Technology</td><td>tec1-tec4</td><td>tec1-tec8</td></tr>
<tr><td>People</td><td>peo1-peo6</td><td>peo1-peo8</td></tr>
<tr><td>Operation</td><td>ope1-ope2</td><td>ope1-ope6</td></tr>
</table>
BA Capability Dimensions:
<table>
<tr><td>Dimension</td><td>Surveys 1, 2</td></tr>
<tr><td>Data Source Capability</td><td>dat1-dat5</td></tr>
<tr><td>Analytics Capability</td><td>cul1-cul4</td></tr>
<tr><td>Technology</td><td>cap1-cap5</td></tr>
<tr><td>Sharing Capability</td><td>sha1-sha5</td></tr>
</table>
Maturity level is determined using Rasch analysis and clustering.
<table>
<tr><td>Level</td><td>Description</td></tr>
<tr><td>1</td><td>Initial</td></tr>
<tr><td>2</td><td>Repeatable</td></tr>
<tr><td>3</td><td>Defined</td></tr>
<tr><td>4</td><td>Managed</td></tr>
<tr><td>5</td><td>Optimising</td></tr>
</table></td></tr>
<tr><td>TDWI Analytics Maturity Model</td><td>Predictive analytics, social media analysis, text analytics, cloud computing, and big data analytics approaches</td><td>(Halper & Stodder 2014)</td><td>5 stages:
1 Nascent
2 Pre-adoption
3 Early adoption
4 Corporate adoption
5 Mature/ visionary</td><td>5 dimensions:
Organisation
Infrastructure
Data Management
Analytics
Governance</td><td>Each dimension has a potential high score of 20 points.
<table>
<tr><td>Score per Dimension</td><td>Stage</td></tr>
<tr><td>4–7.1</td><td>Nascent</td></tr>
<tr><td>7.2–10.1</td><td>Pre-Adoption</td></tr>
<tr><td>10.2–13.3</td><td>Early Adoption</td></tr>
<tr><td>13.4–16.6</td><td>Corporate Adoption</td></tr>
<tr><td>16.7–20</td><td>Mature/ Visionary</td></tr>
</table></td></tr>
</table>

Table 4.3 Comparison of BARCMM with Other BAMMs

<table>
<tr><th>Maturity Model</th><th>Focus</th><th>Origin</th><th>Stages/Levels</th><th>Dimensions</th><th>Interpretation</th></tr>
<tr><td>INFORMS Analytics Maturity Model</td><td>Benchmarking capabilities and identifying actions to improve analytical maturity</td><td>(The Institute for Operations Research and the Management Sciences 2017)</td><td>3 levels:
Beginning
Developing
Advanced</td><td>3 dimensions:
Organisational
Analytics
Capability
Data & Infrastructure</td><td>Each dimension has a potential high score of 10 points.<table><tr><td>Score per Dimension</td><td>Stage</td></tr><tr><td>1 - 3</td><td>Beginning</td></tr><tr><td>4 - 7</td><td>Developing</td></tr><tr><td>9 - 10</td><td>Advanced</td></tr></table></td></tr>
<tr><td>Gartner's ITScore for BI and Analytics Maturity Model</td><td>Help clients assess the maturity of their BI and analytics programs</td><td>(Howson & Duncan 2015)</td><td>5 levels:
Unaware
Opportunistic
Standards
Enterprise
Transformative</td><td>5 dimensions:
Business drivers
People
Program management
Processes
Platform</td><td>Not specified</td></tr>
<tr><td>Defining analytics maturity indicators: A survey approach</td><td>Defining analytics maturity indicators</td><td>(Lismont et al. 2017)</td><td>4 clusters:
1: no analytics
2: analytics bootstrappers
3: sustainable analytics adopters
4: disruptive analytics innovators</td><td>3 dimensions:
Capability
Culture
Technology</td><td>Not specified</td></tr>
<tr><td>International Institute for Analytics (IIA) Analytics Maturity Model</td><td>Comparing and identifying key priorities for optimising performance through improving analytics capabilities</td><td>(International Institute for Analytics n.d.)</td><td>5 stages:
1: Analytically impaired
2: Localised analytics
3: Analytical aspirations
4: Analytical companies
5: Analytical competitors</td><td>5 Dimensions
Data
Enterprise
Leadership
Targets
Analysts</td><td>Analytics Maturity Assessment is evaluated against 33 unique competencies within the five DELTA model categories. DELTA scores are calculated on a 1.00-5.99 scale with descriptive stages of maturity assigned to each of the five score ranges (1-1.99, 2-2.99, etc.) and aligned with the five stages</td></tr>
</table>

Table 4.4 Business Analytics Maturity Models Influencing BARCMM

<table>
<tr><th>Maturity Model</th><th>BARCMM</th><th>TDWI Analytics Maturity Model</th><th>INFORMS Analytics Maturity Model</th><th>International Institute for Analytics (IIA) Analytics Maturity Model</th></tr>
<tr><td>Focus</td><td>Business analytics readiness and capability maturity model for organisations using ERP systems</td><td>Predictive analytics, social media/ text analytics, cloud computing, and big data analytics approaches</td><td>Benchmarking capabilities and identifying actions to improve the analytical maturity</td><td>Optimising performance by improving analytics capabilities</td></tr>
<tr><td>Origin</td><td>Academic
Based on Cosic et al. (2012), Hawking et al. (2011), Halo (2015), Raber et al. (2013b, 2013a)</td><td>Halper and Stodder (2014)</td><td>The Institute for Operations Research and the Management Sciences (2017)</td><td>International Institute for Analytics (n.d.)</td></tr>
<tr><td>Stages/ Levels</td><td>5 levels: based on CMM. Initial, Repeatable, Defined, Managed, Optimising</td><td>5 stages: Nascent, Pre-adoption, Early Adoption, Corporate Adoption, Mature/ Visionary</td><td>3 levels: Beginning, Developing, Advanced</td><td>5 stages: Analytically impaired, Localised analytics, Analytical aspirations, Analytical companies, Analytical competitors</td></tr>
<tr><td>Dimensions</td><td>5 dimensions for BA readiness: Governance, culture, technology, people, operation.
4 dimensions for BA capability: Data Source Capability, Analytics Capability, Collaboration Tools Capability, Sharing Capability</td><td>5 dimensions: Organisation, Infrastructure, Data Management, Analytics, Governance</td><td>3 dimensions: Organisational, Analytics Capability, Data & Infrastructure</td><td>5 dimensions: Data, Enterprise, Leadership, Targets, Analysts</td></tr>
<tr><td>Interpretation</td><td>Methodological approach adopted by Raber et al. (2013a) for BIMM
<table>
<tr><th>Level</th><th>Description</th></tr>
<tr><td>1</td><td>Initial</td></tr>
<tr><td>2</td><td>Repeatable</td></tr>
<tr><td>3</td><td>Defined</td></tr>
<tr><td>4</td><td>Managed</td></tr>
<tr><td>5</td><td>Optimising</td></tr>
</table></td><td>Each dimension has a high score of 20 points.
<table>
<tr><th>Score per Dimension</th><th>Stage</th></tr>
<tr><td>4–7.1</td><td>Nascent</td></tr>
<tr><td>7.2–10.1</td><td>Pre-Adoption</td></tr>
<tr><td>10.2–13.3</td><td>Early Adoption</td></tr>
<tr><td>13.4–16.6</td><td>Corporate Adoption</td></tr>
<tr><td>16.7–20</td><td>Mature/ Visionary</td></tr>
</table></td><td>Each dimension has a potential high score of 10 points.
<table>
<tr><th>Score per Dimension</th><th>Stage</th></tr>
<tr><td>1 - 3</td><td>Beginning</td></tr>
<tr><td>4 - 7</td><td>Developing</td></tr>
<tr><td>9 - 10</td><td>Advanced</td></tr>
</table></td><td>Analytics Maturity Assessment is evaluated against 33 unique competencies within the five DELTA model categories. DELTA scores are calculated on a 1.00-5.99 scale with descriptive stages of maturity assigned to each of the five score ranges (1-1.99, 2-2.99, etc.) and aligned with the five stages</td></tr>
</table>

4.3.2. Measurement of BA Readiness, Capability and Business Analytics Success

BA Readiness refers to an organisation's preparedness and capability to effectively leverage business analytics to drive informed decision-making and achieve strategic objectives (Olszak & Mach-Król 2018). According to an empirical study by Chen and Nath (2017) examining the relationships between managerial perception of IT, BA maturity and BA success, the results show that (1) BA maturity can be measured through BA integration and management support, BA process level benefits, technology and BA capabilities, (2) BA maturity positively affects the overall BA success of organisations. According to Gürdür et al. (2019), BA readiness includes four key dimensions: (1) Resources (People) Readiness, which assesses tangible resources such as workforce competencies and tools necessary for data analytics, focusing on evaluating skilled human resources and tool availability; (2) Information Systems (Technology) Readiness evaluates the maturity of a company's information systems by examining data-related policies, accessibility, and the presence of data analytics teams; (3) Cultural (Culture) Readiness scrutinises a company's culture regarding data-driven decision-making, gauging the recognition of data importance and the presence of supportive internal processes; (4) Organisational (Governance, Operations) Readiness evaluates the internal structure and processes to determine if a defined roadmap for data analytics exists and if the business impacts of analytics results are clear.

In this research, the aim is to develop a BA Readiness and Capability Maturity Model for organisations using ERP systems. The assessment of BA readiness in their ERP systems was measured before respondents ranked their BA capability. This is because their level of BA readiness would affect their BA capability assessment. Specifically, the assessment of the five dimensions of maturity in BA readiness (i.e., governance, culture, technology, people, and operations) was measured. The assessment of the four dimensions of maturity in BA capabilities (i.e., data source capability, analytics capability, collaboration tools capability, and sharing capability) was also measured. Finally, the perceived ERP BA success was assessed by the CSFs for BA success in terms of data accuracy, ease of use, data integration, efficiency, and improvement in individual productivity (see Appendix C). It is assumed that if organisations possess required CSFs for BA success, this will lead to the overall BA success of organisations. Perceived BA capability is assessed by the self-efficacy of an organisation's BA capability in terms of data capabilities, analytics capabilities, collaboration capabilities and dissemination capabilities.

4.4. Design of BARCMM Measurement Instrument

The development of the Business Analytics Readiness and Capability Maturity Model (BARCMM) measurement instruments is founded upon a systematic literature review and methodological approaches outlined in Chapters 4, 5 and 6 of the provided source material. This explanation will briefly detail the process through which BARCMM measurement instruments are formulated. These chapters significantly contribute to the development of BARCMM by establishing a conceptual foundation, selecting measurement items, and employing methodological approaches for its design and assessment. Furthermore, the model integrates insights from ERP systems and BA maturity models to create a comprehensive measurement instrument.

A quantitative survey instrument adapted from previous studies was used to collect data for the development and evaluation of a BARCMM (Cosic et al. 2012; Rouhani & Ravasan 2013; Halo 2015; Rouhani & Mehri 2016). Appendix C outlines the essential characteristics of the five levels of maturity of BARCMM, as formulated for this study. These characteristics have been adapted from the essential characteristics of BIMM for each of the five levels by Halo (2015) and include the corresponding ERP characteristics that support the essential business analytics characteristics.

The development of BARCMM in this research adapted the methodological approach used by Raber et al. (2013b, 2013a) and Lahrmann et al. (2011) for the development of a BI Maturity Model, originally developed by Dekleva and Drehmer (1997). The rigorous approach to developing a maturity model used by Raber et al. (2013b, 2013a) is generalisable and not specific to BI, so it can be used for other related domains in order to overcome methodological weaknesses of other approaches used for developing BAMMs.

An online survey collected data to assess BA capability maturity levels in organisations using ERP systems with BA tools. Nine dimensions (governance, culture, technology, people, operations, data source, analytics, collaboration capability, and sharing capability) were measured by 40 items in Survey 1 and 58 items in Survey 2. Table 4.5 lists the sources for these dimensions and items in Survey 1, while Table 4.6 covers Survey 2.

Table 4.5 Sources of BARCMM Measurement Items for Nine Dimensions (Survey 1)

Dimension (No. of Items)	**Measurement Items**	**Source of construct and measurement items**
Governance (4)	gov1-gov4	Cosic et al. (2012); Rouhani and Ravasan (2013); Angreani et al. (2020)
Culture (4)	cul1-cul4	
Technology (4)	tec1-tec4	
People (6)	peo1-peo6	
Operations (2)	ope1-ope2	Rouhani and Ravasan (2013); Rouhani and Mehri (2016); Angreani et al. (2020)
Data Capability (5)	dat1-dat5	Halo (2015); Hornick (2020)
Analytics Capability (5)	cap1-cap5	
Collaboration Tools Capability (5)	too1-too5	
Sharing Capability (5)	sha1-sha5	

Table 4.6 Sources of BARCMM Measurement Items for Nine Dimensions (Survey 2)

Dimension (No. of Items)	**Measurement Items**	**Source of construct and measurement items**
Governance (8)	gov1-gov8	Cosic et al. (2012); Rouhani and Ravasan (2013); Angreani et al. (2020)
Culture (8)	cul1-cul8	
Technology (8)	tec1-tec8	
People (8)	peo1-peo8	
Operations (6)	ope1-ope6	Rouhani and Ravasan (2013); Rouhani and Mehri (2016); Angreani et al. (2020)
Data Capability (5)	dat1-dat5	Halo (2015); Hornick (2020)
Analytics Capability (5)	cap1-cap5	
Collaboration Tools Capability (5)	too1-too5	
Sharing Capability (5)	sha1-sha5	

4.4.1. Theoretical Framework for the BARCMM

The theoretical framework for the BARCMM is built on an applied research philosophy, draws from existing models in the literature, employs a mixed-methods research design, utilises quantitative research methods, and results in a conceptual framework for assessing and predicting the success of business analytics in ERP systems. The theoretical framework for the Business Analytics Readiness and Capability Maturity Model (BARCMM) is based on the following five key elements, as described in the research:

(1) Research Philosophy: The research philosophy adopted in this study leans towards an applied and practical orientation, typical of Information Systems (IS) research. IS research often prioritises practical and methodological aspects over ontological and philosophical considerations. The choice between deductive and inductive research approaches is guided by the nature of the research question, with deductive methods used for hypothesis testing and inductive methods for comparing existing theories with collected data. This study exclusively employs quantitative methods through self-assessment questionnaires, with a focus on positivism and objective measurement.

(2) Initial Model Sources: The initial BARCMM was developed by drawing inspiration from existing models in the literature. The BA readiness component was influenced by the BI maturity model developed by Cosic et al. (2012), referencing the BI maturity model by Hawking et al. (2011). The BA capability dimension drew from the dimensions used by Halo (2015). Questionnaires and critical success factors used in these models provided a foundational structure for the development of the BARCMM.

(3) Research Design: The research design involves conducting an online questionnaire survey in two stages: Survey 1 and Survey 2. Survey 1 served as the pilot phase, with 1,200 participants invited. Data from Survey 1 were analysed to make necessary modifications for Survey 2. Organisations in various industries in the GCR were invited to participate, with an additional pool of 1,200 invited participants for Survey 2, including IT managers, project managers, and system administrators.

Survey 2 aimed to validate the model and included participants from public listed manufacturing corporations.

(4) Research Methods: Survey questionnaires were developed, with initial questions borrowed from the work of Rouhani and Ravasan (2013) for ERP profile questions and critical success factors from the Halo Business Intelligence Maturity Model (Halo, 2015) for BA profile questions. PLS-SEM, particularly Confirmatory Factor Analysis (CFA), was used to examine hypothesised relations among ordinal variables, such as Likert-type items. Partial Least Squares (PLS) path modelling, an alternative for estimating Structural Equation Models, was adopted to analyse relationships among multiple blocks of variables. Data were analysed and compared using SPSS CFA and PLS Modelling with R.

(5) Research Framework: The research framework involved the development of a conceptual model for an ERP Business Analytics Maturity Model. This model aims to help organisations in the GCR evaluate and predict the success of implementing business analytics in ERP systems based on critical success factors, organisational culture, and maturity stages of the ERP. The framework draws on existing research and models from the literature, adapting and evaluating them through quantitative surveys and data analysis.

4.4.2. Components and Dimensions of the BARCMM

The decision to adapt the first five dimensions (Governance, Culture, Technology, People, and Operations) from the original eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services) identified in SLR 1 in Chapter 2 can be attributed to the need for focus and relevance. These five dimensions are inherently pertinent to the context, holding substantial influence over an organisation's overall functioning, especially concerning the ERP BA readiness of organisations using ERP systems. This selective approach streamlines the management and analysis of data within each dimension, fostering clearer communication and comprehension within and beyond the organisation. Moreover, this focus enables a more manageable and targeted assessment, emphasising these fundamental dimensions recognised as primary drivers of organisational success and change. Recognising their significance aids in informed decision-making. Additionally, this choice aligns with research objectives, ensuring that the study's scope is well-matched with the pursuit of meaningful and actionable outcomes.

The survey instruments for the nine BARCMM dimensions are detailed in Appendix D: 40 items in Survey 1 and 58 items in Survey 2. Items are adapted from Rouhani and Ravasan (2013) for five dimensions (Governance, Culture, Technology, People, Operations) and from Halo (2015) for four capability dimensions (Data Capability, Analytics Capability, Collaboration Tools Capability, Sharing Capability).

4.4.3. Development and Selection of Measurement Items

Table 4.7 outlines the Unified ERP BA Readiness and Capability Maturity Characteristics, integrating ERP readiness with BA capability into a single framework. Essential characteristics of the five-level BARCMM for organisations using ERP systems are also detailed in Appendix C. It presents a holistic view of organisational maturity across five levels:

(1) **Level 1 (Initial)**: Focuses on managing legacy systems and starting ERP projects, with BA systems in the early stages of implementation.

(2) **Level 2 (Repeatable)**: Involves using ERP systems to derive value and basic analytics, with data systems providing historical reports.

(3) **Level 3 (Defined)**: Features normalised ERP systems providing strategic value and advanced BA capabilities, including data cleansing and KPI formalisation.

(4) **Level 4 (Managed)**: Highlights formal processes around data and metrics with senior executives engaged in using ERP and BA as differentiators.

(5) **Level 5 (Optimising)**: Emphasises alignment of people, processes, and technology for optimal metric-driven decisions and the use of modelling algorithms to enhance products and services.

Table 4.7 Unified ERP BA Readiness and Capability Maturity Characteristics

Level	ERP BA Readiness Maturity Characteristics	BA Capability Maturity Characteristics
1 Initial	Companies are managing legacy systems and starting ERP projects and are primarily focused on operations of the organisation having the beginning of an ERP system in place. They decided to invest in ERP or are in the process of implementing ERP systems.	Companies are primarily focused on data collection and data organisation having the beginning of a BA system in place. They made decision to invest in BA and have, or are in the process of implementing data collections systems and data warehousing solutions.
2 Repeatable	Companies have ERP systems in place have the ability to derive some value from the functionality of ERP system being exploited across the organisation.	Companies have data systems in place have the ability to derive some BA value from basic analytics, producing historical reports for key individuals only.
3 Defined	Companies have normalised the ERP systems into the organisation and are obtaining strategic value from ERP system by using additional systems such as those for customer relationship management, knowledge management and supply chain planning.	Companies concentrate most efforts on data cleansing, formalising KPI's and metrics, increasing distribution and data usage throughout the organisation. Companies are deriving value from BA reporting, Analytics and also exploring new capabilities such as predictive analytics.
4 Managed	Companies perceive information as critical for business and have formal processes around data and metrics using ERP systems to make and support key decisions. Senior executives are fully engaged in ERP, focused on better and faster decision making, cost reduction, empowerment through distribution and collaboration. They see ERP as a differentiator between them and their competition.	Companies have formal processes around data and metrics using data to make and support key decisions. Senior executives are fully engaged in BA, focused on better and faster decision making, cost reduction, empowerment through distribution and collaboration. They see BA as a differentiator between them and their competition.
5 Optimising	Companies have aligned people, processes and technology to facilitate optimal metric-driven decisions. They empower their customers, distribution channels and suppliers with key performance data integrating human collaboration in solving problems exposed through ERP, using information across the entire supply chain.	Companies have aligned people, processes and technology to facilitate optimal metric-driven decisions. They empower their customers, distribution channels and suppliers with key performance data integrating human collaboration in solving problems exposed through BA, using modelling algorithms to improve products and services.

Table 4.8 Measurement Items in Surveys 1 and 2

Profile	Dimension	Survey 1 Code	Survey 2 Code	Measurement Item	Scale
ERP BA Readiness	Governance	gov1	gov1	The vision and mission are well understood by employees across the organisation	1 - 7
		gov2	gov2	The goals and objectives of the ERP system are well understood by employees across the organisation	1 - 7
		gov3	gov3	IT plans and activities are integrated with business plans and activities supported and involved by top management	1 - 7
		gov4	gov4	There is enough support from senior management in the ERP Business Analytics project	1 - 7
			gov5	Data management and ownership policies are in place and documented in my organisation	1 - 7
			gov6	A business analytics governance team is in place with key business stakeholders from other departments of the organisation	1 - 7
			gov7	The roles and responsibilities of the business analytics governance team are clearly identified and defined	1 - 7
			gov8	Security policies are in place and enforced for all sensitive data in my organisation	1 - 7
	Culture	cul1	cul1	Majority of staff recognised the need for change	1 - 7
		cul2	cul2	There is a culture that encourages open communication	1 - 7
		cul3	cul3	Employees at different levels are motivated to participate in generating new ideas	1 - 7
		cul4	cul4	Employees are willing to accept new things	1 - 7
			cul5	A well-established funding process is in place for business analytics initiatives driven by both business and IT	1 - 7
			cul6	A business analytics road map is in place and is clearly defined	1 - 7
			cul7	Business processes are refined or improved which are driven by the findings from business analytics	1 - 7

Profile	Dimension	Survey 1 Code	Survey 2 Code	Measurement Item	Scale
			cul8	A strong training culture has been developed in my organisation to provide adequate training to staff in order to acquire with the required skills in advanced business analytics to support the needs of the business	1 - 7
	Technology	tec1	tec1	There is a standardised IT infrastructure	1 - 7
		tec2	tec2	There was a stable and successful business supported by IT legacy systems	1 - 7
		tec3	tec3	There is good integration of Business Analytics between the ERP system and other systems in the organisation to share and transfer information	1 - 7
		tec4	tec4	There is good integration of Business Analytics between the ERP system and other ERP systems in the supply chain to share and transfer information	1 - 7
			tec5	Mobile applications are adopted for end-users to view summary results of business analytics	1 - 7
			tec6	A public, private or hybrid cloud platform is adopted for business analytics	1 - 7
			tec7	A big data analytics infrastructure is implemented in the organisation	1 - 7

Profile	Dimension	Survey 1 Code	Survey 2 Code	Measurement Item	Scale
			tec8	An in-memory computing platform is adopted in the organisation	1 - 7
	People	peo1	peo1	There is a high level of morale and motivation among employees	1 - 7
		peo2	peo2	There are a well-documented education and training strategy to support effective user training	1 - 7
		peo3	peo3	The management has good communication, controlling, leadership skills, planning and IT management skills	1 - 7
		peo4	peo4	The IT staff has good communication, IT management, planning and technical skills	1 - 7
		peo5	peo5	Project team has prior experience in large IT projects and good domain knowledge of the ERP Business Analytics	1 - 7
		peo6	peo6	Expectations are effectively communicated at all levels	1 - 7
			peo7	There are staff in my organisation with technical skills in advanced business analytics	1 - 7
			peo8	Some staff in my organisation with business analytics skills can easily be involved across produce, consume and enable activities	1 - 7
	Operation	ope1	ope1	The ERP system was customised according to the organisation's needs to fit its existing business process	1 - 7
		ope2	ope2	Processes, procedures and functions are regularly audited for efficiency and effectiveness	1 - 7
			ope3	There are existing standards and processes defined for use of business analytics in the organisation	1 - 7
			ope4	Real-time business analytics is available for key users to access integrated summary information from the production system	1 - 7
			ope5	Operational process intelligence is available for managers to create real-time process visibility and propose line-of-business workers appropriate actions to respond immediately on critical business situations	1 - 7
			ope6	Multichannel analytics are available for key users to create and access their desired presentation formats for decision making	1 - 7
Perceived ERP BA Success	Data Accuracy	accu	accu	The level of ERP BA success achieved in your organisation in terms of data accuracy	1 - 5
	Easy to Learn	easy	easy	The level of ERP BA success achieved in your organisation in terms of easy to learn	1 - 5
	Data Integration	inte	inte	The level of ERP BA success achieved in your organisation in terms of data integration	1 - 5
	Efficiency	effi	effi	The level of ERP BA success achieved in your organisation in terms of efficiency	1 - 5

Profile	Dimension	Survey 1 Code	Survey 2 Code	Measurement Item	Scale
	Productivity	prod	prod	The level of ERP BA success achieved in your organisation in terms of improving individual productivity (Score 1-5)	1 - 5
BA Capability	Data Capability	dat1	dat1	The existing BA system extracts from at least one data source	1 - 7
		dat2	dat2	The existing BA system extracts data from multiple data sources	1 - 7
		dat3	dat3	Data quality tools are integrated into the existing BA platform	1 - 7
		dat4	dat4	The existing BA platform is updated in real time as new data becomes available	1 - 7
		dat5	dat5	Unstructured data such as machine sensors, weather and social media feeds, is available in the existing BA platform	1 - 7
	Analytics Capability	cap1	cap1	Data is presented in static reports often raising more questions than answers	1 - 7
		cap2	cap2	Using dashboards and other interactive tools, users can ask and answer their own questions regarding historical data series and learn from past performance	1 - 7
		cap3	cap3	Real-time data can be used to monitor actionable metrics such as key performance indicators (KPIs)	1 - 7
		cap4	cap4	Using historical data and forecasting models, users can see what might happen next month or next quarter and take actions today that impact future events	1 - 7
		cap5	cap5	Business intelligence is leveraged to optimise the future performance of the organisation such as inventory levels and which products customers are most likely to buy	1 - 7
	Collaboration Tools Capability	too1	too1	Users access specific data they need to make the decisions that drive the part of the business for which they are responsible. Data is usually not formally shared between employees	1 - 7
		too2	too2	Data is extracted from the BA system on an ad-hoc, as-needed basis with or without the assistance of IT	1 - 7
		too3	too3	Scheduled emails push relevant data to key stakeholders on a pre-set schedule	1 - 7
		too4	too4	Decision-makers are automatically notified of changes in key metrics anytime, anywhere	1 - 7
		too5	too5	Individuals inside and outside the organisation are able to access data, share views, ask questions and track progress within the BA platform	1 - 7
	Sharing Capability	sha1	sha1	Users can access data and track key metrics specific to their job function only	1 - 7
		sha2	sha2	Users can access data and track key performance metrics at the departmental level	1 - 7

Profile	Dimension	Survey 1 Code	Survey 2 Code	Measurement Item	Scale
		sha3	sha3	Users can access data and track key metrics across multiple departments within the organisation	1 - 7
		sha4	sha4	Access to BA extends beyond the organisation's boundaries to the suppliers and distributors	1 - 7
		sha5	sha5	Customers are able to access self-service BA metrics and data empowering them to make better business decisions	1 - 7
Perceived BA success	Data Capabilities	bas1	bas1	The level of Business Analytics (BA) success achieved in your organisation in terms of data capabilities	1 - 5
	Analytics Capabilities	bas2	bas2	The level of Business Analytics (BA) success achieved in your organisation in terms of analytics capabilities	1 - 5
	Collaboration Capabilities	bas3	bas3	The level of Business Analytics (BA) success achieved in your organisation in terms of collaboration capabilities	1 - 5
	Dissemination Capabilities	bas4	bas4	The level of Business Analytics (BA) success achieved in your organisation in terms of dissemination capabilities	1 - 5

4.4.4. Validation and Testing of the Measurement Instrument

Since the initial assumption is that organisations with higher maturity levels will generate more business benefits, it is necessary to validate this assumption. In Phase C, the study empirically assessed the relationship between BA maturity levels, BA capability, and BA success for organisations using ERP systems. This analysis was conducted using PLS-SEM. The research used SmartPLS, a statistical software tool designed for path modelling in PLS-SEM, which offers a user-friendly graphical user interface (Ringle et al. 2015). PLS-SEM was selected due to its ability to provide accurate estimates even with small sample sizes and constructs containing fewer items (Hair et al., 2016). It was the ideal tool to empirically test the application of the BA Maturity Model within organisations using ERP systems.

4.4.5. Reliability and Validity of Measurement Items

The reliability and validity of the BARCMM measurement items are ensured through a rigorous quantitative approach using IRT, Rasch analysis, and cluster analysis. In the pilot study, Survey 1 classifies maturity levels, evaluates item difficulty, and assesses fit statistics. In the full study, Survey 2 enhances validity by revising or adding items based on the results of Survey 1. Results are compared using person-item maps and theta values to verify the reliability and validity of the instruments. The use of jMetrik software aids in advanced psychometric procedures (Meyer 2014), while comparisons between surveys and person-item maps highlight variations in item difficulty and organisation capabilities, further validating the study.

4.4.6. Pilot Testing and Refinement of the BARCMM Measurement Instrument

Pilot testing and refinement of the BARCMM measurement instrument involve employing two surveys to ensure item reliability and accurate maturity level assessment. Survey 1 administers initial measurement items to a representative sample, identifying ambiguities and evaluating response scales. Feedback is used to refine items for clarity and relevance. Rasch and cluster analysis in Survey 1 check for balanced measurement item distribution across dimensions. Any gaps identified are addressed by revising or adding items in Survey 2. This method constructs a robust BARCMM and provides a reliable maturity level assessment.

4.5. Chapter Summary and Conclusion

This chapter highlights the importance of assessing BA capability maturity in organisations using ERP systems. The BARCMM offers a comprehensive framework and self-assessment questionnaire to evaluate BA readiness and capability, helping organisations identify areas for improvement and advance BA maturity. This can lead to better decision-making, competitive advantages, and successful business outcomes. The BARCMM and self-assessment questionnaire can also be adapted beyond the GCR for cross-regional comparisons, providing valuable insights into industry-specific maturity levels.

4.5.1. Chapter Summary

Chapter 4 outlines the rationale, objectives, scope, and significance of developing the BARCMM for assessing the BA maturity of organisations using ERP systems in the GCR. The research integrated existing models and employed quantitative methods to address research questions and test hypotheses. Rasch Analysis and hierarchical clustering assessed item difficulty, organisational capability, and maturity levels. BARCMM's significance lies in providing a framework for evaluating ERP business analytics maturity. It offers a self-assessment questionnaire to determine BA readiness and capability, enabling global comparisons through rigorous statistical methods such as IRT-based Rasch analysis and cluster analysis. The development involved designing survey instruments, hierarchical clustering, and PLS-SEM analysis to ensure reliability and validity. Measurement items were tailored to assess governance, culture, technology, people, operations, and perceived success in ERP and BA. BARCMM's validation included PLS-SEM analysis and pilot testing with two surveys.

4.5.2. Chapter Conclusion

The development of the Business Analytics Readiness and Capability Maturity Model (BARCMM) addresses the need for organisations using modern ERP systems to assess and enhance their BA capabilities systematically. By reviewing existing models and employing Rasch Analysis and hierarchical clustering, the BARCMM provides a framework for evaluating BA readiness and capability maturity levels. Two detailed surveys assessed organisations' BA maturity levels, addressing key research questions and gaps in the literature. This research offers a rigorous approach to developing a maturity model. It showcases its empirical validation and practical application in improving BA capabilities within ERP environments. Ultimately, the BARCMM equips organisations to optimise their BA potential, align business strategies with technological advancements, and achieve strategic objectives in a data-driven era.

The chapter also detailed the design of BARCMM measurement instruments, based on a thorough literature review and established methodologies. The integration of ERP systems and BA maturity models forms a comprehensive measurement tool. Quantitative surveys, adapted from previous studies, were used to collect data, with measurement items selected and evaluated rigorously. The theoretical framework combined applied research philosophy, mixed-methods design, and quantitative analysis to create a conceptual model assessing BA success in ERP systems. The chapter highlighted the development and selection of measurement items, focusing on governance, culture, technology, people, and operations. The chapter concluded by detailing the measurement items for assessing BA capability maturity levels, providing a robust foundation for evaluating organisational readiness and capability in business analytics.

CHAPTER 5: EMPIRICAL ASSESSMENT RESULTS OF BARCMM FOR ORGANISATIONS USING ERP SYSTEMS

Chapter 5 details the findings from applying and assessing the BA Readiness and Capability Maturity Model (BARCMM) for organisations using ERP systems in the GCR. Section 5.1 covers the empirical application and data collection for Survey 1, which evaluated BA maturity levels in organisations using ERP systems in the GCR. It includes details on survey administration, participant invitation methods, and response demographics. Section 5.2 discusses the data analysis and findings of Survey 1, including the use of Rasch analysis with jMetrik software. It outlines the classification of measurement items across maturity levels and notes the need for additional items to enhance measurement reliability for higher maturity levels. Section 5.3 presents the person-item map analysis from Survey 1, illustrating the distribution of respondents' abilities and item difficulties on a common logit scale. It also shows correlations between organisational capabilities and item performance using the Rasch model. Section 5.4 reviews Survey 1 results by industry sector and BA maturity levels, noting that approximately 55% of organisations were at maturity level 2, and about 37% reached level 3 or above. The IT and Manufacturing sectors showed higher BA maturity levels. Section 5.5 uses radar charts to analyse Survey 1 results, displaying the weighted average scores of BA capability measurement items across five maturity levels and identifying potential issues with measurement items. Section 5.6 presents the results of hypothesis testing for Survey 1, demonstrating that higher BA maturity is positively associated with perceived ERP BA success and BA capability, using PLS-SEM. Section 5.7 discusses revisions to measurement items for Survey 2, including the addition of eighteen new items to better assess organisations at BA Levels 4 and 5. Section 5.8 describes the data collection and application for Survey 2, detailing the administration, response rate, and respondent demographics. Section 5.9 outlines the data analysis for Survey 2, highlighting the incorporation of new measurement items and their distribution and difficulty levels across the maturity spectrum. Section 5.10 presents the person-item map analysis from Survey 2, showing a mean person measure of 0.37 logit and a mean item measure of 0.00 logit, and underscores the

Rasch model's ability to link organisational capabilities with item performance. Section 5.11 reviews Survey 2 results by industry sector and BA maturity levels, noting that 52% of organisations were at maturity level 2, and 47% at level 3 or above, with IT and Manufacturing sectors showing the highest proportions at level 3 or above. Section 5.12 uses radar charts to analyse Survey 2 results, allowing comparisons of BA capability scores with target levels, industry benchmarks, and scores from other organisations. Section 5.13 presents the results of hypothesis testing for Survey 2, showing that higher BA maturity is positively associated with perceived ERP BA success and BA capability, with significant path coefficients indicating a substantial impact. Section 5.14 concludes by summarising the key insights from the empirical exploration of BARCMM within organisational contexts. Figure 5.1 illustrates the structure of Chapter 5.

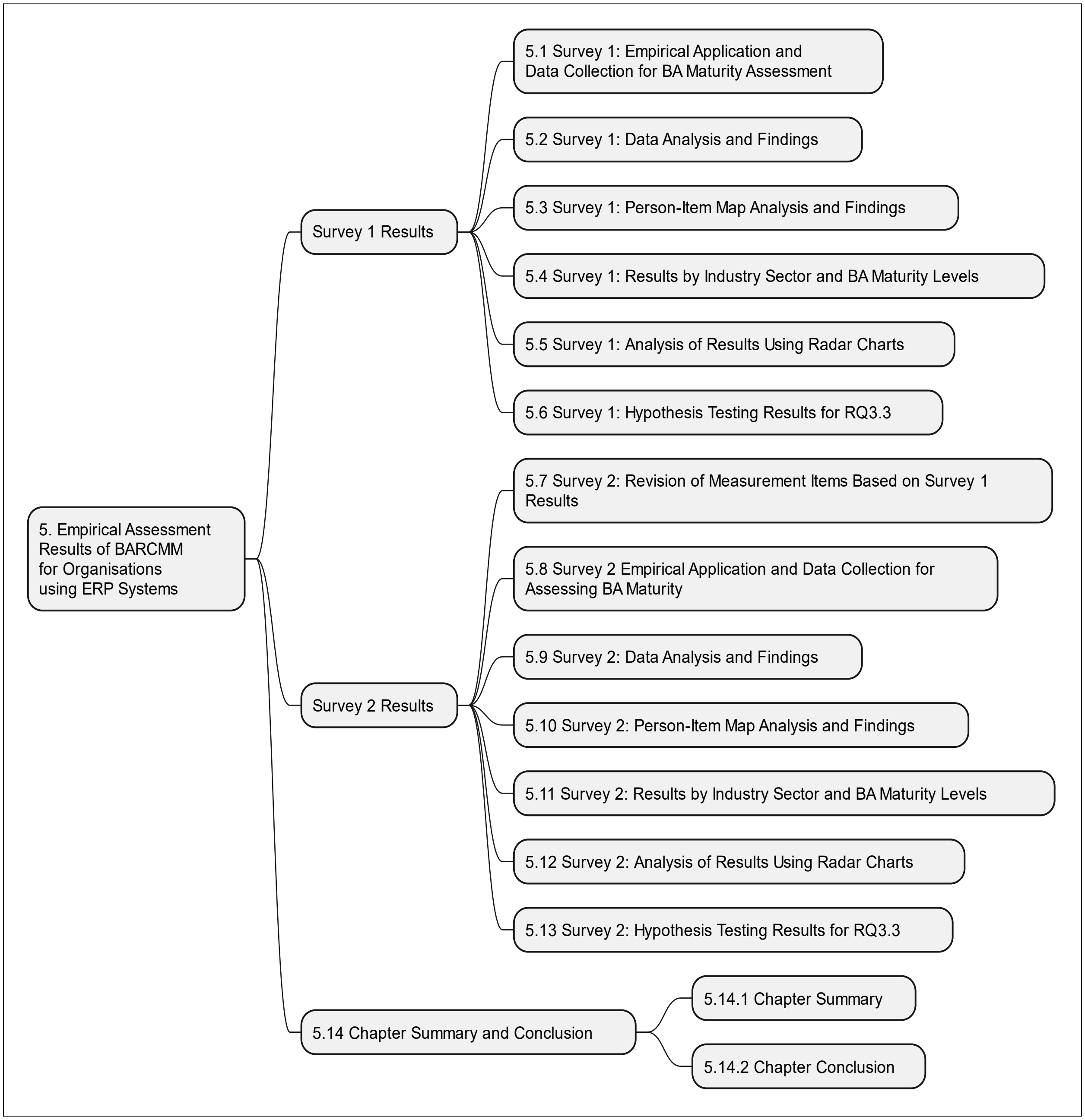

Figure 5.1 Structure of Chapter 5

5.1. Survey 1: Empirical Application and Data Collection for BA Maturity Assessment

The first survey (Survey 1) was used to collect empirical data to measure BA maturity levels achieved by an organisation using an ERP system with BA capability in the GCR. Survey 1 was administered online using LimeSurvey in April 2017 and September 2018. Survey 1 questionnaire is provided in Appendix B-1. An email invitation (Appendix B-3) was sent via the mailing list to potential survey respondents, who were invited to participate via email and personal peer invitations in LinkedIn user groups. Participants were invited to take part in the survey if they had experience with ERP systems and Business Analytics within their organisations. Survey 1 was hosted on the LimeSurvey server, providing participants with the option to respond in either English or Chinese, accommodating those in China who preferred to use Chinese.

Survey 1 included 40 measurement items assessing BA Capability across nine dimensions. Only responses from organisations using BA tools in ERP systems in the GCR were analysed. Invitations were sent via email and LinkedIn. Out of 1,200 invited individuals, 437 surveys were submitted, including 195 fully completed surveys. One hundred and twelve responses were usable, resulting in a response rate of 16.3% and a usable response rate of 9.3%. Table 5.1 Table 5.1 summarises the responses from Survey 1, including the number of invited respondents, total survey submissions, completed surveys, response rate, and usable response rate.

Table 5.1 Survey Period, Respondents, and Response Rates for Survey 1

Survey Period	April 2017 and September 2018	Definition
Number of Invited Respondents	1,200	Total individuals invited to the survey.
Total Survey Submissions	437	All submitted surveys, including completed, incomplete, and partial responses.
Number of Completed Surveys	195	Fully completed surveys.
Number of Completed Responses	112	Usable responses ready for analysis, excluding incomplete or invalid ones.
Response Rate	16.3%	Percentage of completed surveys relative to the total number of invited respondents = 195/1200
Usable Response Rate	9.3%	Percentage of usable responses relative to the total number of invited respondents =112/1200

Table 5.2 summarises the demographics of respondent organisations by location and industry in the GCR. In Survey 1, 34% of respondents were from Information Technology, while 29% were from Manufacturing. Specifically, 55% of respondents were from Hong Kong, and 27% were from China. The distribution reflects regional industry specialisations: Hong Kong's well-established IT sector accounts for its higher representation in Information Technology, whereas China's focus on Manufacturing is evident in its higher proportion of respondents from this sector.

Table 5.2 Geographical Distribution of Survey 1 Respondents by Industry in the GCR

Industry	**China**	**Hong Kong**	**Taiwan**	**Other**	**Total**
Financial		2			2
Information technology	6	29	2	1	38
Logistics	1	3			4
Manufacturing	16	7	7	2	32
Utilities	1	8	1		10
Wholesale/Retail					
Others	6	13	2	5	26
Total	30	62	12	8	112

5.2. Survey 1: Data Analysis and Findings

First, the results and findings of Survey 1 for answering RQ3.1, "How can the BA maturity of an organisation be measured using item response theory as a rigorous and quantitative approach?" are presented. In BARCMM Phase B, in order to classify the BA maturity levels of each organisation, a Rasch analysis was performed with the survey data. jMetrik was used to conduct the Rasch analysis, which is an IRT data analysis software for implementing psychometric methods designed to perform advanced psychometric procedures with a graphical user interface (Meyer 2014).

Table 5.3 shows the results of Rasch analysis for Survey 1 combined with Hierarchical Cluster Analysis to determine the BARCMM with 5 levels for each organisation. The clustered levels of maturity showed the response values for each of items in terms of their predetermined difficulty and their mapping to the corresponding maturity levels. Forty items are listed in Table 5.3, on a continuum from easiest to most difficult. Both “gov4” and “ope1” were found to be easiest with a difficulty value of -0.49

whereas "dat5" is the most difficult with a difficulty value of 0.77. The item "gov4" (There is enough support from senior management in the ERP BA project) and "ope1" (The ERP system was customised according to the organisation's needs) are the easiest items for organisations to achieve because most ERP BA projects are usually initiated by senior management, and most ERP systems are customised by ERP vendors rather than in-house development. The item "dat5" (Unstructured data is available in the existing BA platform) is considered most the difficult item, indicating that not all organisations have the capability to use BA tools with unstructured data.

It is also observed for Survey 1 that four measurement items are classified as level 1, fourteen measurement items are classified as level 2, eighteen items are classified as level 3, but only three items are classified as level 4 and one item is classified as level 5. The advantage of using Rasch analysis is that it can help in the ongoing development of a maturity model by revising the instrument to ensure that there are sufficient measurement items for coverage of all item clusters that correspond to maturity levels (Raber et al. 2012; Lasrado 2018). The results of this stage of our study indicated that more measurement items are required for more reliable measurement of level 4 and level 5 of the BA Maturity model. Therefore, more measurement items to measure higher capability were added in Survey 2 (See the details of measurement instruments for Surveys 1 and 2 in Chapter 4, Table 4.8, and a summary of measurement instruments for Surveys 1 and 2 in Appendix D). The response values for items considered from easy to more difficult are assigned progressively to higher maturity levels from 1 to 5 which in turn determines classification of the organisations in terms of their BA maturity level.

Table 5.3 shows the Logit value of difficulty, standard error, and standardised infit and outfit statistics for each item. Infit is the inlier-sensitive fit that is more sensitive to the pattern of responses for items close to the organisation's capability level. Outfit is the outlier-sensitive fit that is more sensitive to responses to items with difficulty that are far from the organisation's capability level. Standardised infit and outfit values are t-statistics with an expected value of 0 and a standard deviation of 1 (Meyer 2014). Weighted Mean Square (WMS) represents the category infit statistics, which uses an information-weighted average of the squared category residuals. Unweighted Mean

Square (UMS) represents the category outfit statistics, which uses an average of the squared category residuals. According to Dekleva and Drehmer (1997) and Müller (2020), values of infit or outfit greater than two would not be expected more than 5% of the time if the data conforms to the model. According to Raber et al. (2012), the expected value of both fit statistics is 1.0 and the data is considered productive for measurement when infit and outfit values are within the acceptable values of 0.5 and 1.5. In Table 5.3, all items show a good fit with infit values in the acceptable range of 0.59 to 1.49 and outfit values in the acceptable range of 0.58 to 1.81. For the entire scale, person (organisation) reliability is 0.96, and the person (organisation) separation index is 5.18.

In Table 5.3, the infit and outfit values that exceed the acceptable values of 0.5 and 1.5 are “dat1”, “cap1” and “dat5”. Infit and outfit values exceeding 2 should not comprise more than 5% of the items if the data conforms to the model (Dekleva & Drehmer 1997; Müller 2020). The outfit value of “dat5” is greater than 2, i.e. thus 39 out of the 40 survey items (97.5%) had infit and outfit values that were within the acceptable values of 0.5 and 1.5, indicating that the survey data is considered productive (acceptable) for measurement and the survey data conforms to the model.

Rasch analysis can be used to design the maturity model to ensure that there are comparable measurement items in each of the maturity levels. It is observed that only one measurement item (“dat5”) is classified at level 5, which suggests that more measurement items for the characteristics of level 5 should be added to the survey instrument in order to obtain a more robust BARCMM.

Using SPSS, hierarchical cluster analysis was applied, employing Ward's method with Euclidean squared distance to specify a single solution of 5 clusters (Raber et al. 2012; Dalmaijer et al. 2022). The BA maturity levels were classified according to the range of difficulty values by partitioning the continuum of difficulty for the survey items into five clusters. Cluster analysis was used to overcome the problems associated with using subjectivity to define maturity levels.

Table 5.3 Rasch Analysis Results Clustered by BARCMM Levels for Survey 1

Item	Difficulty (Logit)	Standard Error	WMS (Infit)	Standardised Infit Statistics	UMS (outfit)	Standardised Outfit Statistics	Level
gov4	-0.49	0.1	1.19	1.25	1.14	0.97	1
ope1	-0.49	0.1	1.17	1.15	1.07	0.49	
gov3	-0.44	0.1	1.06	0.45	1.02	0.21	
dat2	-0.43	0.1	1.28	1.81	1.25	1.64	
tec1	-0.24	0.1	1.07	0.53	1.11	0.76	2
dat1	-0.21	0.1	1.57	3.4	1.49	3.02	
sha1	-0.21	0.1	0.76	-1.73	0.75	-1.91	
sha2	-0.19	0.1	0.9	-0.7	0.85	-1.06	
ope2	-0.16	0.1	1.02	0.2	0.99	-0.05	
peo4	-0.15	0.1	0.61	-3.16	0.6	-3.22	
cul2	-0.14	0.1	1.06	0.47	1.06	0.44	
peo5	-0.12	0.1	0.73	-2.05	0.73	-2.09	
too1	-0.12	0.1	1.03	0.27	1.15	1.07	
gov2	-0.11	0.09	1.06	0.48	1	0.05	
gov1	-0.08	0.09	0.96	-0.24	1	0.08	
tec2	-0.08	0.09	0.96	-0.24	1.01	0.15	
too2	-0.08	0.09	0.92	-0.53	0.95	-0.29	
cap1	-0.07	0.09	1.69	4.11	1.81	4.68	
peo3	0	0.09	0.62	-3.09	0.64	-2.94	3
cap3	0	0.09	0.92	-0.57	0.88	-0.83	
cul3	0.02	0.09	0.78	-1.62	0.78	-1.62	
cul1	0.03	0.09	1.05	0.38	1.01	0.1	
dat4	0.03	0.09	0.92	-0.51	0.92	-0.54	
cul4	0.05	0.09	0.97	-0.2	1.35	2.28	
tec3	0.05	0.09	0.95	-0.29	0.93	-0.48	
cap5	0.05	0.09	0.85	-1.06	0.86	-1.02	
cap2	0.06	0.09	0.7	-2.4	0.66	-2.72	
peo6	0.09	0.09	0.64	-2.92	0.61	-3.24	
too3	0.11	0.09	1.19	1.36	1.32	2.17	
dat3	0.12	0.09	0.83	-1.28	0.89	-0.76	
cap4	0.13	0.09	0.82	-1.38	0.85	-1.09	
peo1	0.16	0.09	0.56	-3.77	0.62	-3.16	
tec4	0.17	0.09	1.11	0.82	1.15	1.08	
too4	0.17	0.09	0.98	-0.07	0.89	-0.75	
peo2	0.19	0.09	0.78	-1.7	0.81	-1.42	
sha3	0.2	0.09	0.85	-1.13	0.89	-0.78	
sha5	0.39	0.09	1.52	3.48	1.44	2.93	4
too5	0.5	0.09	0.99	-0.03	0.95	-0.31	
sha4	0.5	0.09	1.43	3.02	1.41	2.82	
dat5	0.77	0.08	1.55	3.83	2.23	7.19	5

In Table 5.3, there are 20 ERP BA readiness profile measurement items and 20 BA capability profile measurement items, making a total of 40 items across the five maturity levels. The breakdown of the number of measurement items in each maturity level is as follows:

(1) Level 1: 4 items (gov4, ope1, gov3, dat2)

(2) Level 2: 14 items (tec1, dat1, sha1, sha2, ope2, peo4, cul2, peo5, too1, gov2, gov1, tec2, too2, and cap1)

(3) Level 3: 18 items (peo3, cap3, cul3, cul1, dat4, cul4, tec3, cap5, cap2, peo6, too3, dat3, cap4, peo1, tec4, too4, peo2, and sha3)

(4) Level 4: 3 items (sha5, too5, sha4)

(5) Level 5: 1 item (dat5)

The distribution of items shows most are clustered at level 3 (18 items), followed by level 2 (14 items), with fewer items at levels 4 (3 items) and 5 (1 item). To accurately evaluate organisational maturity, more measurement items are needed at each level to cover varying BA capabilities. The imbalance suggests a need to add items for higher maturity levels (4 and 5) and potentially reduce or rephrase redundant items at lower levels to maintain a balanced and effective questionnaire.

Table 5.4 summarises the theta value ranges for classifying maturity levels in Survey 1.

Table 5.4 Theta Value Ranges for Maturity Level Classification in Survey 1

Level	**Number of cases**	**Theta Ranges**
1	10	-1.8799 to -0.6522
2	61	-0.4842 to 0.5260
3	22	0.6307 to 1.3408
4	17	1.4513 to 3.1857
5	2	4.0394 to 5.4012

5.3. Survey 1: Person-Item Map Analysis and Findings

The person-item map for Survey 1, generated by jMetrik, is shown in Figure 5.2. The mean person is measured at 0.51 logit whereas the mean item is set at 0.00 logit. The rules of the person-item map are measurable on the same logit scale according to the Rasch measurement model (Ismail et al. 2021). All items below mean item = 0.00 logit indicates that all of these items are easy or agreed by the respondents. The maximum item and person measures are +0.77 logit (see Table 5.3). However, there are sufficient easy items, where the minimum item measure was -0.49 logit (see Table 5.3). There are 44 of 112 (39%) respondents above the mean of person abilities (mean person) (+0.51 logit) and 68 of 112 (61%) respondents are below the mean. There are 22 of 40 (55%) items at or above the mean item (0.00 logit) and 18 of 40 (45%) items were below the mean. There are 71 of 112 (63%) respondents who met the item difficulty and above the mean item of 0.00 logit.

Rasch analysis can identify the ability of organisations to perform difficult items at a higher BA maturity level using an ERP system. Based on the results of the Rasch analysis using the person-item map in Figure 5.2 for Survey 1, it provides a clear summary of the correlations between the individuals involved and the items prescribed. The results demonstrate the ability of the predictive feature of the Rasch model to produce an association pattern between organisations' abilities and the performance level for each item.

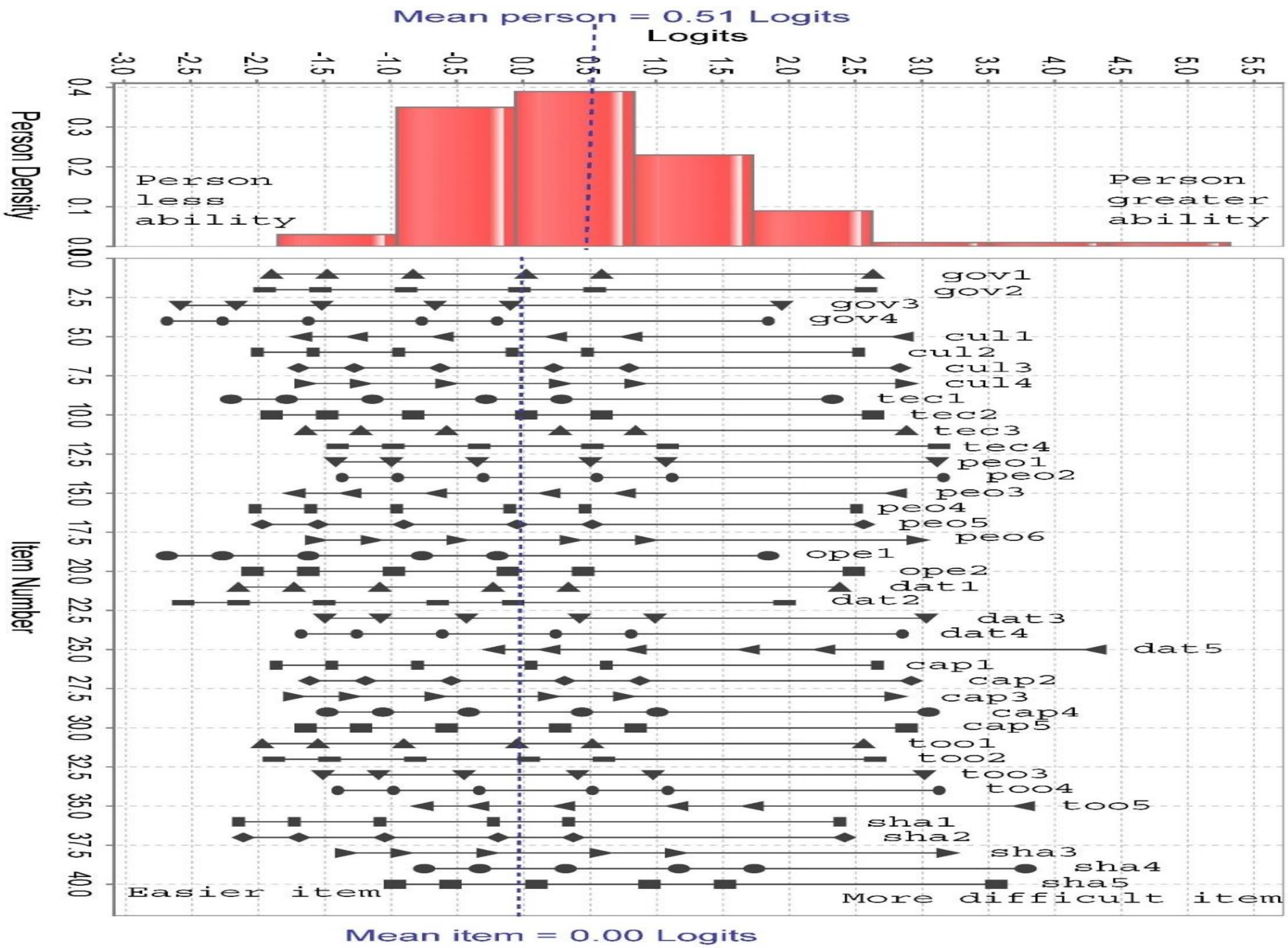

Figure 5.2 Person-Item Map for Survey 1

5.4. Survey 1: Results by Industry Sector and BA Maturity Levels

Table 5.5 summarises the number of respondent organisations classified by BA maturity level and industry sector for Survey 1 and 2. About 55% (Survey 1) of organisations were classified at maturity level 2, and about 37% (Survey 1) of organisations were at level 3 or above. In general, the Information Technology and Manufacturing sectors appear to be the most BA mature sectors with 36% (Survey 1) of organisations in these two sectors reaching BA maturity level 3 or above.

Table 5.5 BA Maturity Levels by Industry Sector for Survey 1

Industry	**Maturity Level**					**Total**
	1	**2**	**3**	**4**	**5**	
Financial		1		1		2
Information technology	2	22	9	4	1	38
Logistics		2	1	1		4
Manufacturing	4	17	3	7	1	32
Utilities		8	1	1		10
Others	3	12	8	3		26
Total	9	62	22	17	2	112
Percentage	8%	55%	20%	15%	2%	100%

5.5. Survey 1: Analysis of Results Using Radar Charts

A radar chart provides a way of visually displaying multivariate data with multiple dimensions (Zhao et al. 2017). The Radar Charts show the weighted average scores of BA capability measurement items for five maturity levels (1 to 5) in Figure 5.3 for Survey 1. By plotting their scores of BA capability in a radar chart, an organisation can easily compare their current BA capability across five levels of maturity with target maturity levels, industry benchmarks, as well as against the maturity levels of multiple organisations in the same industry sector.

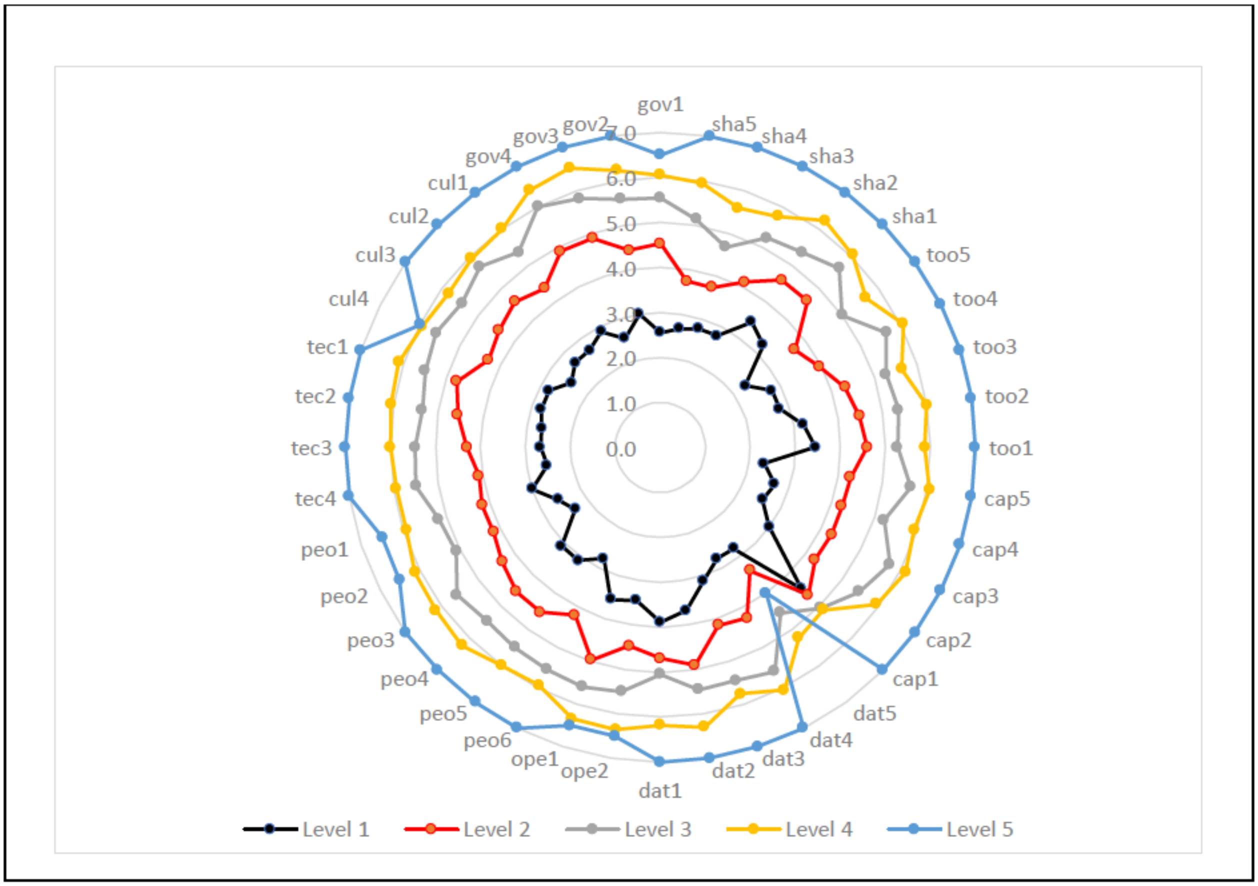

Figure 5.3 Weighted Average Scores by Maturity Levels: Radar Chart for Survey 1

The radar chart can be used to display the score of a particular respondent organisation if the actual score is plotted alongside benchmarking data. It can also help identify issues with measurement items The radar chart showing the weighted average scores of the measurement items for different maturity levels in Survey 1, as presented in Figure 5.3, provides a way to identify any issues with the measurement items. For example, if a higher-level average score for a particular measurement item is very close to or even lower than the lower-level maturity score, it highlights potential issues that may need to be discussed. These issues could include respondents not understanding the question or the measurement items requiring further clarification. The three items identified that may have issues are “cap1”, “cul4”, and “dat5”.

The item "cap1" (Data is presented in static reports often raising more questions than answers) reflects the challenges organisations face in terms of data presentation and reporting. The difficulty value of -0.07 indicates that it is relatively easy for organisations to handle data in static reports. In Table 5.3, item “cap1” is classified as Level 2, suggesting that organisations, on average, are moderately capable in presenting data effectively. However, the weighted average scores from Figure 5.3 show that even within Level 2, there is room for improvement. The close proximity of scores between Levels 1 and 2, and Levels 3 and 4, indicates that lower-level organisations may struggle with presenting data effectively, while higher-level organisations at Level 5 may have a better grasp of this aspect. This may also imply that the item description needs clarification. Therefore, a strange overlapping average score on the radar charts for each maturity level can also be used as a means to identify problems of measurement items that need to be rephrased. This description suggests that when data is presented in static reports, it tends to provoke additional inquiries rather than providing clear solutions or insights. In other words, the information provided in these reports may be insufficient or unclear, leading to confusion or ambiguity and prompting further questions about the underlying data and its implications. In general, organisations should focus on improving their data presentation and reporting capabilities to advance their BA maturity, as this is a fundamental aspect of data-driven decision-making.

In Table 5.3, item “cul4” (Employees are willing to accept new things) is also classified as a Level 3 item. However, in Figure 5.3, the weighted average scores for Level 3 to 5 were very close, indicating that even within Level 5 organisations, some employees are reluctant to accept new things, indicating change management is a key determinant of BA capability and success.

In Table 5.3, item “dat5” (Unstructured data is available in the existing BA platform) is the most difficult item, indicating that not all organisations have the capability to use BA tools with unstructured data. It is observed from Figure 5.3, that Level 5 organisations has an average score of 3 out of 7 for item “dat5” indicating that the application of business analytics to transform unstructured data into meaningful and structured data is difficult to achieve even for Level 5 organisations. Unstructured data has always been very difficult to analyse. With the help of AI and machine learning, new

BA tools are emerging that can search through unstructured data from multiple sources and transform this into structured data to uncover beneficial and actionable business intelligence. The potential for analysing unstructured data in a way that would further enrich the data stored in ERP systems is still a challenge for most organisations.

5.6. Survey 1: Hypothesis Testing Results for RQ3.3

Finally, the results of testing hypotheses H1 and H2 are presented to address RQ3.3: "To what extent is BA maturity an indicator of perceived BA capability and perceived ERP BA success in an organisation?" RQ3.3 aims to determine how the BA maturity level, determined by Rasch analysis and cluster analysis, relates to perceived ERP BA success and perceived BA capability. It hypothesises that higher BA maturity generates greater perceived ERP BA success and perceived BA capability.

The hypotheses to be tested in the PLS-SEM reflective model are as follows:

(H1) BA maturity level is positively associated with perceived ERP BA success
(H2) BA maturity level is positively associated with perceived BA capability

In PLS-SEM, measurement models can be reflective or formative. In reflective models, the latent construct causes the measurement items, while in formative models, the measurement items define the latent construct (Hanafiah 2020). In this case, BA maturity level, perceived ERP BA success, and perceived BA capability are considered latent constructs, meaning they are theoretical concepts that cannot be directly observed. The formative measurement model is not relevant in this context because it assumes that the observed indicators define or cause the latent construct being measured. Reflective measurement allows for the examination of how well the indicators collectively represent the latent construct. For the testing of hypotheses H1 and H2, which aim to assess the associations between the BA maturity level and perceived ERP BA success/perceived BA capability, reflective measurement is appropriate. The PLS-SEM reflective model is constructed in Figure 5.4 using BA maturity as the independent variable and perceived ERP BA success and perceived BA capability as dependent variables.

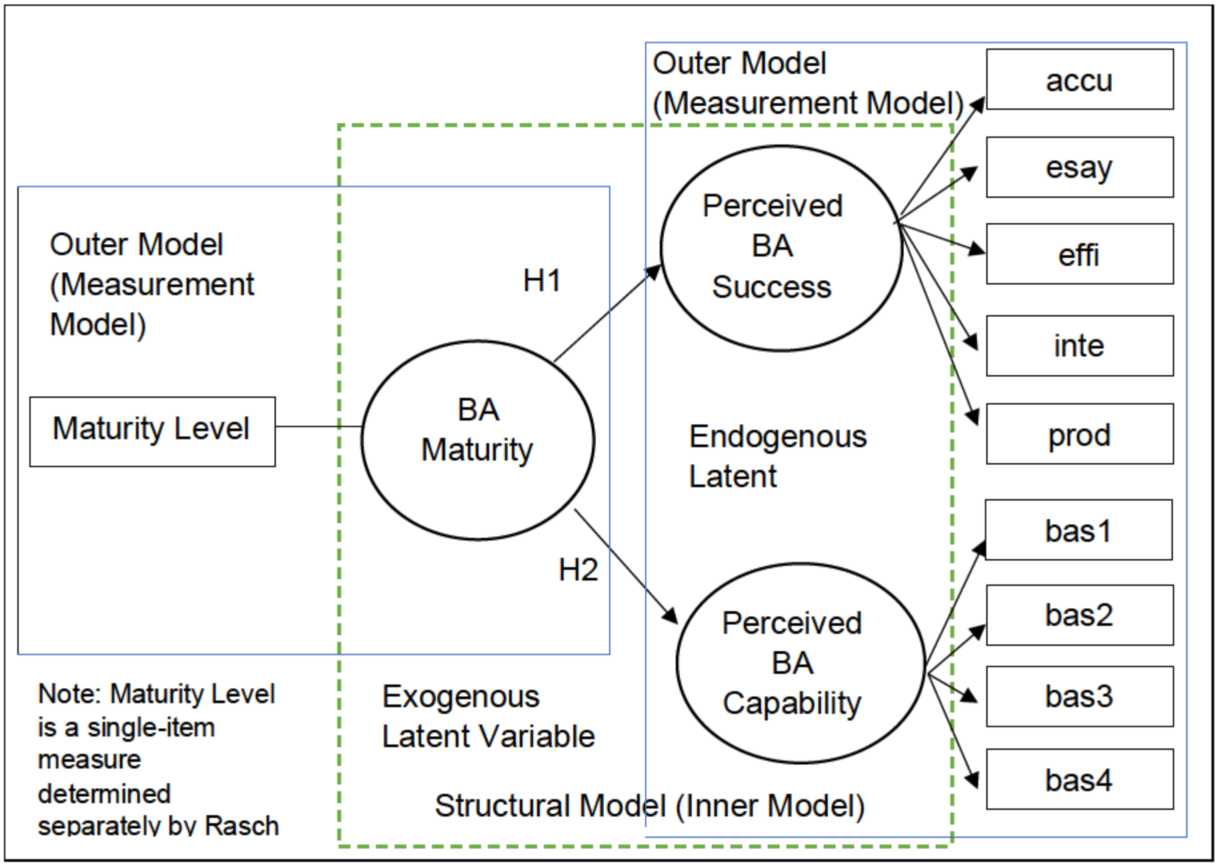

Figure 5.4 PLS-SEM Model for BA Maturity with Perceived ERP BA Success and Perceived BA Capability

In PLS-SEM, the structural model represents the relationships between latent variables. The inner model assesses the strength of these relationships, while the outer model, or measurement model, evaluates how observed variables reflect the latent constructs, ensuring validity and reliability (Venturini & Mehmetoglu 2019; Hair et al. 2021). Exogenous latent variables in PLS-SEM are independent variables, represented by observed indicators, and not influenced by other variables in the model. Endogenous latent variables, on the other hand, are influenced by other variables and are typically latent constructs predicted by exogenous variables, represented by reflective latent variables in PLS-SEM (Venturini & Mehmetoglu 2019). In Figure 5.4, the exogenous latent variable is BA Maturity, and the endogenous variables are Perceived BA Success and Perceived BA Capability.

The measurement instruments for assessing perceived ERP BA success and perceived BA capability are listed in Table 5.6. The PLS-SEM model was specified as a reflective model adapted from Raber et al. (2013b). The constructs assessed include BA Maturity, Perceived ERP BA Success, and Perceived BA Capability. Scores ranging from 1 to 5 were employed for evaluation. BA Maturity is evaluated by its Maturity Level, determined through Rasch analysis and cluster analysis.

Table 5.6 Measurement Instrument for PLS-SEM Model

Construct	**Label (Code)**	**Indicator (Item Description)** **Scores from 1 to 5**
BA Maturity	Maturity Level	BA maturity level determined by Rasch analysis and cluster analysis
Perceived ERP BA success	accu	Level of ERP BA success in terms of data accuracy
	easy	Level of ERP BA success in terms of easy to learn
	inte	Level of ERP BA success in terms of data integration
	effi	Level of ERP BA success in terms of efficiency
	prod	Level of ERP BA success in terms of improving individual productivity
Perceived BA Capability	bas1	Level of BA success in terms of data capabilities
	bas2	Level of BA success in terms of analytics capabilities
	bas3	Level of BA success in terms of collaboration capabilities
	bas4	Level of BA success in terms of dissemination capabilities

Perceived ERP BA Success is evaluated based on five indicators: data accuracy (accu), ease of learning (easy), data integration (inte), efficiency (effi), and improvement in individual productivity (prod). Data accuracy is essential for ERP and BA system success, influencing user satisfaction and overall system performance (Holsapple et al. 2019). Ease of learning and ease of use will lead to more users adopting the new features of ERP and BA systems, increasing user satisfaction and impacting their overall effectiveness and success (Gaardboe et al. 2017; Al-Mamary et al. 2019).

Effective data integration is vital for successful ERP and BA implementations, ensuring seamless connectivity of business processes and data, thereby enhancing collaboration, operational efficiency, and decision-making (Bandara et al. 2024). ERP and BA systems are designed to improve operational efficiency, a major determinant of their success and user satisfaction (Chou & Hong 2013; Makota et al. 2023). Finally, productivity gains from using ERP an BA systems are a key measure of their success, reflecting the system's ability to enhance business performance (Ahmed & Ayman 2011; Shen et al. 2016). Increased individual productivity as a result of ERP system use is a clear indicator of successful implementation and business performance enhancement (Shen et al. 2016).

Perceived BA Capability is measured through four indicators: data capabilities (bas1), analytics capabilities (bas2), collaboration capabilities (bas3), and dissemination capabilities (bas4). Data capabilities involve managing, storing, and retrieving data effectively, which are basic requirements for supporting advanced analytics and decision-making (Wang et al. 2018; Mittal 2020). Analytics capability refers to an organisation's ability to use BA tools and processes to efficiently organise, analyse, and derive insights from data for better decision-making and performance improvement (Trkman et al. 2010; Liberatore et al. 2017). Collaboration capabilities enable efficient teamwork across departments to leverage diverse expertise for better analytics outcomes (Schwade & Schubert 2017; Lazarova-Molnar et al. 2018). Dissemination capabilities ensure effective communication of insights to stakeholders for informed decision-making and strategic planning (Gorman & Klimberg 2014; Seal et al. 2020).

The three key steps in PLS-SEM analysis are:

(1) Measurement Model Evaluation

- Assess reliability and validity of constructs (Perceived ERP BA Success and Perceived BA Capability)
- Check outer loadings, composite reliability, and average variance extracted (AVE)

(2) Structural Model Evaluation

- Assess significance and relevance of path coefficients for H1 and H2

- Evaluate coefficient of determination (R-squared) for endogenous constructs

(3) Interpretation of Results

- Path coefficient for H1 should be positive and significant, indicating a positive relationship between BA maturity and Perceived ERP BA Success
- Path coefficient for H2 should be positive and significant, indicating a positive relationship between BA maturity and Perceived BA Capability
- R-squared (R^2) values should show that BA maturity explains a substantial portion of the variance in Perceived ERP BA Success and Perceived BA Capability

The two primary evaluation criteria are:

(1) Path coefficients: The path coefficients for H1 and H2 should be positive and statistically significant ($p < 0.05$).

(2) R-squared (R^2) values: The R^2 values should be reasonably high, indicating that BA maturity explains a substantial portion of the variance in the dependent variables. In general, R^2 values of 0.25, 0.50, and 0.75 for target constructs are considered weak, medium, and substantial, respectively (Hair et al. 2016).

Table 5.7 shows the construct reliability and convergent validity results for BA Maturity, Perceived BA Capability, and Perceived ERP BA Success from the PLS-SEM analysis in Survey 1.

Bootstrapping is a statistical method for estimating the precision of sample estimates by resampling with replacement from the original dataset (Tibshirani & Efron 1993; Streukens & Leroi-Werelds 2016). It involves generating multiple subsets to evaluate the stability and reliability of statistical estimates, such as regression coefficients. Bootstrapping was used to generate 500 samples to estimate the significance of the path coefficients in the PLS-SEM model (Raber et al. 2013b).

Table 5.7 Construct Reliability and Validity Results for BA Maturity, Perceived ERP BA Success, and Perceived BA Capability (Survey 1)

Latent Construct	Cronbach's Alpha	*ρA*	Composite Reliability	AVE
BA Maturity	1.000	1.000	1.000	1.000
Perceived ERP BA success	0.912	0.921	0.914	0.682
Perceived BA Capability	0.958	0.958	0.958	0.851

For assessing internal consistency or construct reliability, it is necessary to ensure that the values of Cronbach's Alpha, Composite Reliability (ρc), and Rho_A of a reflective measurement model indicate values above or equal to 0.7 (Aparisi-Torrijo et al. 2023). Cronbach's Alpha is commonly used to assess internal consistency, measuring how well a set of items captures a single construct (Hair et al. 2019; Hair Jr et al. 2021; Izah et al. 2023). Composite Reliability (ρc) also assesses the reliability of latent variables in structural equation modelling and is similar to Cronbach's Alpha but does not assume equal indicator loadings (Davčik 2013; Ali et al. 2018; da Silva et al. 2024). However, composite reliability is only applicable in latent constructs with reflective measures (Chin 1998). Dijkstra-Henseler's Rho_A (ρA) provides a precise estimate of internal consistency by accounting for the actual relationship between items. Additionally, for convergent validity, the Average Variance Extracted (AVE) should be at least 0.5, indicating that the construct explains at least 50% of the variance of its items (Ali et al. 2018).

Strong internal consistency is indicated for both surveys. This is evidenced by the Cronbach's Alpha values, which range from 0.912 to 0.958 for the latent variables in Survey 1 and from 0.941 to 0.955 in Survey 2. These values fall within the acceptable range of 0.70 to 0.95 for good internal consistency. According to (Kline 2000), a Cronbach's Alpha Coefficient ≥ 0.9 indicates that the reliability of the instrument can be considered "excellent". The composite reliability for the latent variables ranged from 0.914 to 0.958 for Survey 1 and from 0.958 to 0.965 for Survey 2. Both values are greater than 0.7, indicating good internal consistency and reliability of the measurement model. The consistent reliability measure of partial least squares (rho_A) is greater than 0.7. The Average Variance Extracted (AVE) for each construct of the latent variables ranged from 0.682 to 0.851 in Survey 1 and from 0.847 to 0.85, which exceeds the required threshold of 0.5 for acceptable convergent validity.

ρA (rho_A) is an alternative reliability measure used in PLS-SEM. Similar to Cronbach's alpha, *ρA* values range from 0 to 1, where higher values indicate better reliability. Generally, a *ρA* value above 0.7 is considered acceptable for reliability in PLS-SEM. It assesses internal consistency similarly to Cronbach's alpha but is considered a more accurate measure in certain situations (Kline 2000; Russo & Stol 2021). *ρA* is calculated as the ratio of the sum of the squares of the latent variable scores to the sum of the squares of the measurement residuals. This measure reveals the proportion of variance in observed variables due to common factors versus measurement error, aiding in evaluating construct reliability in PLS-SEM.

The factor loadings for Perceived BA Capability and Perceived ERP BA Success, shown in Figure 5.5, demonstrate adequate reliability, with all item loadings meeting the minimum of 0.7 (Nunnally & Bernstein 1994), except for the "easy" item, which has a loading of 0.669. This is above the minimum of 0.6 (Bradley et al. 2006; Raber et al. 2012). Overall, factor loadings, reliability scores, and AVE values from Survey 1 confirm that the measurement model is satisfactory, with acceptable reliability and convergent validity.

The two hypotheses tested in Survey 1 to answer RQ3.3 in the PLS-SEM path model are: (H1) BA maturity level is positively associated with Perceived ERP BA success; and (H2) BA maturity level is positively associated with BA capability.

The primary evaluation criteria for hypothesis testing are R^2, statistical significance and relevance of the path coefficients (Hair et al. 2016). R^2 values represent the proportion of variance of a dependent variable explained by each of the endogenous constructs in the model, and the path coefficients represent the connection strengths between the dependent and independent variables (Chin 2010; Rabaa'i 2021).

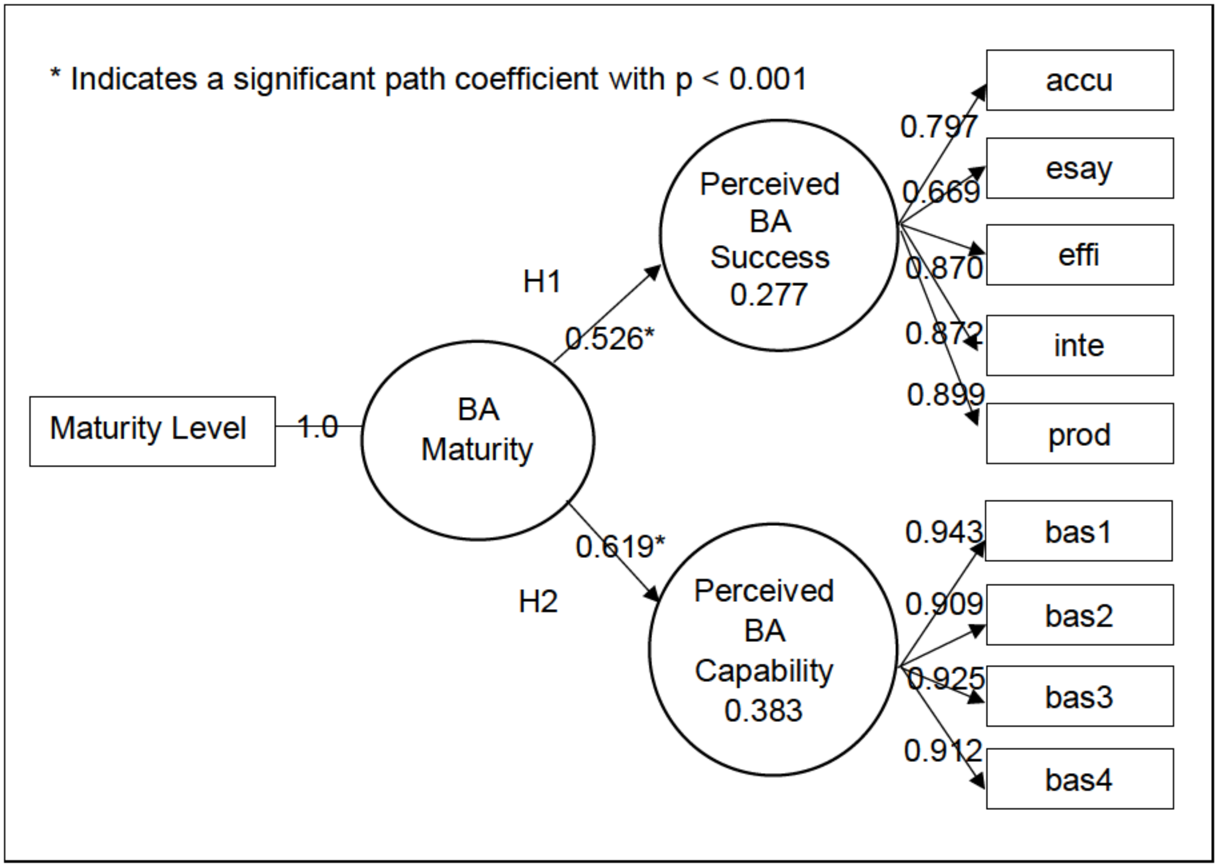

Figure 5.5 PLS-SEM Model for BA Maturity with Perceived ERP BA Success and Perceived BA Capability for Survey 1

In Survey 1, the path coefficient of (H1) BA Maturity and Perceived ERP BA Success indicates a positive and highly significant (0.526*) relationship, while the path coefficient of (H2) BA Maturity and Perceived BA Capability indicates a positive and highly significant (0.619*) relationship. The structural model explained 27.7% (R^2=0.277) of the variance in the dependent latent variable Perceived ERP BA success and explained 38.3% (R^2=0.383) of the variance in the dependent latent variable Perceived BA Capability. The R^2 values show that BA maturity is one of the organisational factors affecting the Perceived ERP BA success and the perceived BA capability in organisations.

5.7. Survey 2: Revision of Measurement Items Based on Survey 1 Results

The results in Survey 1 showed that there were very few measurement items assessing the characteristics of organisations at BA Level 4 and Level 5 maturity. Therefore, eighteen items were added to the original questionnaire in Survey 2. Using different versions of the survey questions shows that this rigorous assessment method can be used to classify organisations into five levels of maturity with item anchors even if some items are different. Table 5.8 shows the comparison of the number of items for each maturity level in Survey 1 and 2. Items at a specific maturity level indicate that they have the same level of difficulty in those items.

Table 5.8 Comparison of Number of Items for Each Maturity Level in Surveys 1 and 2 (Common and Unique)

Maturity Level	**Survey 1**	**Survey 2**	**Common (Anchor) Items in both surveys**
1	gov4, ope1, gov3, dat2 (4 items)	ope1, dat2, tec1, gov3, gov4, tec2 (6 items)	gov4, ope1, gov3, dat2 (4 items)
2	tec1, dat1, sha1, sha2, ope2, peo4, cul2, peo5, too1, gov2, gov1, tec2, too2, cap1 (14 items)	dat1, *gov8*, ope2, *peo7*, *gov5*, gov2, cap2, cap3 (8 items)	dat1, ope2, gov2 (3 items)
3	peo3, cap3, cul3, cul1, dat4, cul4, tec3, cap5, cap2, peo6, too3, dat3, cap4, peo1, tec4, too4, peo2, sha3 (18 items)	peo4, *peo8*, cul2, sha1, tec3, gov1, *gov7*, *cul7*, peo3, *ope4*, peo5, *ope3*, peo6, too1, peo2, cul1, cul3, too2, tec4, peo1, sha2, *gov6*, cap4, cap5 (24 items)	peo3, peo6, peo2, cul1, cul3, tec4 (6 items)
4	sha5, too5, sha4 (3 items)	cul4, *cul6*, cap1, *cul8*, *cul5*, *ope5*, *ope6*, too3, too4, dat4, dat3, sha3, *tec8* (13 items)	Nil
5	dat5 (1 item)	*tec6*, *tec5*, sha5, *tec7*, too5, sha4, dat5 (7 items)	dat5 (1 item)

Note: items that are newly added in Survey 2 are marked by *italics*.

5.8. Survey 2 Empirical Application and Data Collection for Assessing BA Maturity

The second survey (Survey 2) was used to collect empirical data to measure BA maturity levels achieved by an organisation using an ERP system with BA capability in the GCR. Survey 2 was administered online using LimeSurvey in October 2018 and October 2021. The Survey 2 questionnaire is provided in Appendix B-2. An email invitation (Appendix B-4) was sent via the mailing list, to potential survey respondents who were invited to participate via email and personal peer invitations in LinkedIn user groups. Participants were invited to take part in the survey if they had experience with ERP systems and Business Analytics within their organisations. Survey 2 was hosted on the LimeSurvey server, providing participants with the option to respond in either English or Chinese, accommodating those in China who preferred to use Chinese.

Survey 1 results showed only three items for Level 4 and one for Level 5, prompting the addition of more items for higher maturity levels in Survey 2. Survey 2 included 58 items (40 from Survey 1 and 18 new), measuring BA capability across nine dimensions. Only responses from organisations using BA tools in ERP systems were analysed. Eighty-nine responses were usable, yielding a response rate of 9.5% and a usable response rate of 7.4%. Table 5.9 summarises the Survey 2 responses, including the number of respondents, completed responses, and response rates.

Table 5.10 summarises respondent organisations' demographics by location and industry in the GCR for Survey 2. In Survey 2, 25% of respondents were from Information Technology (IT), and 51% were from Manufacturing. Specifically, 44% were from China, and 31% were from Hong Kong. The distribution reflects regional industry specialisations: China's focus on Manufacturing and Hong Kong's established IT sector.

Table 5.9 Survey Period, Respondents, and Response Rates for Survey 2

Survey Period	October 2018 and October 2021	Definition
Number of Invited Respondents	1,200	Total individuals invited to the survey.
Total Survey Submissions	391	All submitted surveys, including completed, incomplete, and partial responses.
Number of Completed Surveys	114	Fully completed surveys.
Number of Completed Responses	89	Usable responses ready for analysis, excluding incomplete or invalid ones.
Response Rate	9.5%	Percentage of completed surveys relative to the total number of invited respondents = 114/1200
Usable Response Rate	7.4%	Percentage of usable responses relative to the total number of invited respondents =89/1200

Table 5.10 Geographical Distribution of Survey 2 Respondents by Industry in the GCR

Industry	**China**	**Hong Kong**	**Taiwan**	**Other**	**Total**
Financial		2			2
Information technology	7	10	5		22
Logistics	2		2		4
Manufacturing	25	7	12	1	45
Utilities		1			1
Wholesale/Retail	1	3			4
Others	4	5	2		11
Total	39	28	21	1	89

5.9. Survey 2: Data Analysis and Findings

The same methods were employed in Survey 2 to answer RQ3.1, using Rasch analysis with jMetrik to classify the BA maturity levels of each organisation. Table 5.11 shows the results of Rasch analysis clustered into 5 levels of BARCMM using hierarchical cluster analysis (item difficulty) for Survey 2.

In Table 5.8, it is observed that the items that represent the difficulty varies for each survey with the number of organsations in that maturity level. Those newly added items are characteristics required for higher maturity levels which are allocated higher difficulty at Level 4 and 5. The common items for each maturity level in both surveys listed in Table 5.8 can be used as anchor items if another survey is needed to improve reliability and validity of the BARCMM.

Table 5.11 Rasch Analysis Results Clustered by BARCMM Levels for Survey 2

Item	Difficulty (Logit)	Standard Error	WMS (Infit)	Standardised Infit Statistics	UMS (outfit)	Standardised Outfit Statistics	Level
ope1	-0.58	0.11	0.99	0.02	0.91	-0.41	1
dat2	-0.42	0.11	1.02	0.15	0.93	-0.34	
tec1	-0.41	0.11	0.85	-0.78	0.77	-1.27	
gov3	-0.37	0.11	0.81	-1.02	0.82	-0.98	
gov4	-0.36	0.11	0.89	-0.57	0.91	-0.44	
tec2	-0.31	0.1	0.98	-0.05	0.85	-0.77	
dat1	-0.25	0.1	1.32	1.67	1.25	1.35	2
gov8	-0.21	0.1	1.39	2.05	1.29	1.51	
ope2	-0.19	0.1	0.72	-1.74	0.75	-1.46	
peo7	-0.16	0.1	1.2	1.17	0.96	-0.16	
gov5	-0.14	0.1	0.93	-0.34	0.84	-0.88	
gov2	-0.13	0.1	0.74	-1.62	0.72	-1.64	
cap2	-0.12	0.1	0.71	-1.8	0.66	-2.08	
cap3	-0.11	0.1	0.91	-0.47	0.91	-0.47	
peo4	-0.09	0.1	0.56	-3.05	0.51	-3.28	3
peo8	-0.09	0.1	0.88	-0.67	0.77	-1.34	
cul2	-0.08	0.1	0.92	-0.4	0.98	-0.03	
sha1	-0.08	0.1	0.86	-0.84	0.92	-0.39	
tec3	-0.07	0.1	0.82	-1.05	0.8	-1.16	
gov1	-0.05	0.1	0.85	-0.87	0.89	-0.59	
gov7	-0.05	0.1	1.27	1.52	1.1	0.58	
cul7	-0.05	0.1	0.9	-0.55	0.87	-0.68	
peo3	-0.05	0.1	0.64	-2.38	0.63	-2.34	
ope4	-0.05	0.1	1.19	1.11	1.01	0.13	
peo5	-0.04	0.1	0.59	-2.88	0.59	-2.68	
ope3	-0.03	0.1	1.1	0.62	1.02	0.19	
peo6	-0.02	0.09	0.66	-2.25	0.61	-2.48	
too1	-0.02	0.09	1.46	2.49	1.59	2.9	

Item	Difficulty (Logit)	Standard Error	WMS (Infit)	Standardised Infit Statistics	UMS (outfit)	Standardised Outfit Statistics	Level
peo2	-0.01	0.09	0.6	-2.79	0.67	-2.04	
cul1	0	0.09	0.87	-0.74	0.94	-0.28	
cul3	0	0.09	0.84	-0.97	0.9	-0.53	
too2	0.01	0.09	1.07	0.44	1.1	0.58	
tec4	0.02	0.09	0.82	-1.14	0.82	-1	
peo1	0.02	0.09	0.54	-3.37	0.59	-2.72	
sha2	0.02	0.09	0.76	-1.52	0.77	-1.39	
gov6	0.03	0.09	0.77	-1.49	0.71	-1.78	
cap4	0.04	0.09	1	0.08	1.07	0.47	
cap5	0.04	0.09	0.69	-2.07	0.74	-1.58	
cul4	0.08	0.09	0.9	-0.59	0.88	-0.65	4
cul6	0.08	0.09	1.03	0.22	1.04	0.27	
cap1	0.09	0.09	1.52	2.84	1.83	3.92	
cul8	0.1	0.09	1.28	1.65	1.45	2.34	
cul5	0.11	0.09	1	0.07	1.05	0.33	
ope5	0.11	0.09	1.31	1.8	1.43	2.25	
ope6	0.12	0.09	1.02	0.18	1.03	0.23	
too3	0.12	0.09	0.92	-0.49	0.98	-0.03	
too4	0.12	0.09	1	0.06	0.98	-0.06	
dat4	0.13	0.09	0.75	-1.67	0.74	-1.61	
dat3	0.14	0.09	0.81	-1.27	0.82	-1.04	
sha3	0.17	0.09	1	0.07	1.15	0.88	
tec8	0.18	0.09	1.43	2.49	1.42	2.25	
tec6	0.28	0.09	1.56	3.17	1.54	2.79	5
tec5	0.31	0.09	1.88	4.67	2.03	4.8	
sha5	0.31	0.09	1.06	0.46	1.15	0.88	
tec7	0.32	0.09	1.28	1.73	1.2	1.17	
too5	0.41	0.09	1.34	2.13	1.89	4.31	
sha4	0.52	0.08	1.01	0.13	1.11	0.72	
dat5	0.65	0.08	1.42	2.65	2.04	4.98	

In Table 5.11, after adding eighteen new ERP BA profile measurement items (*gov5, gov6, gov7, gov8, cul5, cul6, cul7, cul8, tec5, tec6, tec7, tec8, peo7, peo8, ope3, ope4, ope5, ope6*) in Survey 2, there are 38 ERP BA readiness profile measurement items and 20 BA capability profile measurement items, making a total of 58 items across the five maturity levels. The breakdown of the number of measurement items in each maturity level is as follows:

(1) Level 1: 6 items (ope1, dat2, tec1, gov3, gov4, tec2)

(2) Level 2: 8 items (dat1, *gov8*, ope2, *peo7*, *gov5*, gov2, cap2, cap3)

(3) Level 3: 24 items (peo4, *peo8*, cul2, sha1, tec3, gov1, *gov7*, *cul7*, peo3, *ope4*, *peo5*, ope3, peo6, too1, peo2, cul1, cul3, too2, tec4, peo1, sha2, *gov6*, cap4, cap5)

(4) Level 4: 13 items (cul4, *cul6*, cap1, *cul8*, *cul5*, *ope5*, *ope6*, too3, too4, dat4, dat3, sha3, *tec8*)

(5) Level 5: 7 items (tec6, tec5, sha5, tec7, too5, sha4, dat5)

The distribution of measurement items across the five maturity levels appears to follow a normal distribution pattern. The number of items increases from Level 1 (6 items) to the peak at Level 3 (24 items), and then decreases to Level 5 (7 items). This suggests that Level 3 has the most comprehensive set of items, while Levels 1 and 5 represent the least complex and most advanced maturity levels, respectively. The middle range Levels 2 (8 items) and 4 (13 items) seem to be transitional or intermediate maturity levels. The gradual increase and decrease in the number of items across the levels indicates a logical and structured progression of the maturity model, with each level building on the previous one as the organisation matures.

Rasch analysis produces an ordinal value representing the logit measure of each item (Raber et al. 2013a) and a theta (θ) value for each organisation to measure their capability (Kuhfeld & Soland 2020; Yu 2020; Rios & Soland 2021). Cluster analysis is then applied to the logit measure by five clusters to derive five distinct maturity levels. Response values for items are scored with a logit value from easy to more difficult and progressively assigned to higher maturity levels from 1 to 5. Rasch analysis scores organisations with ordered levels of capability, referred to as theta (θ) values. This allows measurement of an organisation's capability from least to most capable in relation to all items on the same difficulty continuum (Raber et al. 2012). This approach allows classification of organisations into five clusters representing five BA maturity levels.

Table 5.12 summarises the theta value ranges for classifying maturity levels in Survey 2.

Table 5.12 Theta Value Ranges for Maturity Level Classification in Survey 2

Level	Number of cases	Theta Ranges
1	1	-6.2925
2	46	-1.2309 to 0.3655
3	30	0.4400 to 1.2484
4	11	1.3946 to 2.4763
5	1	4.9410

5.10. Survey 2: Person-Item Map Analysis and Findings

The person-item map for Survey 2, generated by jMetrik, is shown in Figure 5.6. The mean person is measured at 0.37 logit whereas the mean item is set at 0.00 logit. The maximum item and person measures are +0.65 logit (see Table 5.11) and +4.94 logit (see Table 5.6), respectively. Again, there are sufficient easy items, where the minimum item measure was -0.58 logit (see Table 5.11), in contrast to the least number of respondents in agreement at -6.29 logit (see Table 5.6). There are 42 of 89 (47%) respondents above the mean person (+0.37 logit) and 47 of 89 (53%) respondents are below the mean. There are 29 of 58 (50%) items at or above the mean item (0.00 logit) and 29 of 58 (50%) items were below the mean. There are 62 of 89 (70%) respondents who met the item difficulty and above the mean item of 0.00 logit, which shows that the group of respondents has higher ability in Survey 2 than respondents in Survey 1.

Based on the Survey 2 results from the Rasch analysis using the person-item map in Figure 5.6, it provides a clear summary of the correlations between the individuals involved and the items prescribed. The Survey 2 results also demonstrate the predictive capability of the Rasch model to produce an association pattern between organisations' abilities and the performance levels for each item.

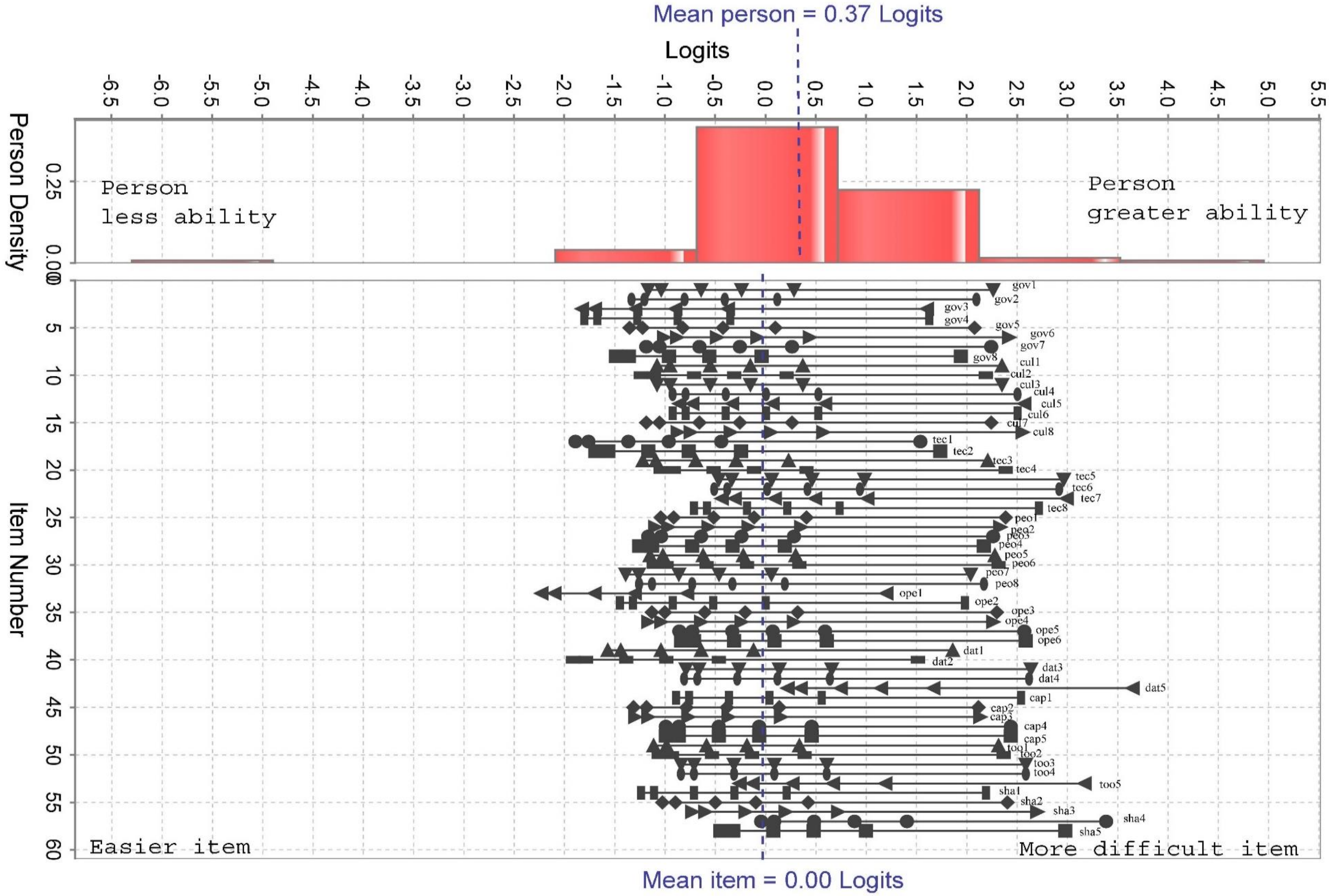

Figure 5.6 Person-Item Map for Survey 2

5.11. Survey 2: Results by Industry Sector and BA Maturity Levels

Table 5.13 summarises the number of respondent organisations classified by BA maturity level and industry sector for Survey 2. About 52% (Survey 2) of organisations were classified at maturity level 2, and about 47% (Survey 2) of organisations were at level 3 or above. In general, the Information Technology and Manufacturing sectors appear to be the most BA mature sectors with 49% (Survey 2) of organisations in these two sectors reaching BA maturity level 3 or above.

Table 5.13 BA Maturity Levels by Industry Sector for Survey 1

Industry	**Maturity Level**					**Total**
	1	**2**	**3**	**4**	**5**	
Financial		1		1		2
Information technology		10	8	4		22
Logistics		1	2	1		4
Manufacturing	1	23	16	4	1	45
Utilities		1				1
Others		10	4	1		15
Total	1	46	30	11	1	89
Percentage	1%	52%	34%	12%	1%	100%

5.12. Survey 2: Analysis of Results Using Radar Charts

The Radar Charts show the weighted average scores of BA capability measurement items for five maturity levels (1 to 5) in Figure 5.7 for Survey 2. By plotting their scores of BA capability in a radar chart, an organisation can easily compare their current BA capability across five levels of maturity with target maturity levels, industry benchmarks, as well as against the maturity levels of multiple organisations in the same industry sector.

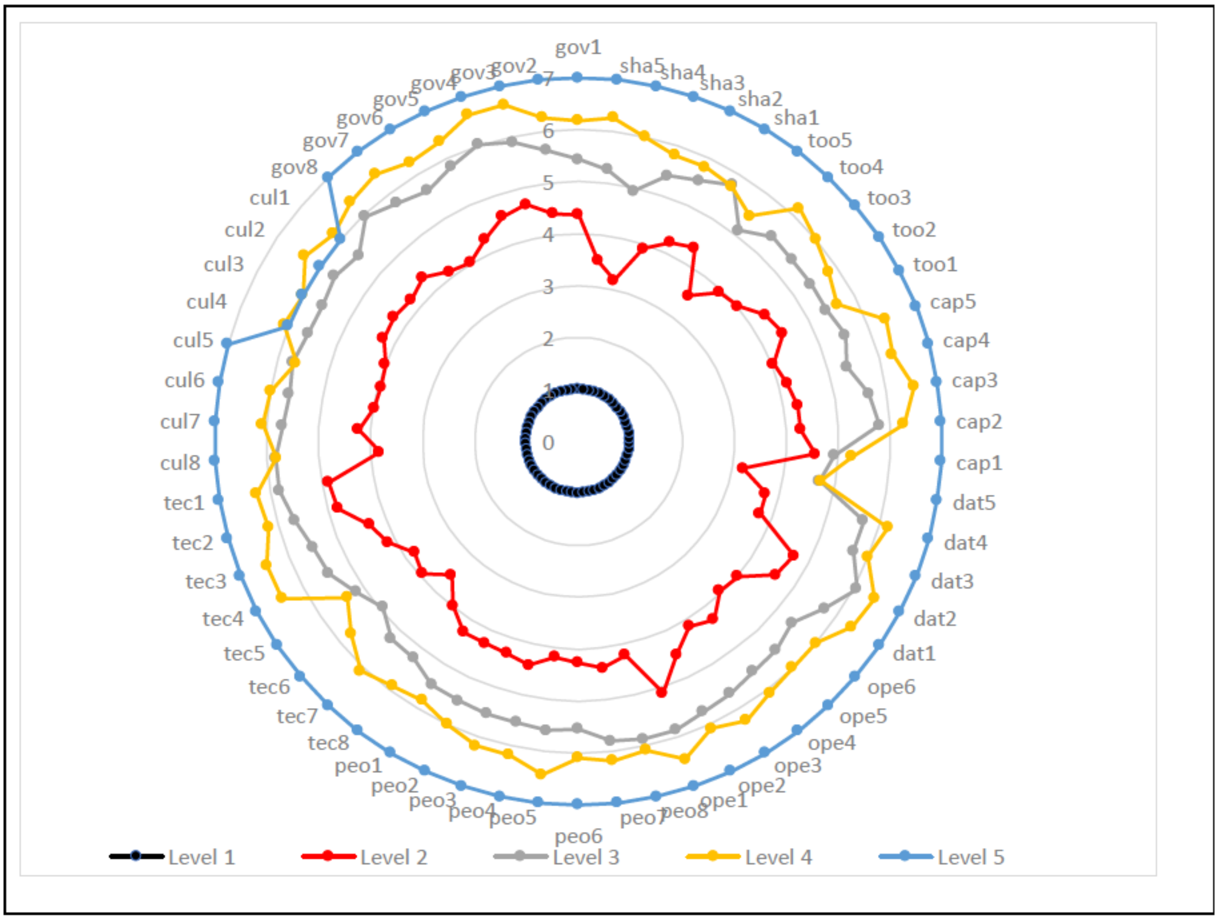

Figure 5.7 Weighted Average Scores by Maturity Levels: Radar Chart for Survey 2

The radar chart displays an organisation's score alongside benchmarking data, identifying issues with measurement items. Figure 5.7 shows a radar chart of weighted average scores for different maturity levels in Survey 2, highlighting potential issues. If a higher-level average score is close to or lower than a lower-level score, it suggests possible problems, such as respondent misunderstanding or the need for clearer measurement items. Items with potential issues are “cul1”, “cul2”, “cul3”, “cul4”, and “dat5”. Issues with “cap1”, “cul4”, and “dat5” were discussed for Survey 1 results using the radar chart.

Overlapping average scores between higher and lower maturity levels can occur due to outliers, especially in smaller samples. These outliers can skew results, making higher-level average scores appear close to or lower than those of lower levels. This suggests respondent misunderstanding or the need for clearer measurement items. Outliers impact smaller samples more because each data point has a larger influence on the overall average, leading to potential inaccuracies in reflecting true maturity levels.

5.13. Survey 2: Hypothesis Testing Results for RQ3.3

Finally, the results for Survey 2 testing hypotheses H1 and H2 are presented to address RQ3.3: “To what extent is BA maturity an indicator of perceived BA capability and perceived ERP BA success in an organisation?” RQ3.3 aims to determine how the BA maturity level, determined by Rasch analysis and cluster analysis, relates to perceived ERP BA success and perceived BA capability. It hypothesises that higher BA maturity generates greater perceived ERP BA success and perceived BA capability.

The hypotheses to be tested in the PLS-SEM reflective model are as follows:

(H1) BA maturity level is positively associated with perceived ERP BA success
(H2) BA maturity level is positively associated with perceived BA capability

Table 5.14 presents the construct reliability and validity results for BA Maturity, Perceived ERP BA Success, and Perceived BA Capability in Survey 2.

Table 5.14 Construct Reliability and Validity Results for BA Maturity, Perceived ERP BA Success, and Perceived BA Capability (Survey 2)

Latent Construct	**Cronbach's Alpha**	***ρA***	**Composite Reliability**	**AVE**
BA Maturity	1.000	1.000	1.000	1.000
Perceived ERP BA success	0.941	0.947	0.958	0.850
Perceived BA Capability	0.955	0.958	0.965	0.847

ρA (rho_A) is an alternative reliability measure used in PLS-SEM. Similar to Cronbach's alpha, *ρA* values range from 0 to 1, where higher values indicate better reliability. Generally, a *ρA* value above 0.7 is considered acceptable for reliability in PLS-SEM. It assesses internal consistency similarly to Cronbach's alpha but is considered a more accurate measure in certain situations (Kline 2000; Russo & Stol 2021). *ρA* is calculated as the ratio of the sum of the squares of the latent variable scores to the sum of the squares of the measurement residuals. This measure provides insights into the proportion of variance in observed variables due to common factors versus measurement error, aiding in evaluating the reliability of constructs in the PLS-SEM context.

The factor loadings for Perceived BA Capability and Perceived ERP BA success shown in Figure 5.8 (for Survey 2) demonstrate adequate reliability with all item loadings meeting the optimal minimum of 0.7 (Nunnally & Bernstein 1994). Overall, the factor loadings, reliability scores and AVE values from Survey 2 confirm that the measurement model is satisfactory and demonstrates acceptable reliability and convergent validity.

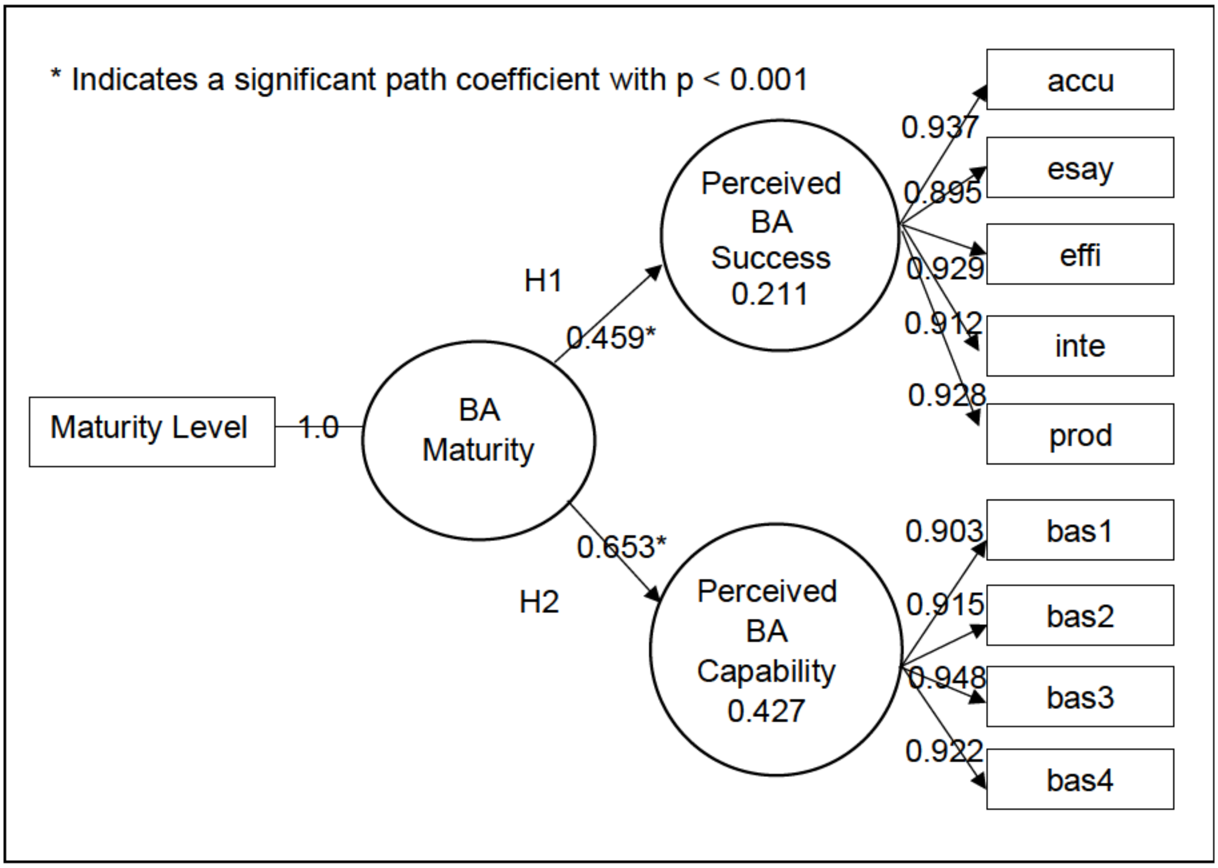

Figure 5.8 PLS-SEM Model for BA Maturity with Perceived ERP BA Success and Perceived BA Capability for Survey 2

The two hypotheses tested in Survey 2 to answer RQ3.3 in the PLS-SEM path model are: (H1) BA maturity level is positively associated with Perceived ERP BA success; and (H2) BA maturity level is positively associated with BA capability.

The primary criteria for hypothesis testing are R^2, statistical significance, and the relevance of path coefficients (Hair et al. 2016). R^2 values indicate the proportion of variance in a dependent variable explained by endogenous constructs, while path coefficients reflect the strength of relationships between dependent and independent variables (Chin 2010; Rabaa'i 2021).

In Survey 2, the path coefficient of (H1) BA Maturity and Perceived ERP BA Success indicates a positive and highly significant (0.459*) relationship, while the path coefficient of (H2) BA Maturity and Perceived BA Capability indicates a positive and highly significant (0.619*) relationship. The structural model explained 21.1% (R^2=0.211) of the variance in the dependent latent variable Perceived ERP BA success and explained 42.7% (R^2=0.427) of the variance in the dependent latent variable Perceived BA Capability. The R^2 values show that BA maturity is one of the organisational factors affecting the Perceived ERP BA success and the perceived BA capability in organisations.

5.14. Chapter Summary and Conclusion

Chapter 5 presented the findings from applying and assessing the BARCMM for organisations using ERP systems in the GCR. It covered empirical applications, data collection and analysis, and survey results by industry sector and maturity levels. The chapter also included hypothesis testing and revisions to measurement items.

5.14.1. Chapter Summary

Chapter 5 presents an empirical exploration of the proposed BARCMM for organisations using ERP systems in the GCR. The analysis involves Rasch analysis, industry-specific trends, alternative data perspectives, and a comparative analysis using PLS-SEM. The results classify organisations into five maturity levels and address measurement reliability concerns at higher levels. Industry-specific insights and alternative perspectives provide a comprehensive view of the BA maturity of organisations using ERP systems. Meanwhile, PLS-SEM tests hypotheses H1 and H2, confirming the reliability and validity of the BARCMM measurement instruments in both Survey 1 and Survey 2, based on the assumption that organisations with higher maturity levels will have higher perceived BA capability and success. The detailed discussion of various aspects of the findings from the empirical exploration is presented in Chapter 6.

Survey 1 assessed BA maturity levels in organisations with ERP systems in the GCR. Survey 1 was conducted online via LimeSurvey from April 2017 to September 2018, targeting individuals with ERP and Business Analytics experience.Survey 1 featured 40 items measuring BA capability across nine dimensions. Responses were analysed from organisations using BA tools in ERP systems in the GCR. Of 1,200 invited participants, 437 surveys were submitted, including 195 fully completed. One hundred and twelve responses were usable, yielding a response rate of 16.3% and a usable response rate of 9.3%. Key participation came from the Information Technology and Manufacturing sectors, primarily from Hong Kong and China. Data analysis, using Rasch and Hierarchical Cluster Analysis, revealed an imbalance in item difficulties, with a concentration at levels 2 and 3. This suggested a need for more items at higher maturity levels. The person-item map analysis showed a mean person ability of 0.51 logit and a mean item difficulty of 0.00 logit. It indicated that 39% of respondents were above the mean, while 61% were below it, demonstrating the effectiveness of Rasch analysis. The overview highlighted that 55% of organisations were at maturity level 2, and 37% at level 3 or higher, with the Information Technology and Manufacturing sectors showing the highest maturity levels. Radar charts used to analyse BA capability data identified potential measurement issues, such as discrepancies in clarity for items “cap1” and “cul4” and challenges with “dat5” even for high-maturity organisations. Hypothesis testing revealed that higher BA maturity significantly correlates with both perceived ERP BA success (path coefficient = 0.526) and perceived BA capability (path coefficient = 0.619). The model explained 27.7% of the variance in ERP BA success and 38.3% in BA capability, confirming the model's reliability and validity.

Survey 2 introduced eighteen new measurement items to address gaps identified in Survey 1, specifically for assessing BA maturity levels 4 and 5. This update aimed to enhance the classification of organisations into five maturity levels. The revised Survey 2 featured 58 items (40 from Survey 1 and 18 new), measuring BA capability across nine dimensions. Responses from organisations using BA tools in ERP systems were analysed, resulting in 89 usable responses, a response rate of 9.5%, and a usable response rate of 7.4%. The majority of responses came from the Manufacturing sector (51%) and Information Technology (25%), with significant representation from China (44%) and Hong Kong (31%). Rasch analysis of the 58 items revealed a normal distribution across maturity levels, with Level 3 having the most items and Levels 1 and 5 the fewest. The person-item map indicated a mean person measure of 0.37 logit and a mean item measure of 0.00 logit, showing that respondents generally demonstrated higher capabilities compared to Survey 1. In Survey 2, organisations were classified into five BA maturity levels, with approximately 52% at level 2 and 47% at level 3 or higher. The Information Technology and Manufacturing sectors displayed the highest maturity levels, especially in Manufacturing. Radar charts from Survey 2 highlighted potential issues with certain measurement items, suggesting that clearer questions are needed. Hypothesis testing confirmed a significant positive relationship between BA maturity and both perceived ERP BA success and perceived BA capability, with path coefficients of 0.459 and 0.619, respectively. The PLS-SEM model demonstrated satisfactory reliability and validity, with BA maturity explaining 21.1% of the variance in ERP BA success and 42.7% in BA capability, underscoring its significance in influencing these outcomes.

5.14.2. Chapter Conclusion

Chapter 5 concludes by providing valuable insights into the application of BARCMM and the assessment of BA readiness and capability of organisations using ERP systems in the GCR. It highlights key findings, including the classification of maturity levels, measurement enhancements, industry-specific trends, and the robustness achieved through PLS-SEM. The presented research contributes to understanding and advancing business analytics maturity assessment, paving the way for future research and practical implications in the field.

Survey 1 assessed BA maturity in organisations using ERP systems in the GCR from April 2017 to September 2018. The survey featured 40 items across nine BA dimensions. Of the 1,200 invited participants, 437 surveys were submitted, 195 were fully completed, and 112 were usable. This resulted in a response rate of 16.3% and a usable response rate of 9.3% (see Table 5.1). Analysis using Rasch and Hierarchical Cluster Analysis revealed an imbalance, with too few items at higher maturity levels, indicating a need for more items to improve assessment robustness. The person-item map showed 39% of respondents had abilities above the mean, while 55% of items were at or above the mean difficulty, indicating good alignment. Approximately 55% of organisations were at maturity level 2, and 37% were at level 3 or higher, with higher maturity levels notably in IT and Manufacturing sectors. Radar charts highlighted potential measurement issues. Hypothesis testing confirmed a significant positive relationship between BA maturity and both perceived ERP BA success and capability, with the PLS-SEM model explaining 27.7% of the variance in ERP BA success and 38.3% in BA capability.

In Survey 2, eighteen new items were added to address gaps identified in Survey 1, particularly for assessing BA maturity levels 4 and 5. Conducted online via LimeSurvey from October 2018 to October 2021, Survey 2 comprised 58 items (40 from Survey 1 and 18 new), measuring BA capability across nine dimensions. Only responses from organisations using BA tools in ERP systems were analysed. Eighty-nine responses were usable, resulting in a 9.5% response rate and a 7.4% usable response rate (see Table 5.9). Rasch analysis with jMetrik showed a normal distribution of items across maturity levels, with Level 3 having the most items. The person-item map revealed that respondents generally had higher capabilities than in Survey 1, with 47% scoring above the mean. About 52% of organisations were at maturity level 2, and 47% at level 3 or higher, with higher maturity levels common in IT and Manufacturing sectors. Radar charts suggested issues with some measurement items, indicating a need for clearer questions. Hypothesis testing confirmed a significant positive relationship between BA maturity and both perceived ERP BA success and capability, with the PLS-SEM model explaining 21.1% of the variance in ERP BA success and 42.7% in BA capability. The comparison of response rates between Survey 1 and Survey 2 highlights several key factors. The increase in questionnaire length and the impact of the COVID-19 pandemic likely contributed to the lower response rates and reduced usability in Survey 2. This underscores the need to balance survey length with the requirement for comprehensive data and to consider external factors in future data collection efforts.

CHAPTER 6: DISCUSSION

In Chapter 6, the research questions are addressed and discussed in relation to the empirical results of the BARCMM assessment. The chapter reviews critical success factors for ERP business analytics readiness and stresses methodological rigour in business analytics capability measurement. It presents BARCMM assessment results that validate constructs and suggest improvements for enhancing business analytics in ERP systems. Chapter 6 will focus on broader high-level questions (RQ1, RQ2, RQ3) and low-level questions (RQ3.1, RQ3.2, RQ3.3), providing a detailed analysis of how these questions relate to existing literature and the study's key findings. Section 6.1 discusses SLR 1 findings for Research Phase I, focusing on Research Question 1 (RQ1) and essential critical success factors (CSFs) for ERP business analytics (BA) readiness. It highlights the need for targeted research on CSFs, especially in global ERP contexts and the GCR. Despite the growing importance of ERP BA, research is limited. An eight-dimensional CSF framework is introduced for evaluating ERP BA readiness within the BARCMM model. The section also proposes a hypothesis that integrated ERP systems may enhance BA capabilities via shared data, potentially improving perceived BA success. It highlights the practical contribution of applying SLR findings to the BARCMM design in Chapter 4. Section 6.2 discusses the findings of SLR 2 and SLR 3 for Research Phase I, focusing on Research Question 2 (RQ2). It identifies CSFs that enhance BA capability and establishes standardised measurement methods. It addresses critical gaps in BA capability measurement within BAMMs, particularly regarding methodological rigour in designing and validating BAMMs for contemporary ERP systems. These efforts aim to improve methodological precision and reliability, enhancing BA maturity assessments in ERP environments and highlighting the need for rigorous methodology in developing questionnaires for the BARCMM. Section 6.3 discusses the empirical assessment results of BARCMM for Research Phase III, focusing on ERP BA readiness and capability and proposing methods to validate the maturity model hypothesis within ERP systems. These findings, along with contributions from RQ1 and RQ2, advance theoretical and practical understanding. They support a rigorous approach to designing and developing BARCMM for assessing ERP BA readiness and capability in organisations. A self-assessment questionnaire is provided for adaptation by researchers and practitioners. Rasch

Analysis from Surveys 1 and 2 clarifies the measurement of organisational capability across maturity levels, with Survey 2 showing increased accuracy in assessing progress. Discussions on person-item maps reveal insights into respondent capability and item difficulty, suggesting tailored approaches to enhancing organisational BA practices. Radar chart results illustrate BA readiness and capability, helping organisations identify strengths and weaknesses for targeted improvements. Specific item analysis highlights challenges and emphasises the need for ongoing efforts to strengthen BA capabilities. PLS-SEM results validate constructs, affirming internal consistency and robust measurement instruments, with practical implications for enhancing BA initiatives in organisations and contributing to the field of business analytics. Section 6.4 synthesises findings from SLRs 1, 2, and 3 and empirical assessments to highlight CSFs for ERP BA readiness and capability of organisations using ERP systems. The focus is on developing and validating the BARCMM. This model provides practical tools for organisations to enhance their BA maturity and performance. Section 6.5 outlines the contributions of the study. These include the development of an eight-dimensional CSF framework, the enhancement of methodological rigour in BAMMs, and the refinement of measurement techniques. The section also provides insights into sector-specific BA maturity variations and offers empirical validation of theoretical models. Collectively, these contributions advance the understanding of ERP BA readiness and capability. Section 6.6 compares the BARCMM with previous maturity models, emphasising its ERP-specific focus and unique features. It also validates the measurement instrument against prior studies, which underscores its credibility and relevance in assessing ERP BA readiness and capability. Section 6.7 outlines the limitations of the study. It addresses methodological issues, including perception-based measures, geographic focus, and constraints of quantitative methods. Additionally, it highlights practical limitations, such as sample size, geographic applicability, and translation accuracy. Section 6.8 outlines future research directions. It recommends expanding the geographic scope, increasing sample size and diversity, adopting mixed methods, incorporating diverse data sources, utilising longitudinal studies, minimising social desirability bias, and exploring broader applications. Key areas for further investigation include enhancing radar chart use, clarifying measurement items, examining the impact of outliers, refining survey instruments, and applying AI and machine learning in smart ERP systems. Section 6.9 summarises the final remarks of the study. It highlights the study's significant contributions to ERP BA readiness and capability maturity through the development of the BARCMM. Additionally, it reflects on the research journey, noting key insights and challenges. These include the importance of collaborative support, methodological rigour, and persistence. Finally, Section 6.10 summarises and concludes the chapter, presenting key findings from the BARCMM assessment. The study emphasises the significance of measuring BA maturity. It employs Rasch analysis and cluster analysis to assess organisational maturity levels and highlights practical applications for enhancing BA initiatives, monitoring performance, and benchmarking organisations using ERP systems in the GCR. Figure 6.1 shows the structure of Chapter 6.

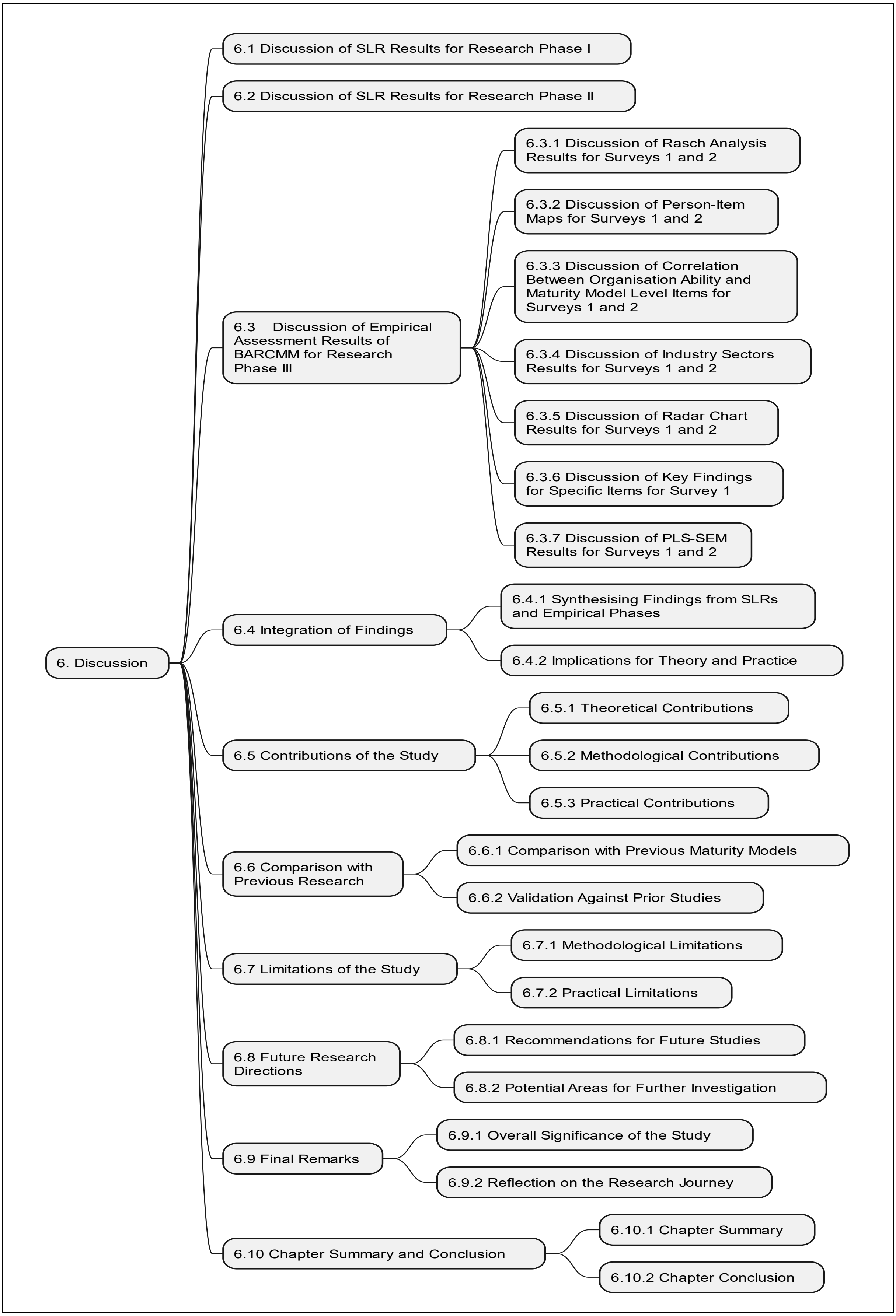

Figure 6.1 Structure of Chapter 6

6.1. Discussion of SLR Results for Research Phase I

Research Question 1 (RQ1): What are the critical success factors that contribute to ERP BA readiness, and how can ERP BA readiness be effectively measured? In SLR 1 in Chapter 2, Research Question 1 (RQ1) sought to identify CSFs contributing to ERP BA readiness. These CSFs compare existing measurement methods for ERP BA readiness, driven by the necessity for more targeted research on CSFs related to BA readiness, particularly for global ERP implementations and especially in the GCR. The study highlighted a limited body of research in this domain, despite the rising importance of ERP BA for organisations to achieve a competitive edge. ERP BA enables organisations to leverage valuable insights from data, yet many organisations are ill-prepared, leading to significant BA initiative failures (Ariyarathna & Peter 2019). This SLR identified an eight-dimensional CSF classification framework (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services) used to assess ERP BA Readiness within the BARCMM. Among these, the first five dimensions (Governance, Culture, Technology, Operation, People) were specifically chosen as measurement items for evaluating ERP BA readiness in organisations using ERP systems. The CSF dimensions Project, Performance, and Products/Services were not selected as measurement dimensions in the BARCMM assessment questionnaire because they are less directly related to BA readiness for organisations using ERP systems. The Project dimension is more related to the implementation of BA and ERP systems. The Performance dimension involves the internal performance data of ERP systems, such as metrics generated from these systems, which may not be possible for all respondent organisations to answer. The Products/Services dimension is related to Industry 4.0 technologies. The survey should encompass diverse industry sectors, including Financial, Information Technology, Logistics, Manufacturing, Utilities, and others, ensuring representation beyond manufacturing, especially in regions like Greater China where some manufacturers may not have adopted Industry 4.0 technologies. Instead, Governance, Culture, Technology, Operation, and People were chosen as they are core elements influencing BA integration and effectiveness. Including all eight dimensions would complicate the survey, reducing response rates and data quality. The selected dimensions are well-established frameworks for assessing BA readiness and have consistent relevance across diverse organisational contexts, particularly in the GCR. This focused approach avoids overlaps and ensures a practical assessment of BA readiness. These dimensions are fundamental CSFs both in ERP implementations and for assessing BA readiness of organisations using ERP systems. It is hypothesised that organisations leveraging ERP systems with integrated business partnerships will have enhanced BA capabilities through shared data, potentially leading to increased perceived BA success.

Research Question 1 (RQ1) focused on identifying CSFs essential for ERP BA readiness which resulted in the development of effective measurement methods and an eight-dimensional CSF classification framework that underpinned the BARCMM model. This framework is underscored by key dimensions such as Governance, Culture, Technology, Operation, and People. Furthermore, a hypothesis was posited, suggesting that companies leveraging integrated ERP systems could augment BA capabilities through shared data, potentially amplifying perceived BA success.

Research Question 1 (RQ1) aims to identify CSFs essential for ERP BA readiness. The study introduces an eight-dimensional CSF classification framework, encompassing Governance, Culture, Technology, Operation, and People dimensions, providing a methodical approach for assessing ERP BA readiness. The practical contribution lies in applying the research findings from the systematic literature review (SLR) to select CSFs as measurement items for the design and development of the BARCMM in Chapter 4.

6.2. Discussion of SLR Results for Research Phase II

Research Question 2 (RQ2): What are the CSFs that contribute to BA capability, and how can BA capability be measured? In Chapter 2, SLR 2 reviews existing methodological approaches for designing, assessing, and validating BAMMs that can be adapted for the design, assessment, and validation of the proposed BARCMM. These gaps encompass enhancing methodological rigour in designing and validating BAMMs, adapting BAMMs to modern ERP systems, and enhancing the transparency and documentation of BAMMs created by practitioners. Addressing these gaps has the potential to improve the precision and dependability of BA maturity assessments within ERP system environments. SLR 3 focuses on Research Question 2 (RQ2), which addressed research gaps concerning critical success factors for measuring BA capability.

Research Question 2 (RQ2) focused on addressing research gaps concerning BA capability measurement in BAMMSs. This research aimed to enhance methodological rigour in designing and validating BAMMs, specifically tailored for modern ERP systems. Its primary goal was to establish rigorous methodological measurement methods by assessing and validating BAMMs specifically for modern ERP systems. The practical significance of these findings is to adapt and apply BA maturity assessments within ERP environments, emphasising methodological rigour in designing, developing, and implementing the questionnaire for assessing the BARCMM.

6.3. Discussion of Empirical Assessment Results of BARCMM for Research Phase III

Research Question 3 (RQ3) was addressed and discussed in Chapters 4 to 6. It investigates how ERP BA readiness influences BA capability and proposes methods to test the hypothesis of a maturity model for BA capability in ERP systems. RQ3 focuses on uncovering and understanding the CSFs related to ERP BA readiness, crucial for improving BA capability. This research aims to bridge the gap by investigating the factors that play a significant role in the BA capability of organisations using ERP systems.

The contributions of high-level research questions RQ1, RQ2, and RQ3 collectively represent significant theoretical advancements. They (1) introduce a rigorous empirical approach to developing BARCMM, (2) create a maturity model for assessing ERP BA readiness and capability, (3) employ quantitative evaluation methods, (4) validate the ERP BA Maturity Model, and (5) provide a practical self-assessment questionnaire measurement instrument that can be adapted by researchers and practitioners to assess BA readiness and capability of organisations using ERP systems.

Research Question 3 (RQ3) spans Chapters 7, 8, and 9, where the complex relationship between ERP BA readiness and BA capability is explored. It proposes methodologies to test the maturity model hypothesis for BA capability within ERP systems. Through empirical assessments, Rasch Analysis, and its application, the practical contribution is to uncover critical success factors relevant to ERP BA readiness, thereby enhancing organisations' BA capability.

The contributions of RQ1, RQ2, and RQ3 also collectively represent significant practical advancements by introducing a rigorous and quantitative approach with fully documented steps for designing and measuring BA maturity in organisations using ERP systems. This offers practitioners a systematic method for objective assessment. This approach, facilitated by Rasch analysis and hierarchical cluster analysis, results in the creation of the proposed BARCMM, enabling organisations to determine and evaluate their BA maturity levels. Furthermore, the study applies IRT to enhance the reliability of measurement items. The hypothesised relationships between BA maturity, perceived BA capability, and perceived ERP BA success were tested using PLS-SEM. The results of the PLS-SEM highlight the practical relevance of assessing and improving BA maturity within organisations. These contributions provide organisations with valuable tools for evaluating their BA maturity levels, aiding in performance improvement, strategic decision-making, and benchmarking practices within the GCR and potentially other domains.

6.3.1. Discussion of Rasch Analysis Results for Surveys 1 and 2

The Rasch analysis and cluster analysis approach allows measuring an organisation's capability across a continuum from least to most capable, and classifying organisations into five distinct maturity levels. The initial distribution of measurement items in Survey 1 (see Table 5.3) showed an unbalanced coverage, with more items concentrated in the middle maturity levels 2 and 3, and fewer items in the higher levels 4 and 5. This suggests a potential lack of measurement depth at the upper end of the maturity spectrum, which could limit the model's ability to accurately evaluate an organisation's progress and provide meaningful insights to support advancement across all levels of maturity.

In Survey 2 (see Table 5.11), by adding 18 new measurement items, the revised distribution followed a more normal pattern, with the number of items increasing from level 1 to a peak at level 3, and then decreasing towards the higher maturity level of 5. This structured progression of measurement items across the maturity levels indicates a logically designed model that can comprehensively assess an organisation's capabilities and provide appropriate sets of measurement items based on critical success factors for each dimension. This approach helps ensure the maturity model can accurately evaluate an organisation's maturity and effectively support its advancement to higher levels of BA maturity.

The range of theta values to classify the maturity level into 5 levels for Survey 1 and 2 are summarised in Table 6.1.

Table 6.1 Theta Value Ranges for Maturity Levels in Surveys 1 and 2

Level	Survey 1		Survey 2	
	Number of cases	**Theta Ranges**	**Number of cases**	**Theta Ranges**
1	10	-1.8799 to -0.6522	1	-6.2925
2	61	-0.4842 to 0.5260	46	-1.2309 to 0.3655
3	22	0.6307 to 1.3408	30	0.4400 to 1.2484
4	17	1.4513 to 3.1857	11	1.3946 to 2.4763
5	2	4.0394 to 5.4012	1	4.9410

The Results of Rasch Analysis involve the range of theta (θ) values used to classify maturity levels for Surveys 1 and 2 based on Table 5.6. These theta values are significant in assessing organisational capability as they provide a quantitative measure of an organisation's proficiency or competence.

The range of theta values for Surveys 1 and 2 indicates distinct maturity levels in assessing the BA capability of organisations using ERP systems. In Survey 1, theta values span from -1.8799 to 5.4012 across five maturity levels, with higher theta values indicating greater proficiency. Conversely, Survey 2 exhibits a broader spectrum, ranging from -6.2925 to 4.9410, encompassing five maturity levels as well. These theta values serve as markers along a latent trait continuum, providing a nuanced understanding of an organisation's BA capability.

Lower theta values, such as -6.2925 in Survey 2, suggest relatively lower organisational capability, whereas higher values, like 5.4012 in Survey 1, denote heightened proficiency. The precision afforded by these theta values allows for accurate classification of organisations into maturity levels, aiding in benchmarking, performance assessment, and identification of improvement areas. Stakeholders can leverage this information to make informed decisions, fostering organisational development and growth based on a thorough analysis of maturity level distributions (Subramaniam et al. 2023).

6.3.2. Discussion of Person-Item Maps for Surveys 1 and 2

In Survey 1, the mean person is measured at 0.51 logit, indicating the average capability of respondents. The mean item measure is set at 0.00 logit, indicating the average difficulty of the survey items. All items below the mean item measure of 0.00 logit are considered easy or agreed upon by the respondents. The maximum item measure is +0.77 logit, representing the most difficult item. Conversely, the maximum person measure is +5.40 logit, indicating the highest capability among respondents. There are more easy items, with a minimum item measure of -0.49 logit, than respondents in agreement at -1.88 logit.

In Survey 2, the mean person is measured at 0.37 logit, suggesting a slightly lower average capability of respondents compared to Survey 1. Similar to Survey 1, the mean item measure is set at 0.00 logit. The maximum item measure for Survey 2 is +0.65 logit, which is slightly lower than Survey 1. The maximum person measure in Survey 2 is +4.94 logit, indicating the highest capability among respondents. There are 42 of 89 (47%) respondents above the mean person measure (+0.37 logit) in Survey 2, while 47 of 89 (53%) respondents are below the mean. The distribution of items in Survey 2 is similar to Survey 1, with 29 of 58 (50%) items at or above the mean item (0.00 logit).

The implications of the mean person logit values in the Person-Item Map being equal to 0, greater than 0, and less than 0 are as follows (Andersen 1973; Lamoureux et al. 2008; Gómez et al. 2012):

(1) When the mean person logit is equal to 0, it indicates that the average capability or ability of the respondents is exactly equal to the average difficulty of the survey items. This suggests a good match between the capability of the respondent organisation and the item difficulty, meaning the assessment is well-targeted and can effectively differentiate between the respondents. It also implies that the measurement items are appropriately designed to cover the range of abilities present in the respondent organisation within the respondent population.

(2) When the mean person logit is greater than 0, it indicates that the average capability or ability of the respondents is higher than the average difficulty of the

survey items. This suggests that, on average, the respondent organisation finds the survey items relatively easy or has a higher level of capability compared to the difficulty of the items. It implies that the test or assessment may need to incorporate more challenging or difficult items to better differentiate between the higher-performing respondent organisations.

(3) When the mean person logit is less than 0, it indicates that the average capability or ability of the respondents is lower than the average difficulty of the survey items. This suggests that, on average, the respondent organisation finds the survey items relatively difficult or has a lower level of capability compared to the difficulty of the items. It implies that the test or assessment may need to include easier items to better capture the capability levels of the lower-performing respondent organisations.

In Survey 1, the mean person measure is 0.51 logit, which is greater than 0. This suggests the respondents, on average, have a higher capability than the difficulty of the survey items. In Survey 2, the mean person measure is 0.37 logit, which is still positive but slightly lower than in Survey 1. This indicates a slightly lower average capability of respondents compared to Survey 1. However, the mean person logit value of 0.37 in Survey 2 being closer to 0 substantiates that the overall questionnaire was well-targeted, more so than Survey 1 with the mean person logit value of 0.51. This suggests the respondents had a marginally higher level of ability than the average of the scale items, which is 0 logit. This implies that the eighteen new ERP BA profile measurement items (gov5, gov 6, gov 7, gov8, cul5, cul6, cul7, cul8, tec5, tec6, tec7, tec8, peo7, peo8, ope3, ope4, ope5, ope6) added were well-targeted for the respondents in Survey 2.

The mean person and mean item measures provide insights into the central tendencies of respondent capability and item difficulty. Survey 2 generally shows a lower average capability among respondents compared to Survey 1, as indicated by the lower mean person measure. The distribution of respondents and items on the logit scale in both surveys highlights variations in capability and item difficulty. The presence of easy items suggests that certain aspects of the survey were well-understood and agreed upon by respondents. The maps provide a visual representation of how respondents' capability aligns with item difficulty, which is valuable for understanding the survey's performance and identifying areas of improvement.

6.3.3. Discussion of Correlation Between Organisation Ability and Maturity Model Level Items for Surveys 1 and 2

Rasch analysis assesses both a person's ability (or an organisation's capability) and the performance of individual survey items on the same logit scale (Boone, W. & Noltemeyer, A. 2017; Tennant & Küçükdeveci 2023). A person's ability (or an organisation's capability) is represented by "theta" (θ) values, indicating a person's ability (or an organisation's capability), with higher θ values suggesting greater ability (Boone, W. & Noltemeyer, A. 2017; Batchelder et al. 2020). Survey items are scored on a logit scale, where easier items have lower values and more difficult items have higher values. Rasch analysis assigns these logit measures to each item and produces θ values for organisations. Cluster analysis then groups these measures into five maturity levels, scoring items from easy to difficult and corresponding to higher maturity levels from 1 to 5. Organisations are classified into five clusters based on their θ values, reflecting a continuum from least to most capable. In Table 5.6, which shows the range of theta values used to classify the maturity levels into five categories for Surveys 1 and 2, the theta (θ) values range from -1.8799 to 5.4012 in Survey 1, while in Survey 2, they range from -6.2925 to 4.9410. The theta values indicate that Survey 1 respondent organisations generally have higher baseline capabilities and less variability in organisational maturity, while Survey 2 shows a greater diversity in capabilities with some organisations having much lower capabilities.

Correlations between organisational ability and item performance reveal how well organisations perform on specific tasks or items. In Rasch analysis, person and item parameters are converted into a unit of measurement, θ (theta), distributed along a continuum, with the person's ability θ measured in logits, representing log-odds units, typically ranging between ±5, and 0 indicating the average difficulty point for the measure (Elhan et al. 2010; da Motta et al. 2022). Organisations with θ values higher than item logit values perform well on those items, indicating a higher capability to handle those tasks. Conversely, organisations with θ values lower than item logit values may struggle with those items, suggesting areas where improvement is needed (Tesio et al. 2024). These correlations allow organisations to identify their strengths and weaknesses, enabling targeted efforts for improvement (Spanos & Prastacos 2004). Understanding these correlations aids in making data-driven decisions for organisational development and resource allocation.

6.3.4. Discussion of Industry Sectors Results for Surveys 1 and 2

Table 6.2 summarises the number of respondent organisations classified by BA maturity level and industry sector for Surveys 1 and 2.

About 55% (Survey 1) and 52% (Survey 2) of organisations were classified at maturity level 2, and about 37% (Survey 1) and 47% (Survey 2) of organisations were at level 3 or above. In general, the Information Technology and Manufacturing sectors appear to be the most BA mature sectors with 36% (Survey 1) and 49% (Survey 2) of organisations in these two sectors reaching BA maturity level 3 or above.

Table 6.2 BA Maturity Levels by Industry Sector for Surveys 1 and 2

Industry	Survey 1						Survey 2					
	Maturity Level					Total	Maturity Level					Total
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
Financial		1		1		2		1		1		2
Information technology	2	22	9	4	1	38		10	8	4		22
Logistics		2	1	1		4		1	2	1		4
Manufacturing	4	17	3	7	1	32	1	23	16	4	1	45
Utilities		8	1	1		10		1				1
Others	3	12	8	3		26		10	4	1		15
Total	9	62	22	17	2	112	1	46	30	11	1	89
Percentage	8%	55%	20%	15%	2%	100%	1%	52%	34%	12%	1%	100%

The implication of this finding is that there are variations in the distribution of organisations across different maturity levels and industry sectors between Surveys 1 and 2, as the maturity of each industry sector varies with the industry, as well as the regions where these organisations are in China, Taiwan, or Hong Kong.

In Chapter 5, Table 5.2 summarises the demographics of respondent organisations in the GCR for Survey 1, while Table 5.10 provides the corresponding details for Survey 2. In Survey 1, out of 112 respondents, 34% were from

Information Technology, and 29% from Manufacturing, with 55% from Hong Kong and 27% from China. Survey 2 had 89 respondents, with 25% from Information Technology and 51% from Manufacturing, including 44% from China and 31% from Hong Kong. The distribution of respondent organisations across industry sectors in Surveys 1 and 2 reveals that a significant proportion of respondents from China are in the Manufacturing sector in Survey 1. Meanwhile, the majority of respondents from Hong Kong are observed in the Information Technology sector for Survey 2.

Two consecutive surveys were conducted with GCR participants. Survey 1 collected data from April 2017 to September 2018, while Survey 2 gathered data from October 2018 to October 2021. The COVID-19 lockdown, which began in Wuhan on 23 January 2020 and spread across China (Yuan et al. 2020; Guo et al. 2022), may have impacted Survey 2 due to travel restrictions and business closures. By late 2022, China had begun easing these measures, with notable relaxations by December 2022. Survey 1 had a response rate of 16.3% and a usable rate of 9.3%, whereas Survey 2 had a response rate of 9.5% and a usable rate of 7.4%.

The classification of respondent organisations by BA maturity level and industry sector is summarised in Table 6.2, with percentage distributions for Survey 1 in Table 6.3 and for Survey 2 in Table 6.4. In both Surveys 1 and 2, the Information Technology sector has a significant number of organisations classified at maturity level 2, indicating a moderate level of BA maturity. However, it also has a notable presence at higher maturity levels, especially in Survey 2, suggesting improvements in BA capabilities. The Manufacturing sector stands out as one of the most BA mature sectors in both surveys, with a substantial number of organisations reaching BA maturity level 3 or above. This sector demonstrates a strong commitment to advanced BA practices. The Utilities sector has a substantial presence at maturity level 2 in both surveys, indicating that many organisations in this sector have room for improvement in their BA capabilities. Other sectors show varying patterns, with some organisations demonstrating moderate to high BA maturity levels, while others are at lower maturity levels. These variations highlight the diverse landscape of BA maturity across different industry sectors, indicating the need for tailored approaches to improve organisational capabilities in BA practices.

Table 6.3 Percentage Distribution of BA Maturity Levels by Industry Sector for Survey 1

Industry	Survey 1					
	Maturity Level					Total
	1	2	3	4	5	
Financial		1 (50%)		1 (50%)		2 (100%)
Information technology	2 (5.3%)	22 (57.9%)	9 (23.7%)	4 (10.5%)	1 (2.6%)	38 (100%)
Logistics		2 (50%)	1 (25%)	1 (25%)		4 (100%)
Manufacturing	4 (12.5%)	17 (53.1%)	3 (9.4%)	7 (21.9%)	1 (3.1%)	32 (100%)
Utilities		8 (80%)	1 (10%)	1 (10%)		10 (100%)
Others	3 (11.5%)	12 (46.2%)	8 (30.8%)	3 (11.5%)		26 (100%)
Total	9	62	22	17	2	112
Percentage	8%	55%	20%	15%	2%	100%

Table 6.4 Percentage Distribution of BA Maturity Levels by Industry Sector for Survey 2

Industry	Survey 2					
	Maturity Level					Total
	1	2	3	4	5	
Financial		1 (50%)		1 (50%)		2 (100%)
Information technology		10 (45.4%)	8 (36.4%)	4 (18.2%)		22 (100%)
Logistics		1 (25%)	2 (50%)	1 (25%)		4 (100%)
Manufacturing	1 (2.2%)	23 (51.1%)	16 (35.6)	4 (8.9%)	1 (2.2%)	45 (100%)
Utilities		1 (100%)				1 (100%)
Others		10 (66.7%)	4 (26.7%)	1 (6.6%)		15 (100%)
Total	1	46	30	11	1	89
Percentage	1%	52%	34%	12%	1%	100%

6.3.5. Discussion of Radar Chart Results for Surveys 1 and 2

The radar charts in Chapter 5, Figure 5.3 for Survey 1 and Figure 5.7 for Survey 2, provide a visual representation of the weighted average scores of ERP BA readiness and BA capability measurement items for five maturity levels (1 to 5) in Surveys 1 and 2.

These radar charts allow organisations to quickly assess and compare their BA capability across different maturity levels, facilitating easy identification of strengths and weaknesses. By plotting the scores of each measurement item of an organisation on the radar chart, the organisation can visualise which specific measurement items or dimensions need improvement to achieve a higher maturity level. This visual tool assists organisations in understanding their current BA maturity and identifying key areas for improvement to progress to the next maturity level. Radar charts provide a concise and intuitive way to evaluate the ERP BA readiness and BA capability of an organisation holistically. They enable more informed decision-making and targeted efforts to enhance overall BA maturity.

In Chapter 5, when interpreting Figure 5.3 (Radar chart showing the weighted average scores of the measurement items for different maturity levels for Survey 1), it is observed that for item "cap1," which relates to data presentation in static reports, there is a close similarity in scores between Levels 1 and 2, and Levels 3 and 4. This suggests that lower-level organisations may need further user processing of static reports, while Level 5 organisations likely have well-developed, tailored reports. Moreover, for item "cul4," concerning employees' willingness to accept new things, the scores between Levels 3 to 5 are closely aligned. Even within Level 5 organisations, some employees may resist change, emphasising the importance of change management for achieving BA success.

In Chapter 5, Table 5.3, the item "dat5" stands out as the most challenging, indicating that many organisations struggle with using BA tools for unstructured data. Figure 5.3 reveals that even Level 5 organisations have an average score of only 3 out of 7 for "dat5," highlighting the difficulty in transforming unstructured data into structured, actionable insights. While AI and machine learning offer opportunities, analysing unstructured data remains a challenge. These findings underscore the critical role of change management, the need for improved capabilities in dealing with unstructured data, and the potential for emerging BA tools to enhance data analysis capabilities across organisations.

6.3.6. Discussion of Key Findings for Specific Items for Surveys 1 and 2

In Survey 1, analysing specific items "cap1," "cul4," and "dat5" from Chapter 5, Table 5.3, “Results of Rasch Analysis clustered into 5 levels of BARCMM using Hierarchical Cluster Analysis (Item Difficulty) for Survey 1” provides insights into the challenges and strengths of organisations regarding BA capability. These specific items shed light on critical areas that organisations need to address to improve their BA capability. Enhancing data presentation, fostering a culture of acceptance for innovation, and developing the capacity to work with unstructured data are essential steps toward advancing BA maturity and ensuring organisations can leverage data effectively for decision-making. These findings emphasise the need for ongoing efforts to strengthen these aspects of BA capability, as they play a vital role in an organisation's ability to harness the full potential of data analytics.

Figure 5.3 is reproduced in Figure 6.2, showing specific items “cap1,” “cul4,” and “dat5” with a pointer indicating issues of overlapping weighted average scores of a higher level with the lower levels. If a higher-level average score is close to or lower than a lower-level score, it suggests possible problems, such as misunderstanding by respondents or the need for clearer measurement items. Clearer measurement items are more precise, understandable, and unambiguous. They should be designed to make it easier for respondents to understand and interpret them correctly, thereby reducing any potential confusion or misinterpretation.

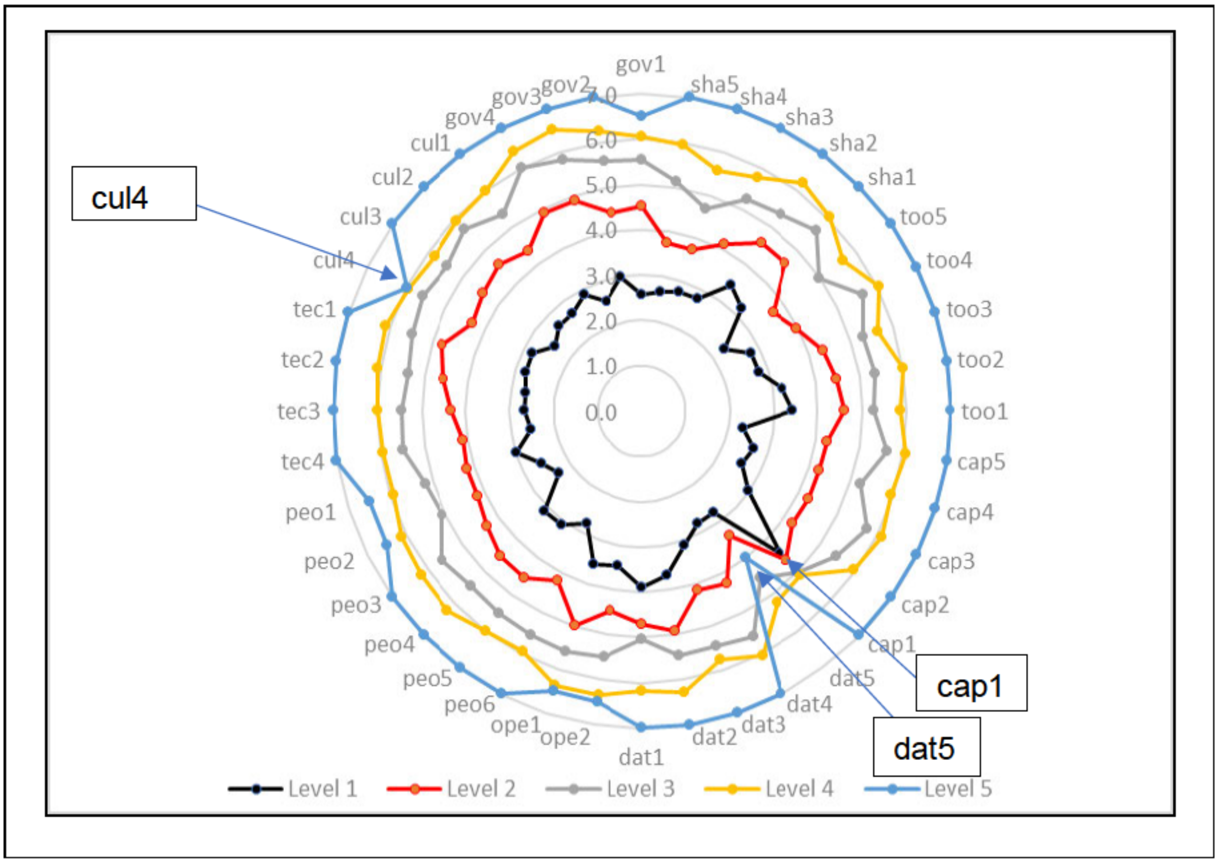

Figure 6.2 Radar Chart Showing the Weighted Average Scores of the Measurement Items for Different Maturity Levels for Survey 1 (cap1, cul4, dat5)

Figure 5.7 is reproduced in Figure 6.3, showing specific items “cul1”, “cul2”, “cul3”, “cul4”, and “dat5” with a pointer indicating issues of overlapping weighted average scores of a higher level with the lower levels. It is observed that “cul4” and “dat5” have common issues in Survey 1 and Survey 2, which means that these two measurement items need to be investigated in more detail to understand why the weighted average scores overlapped.

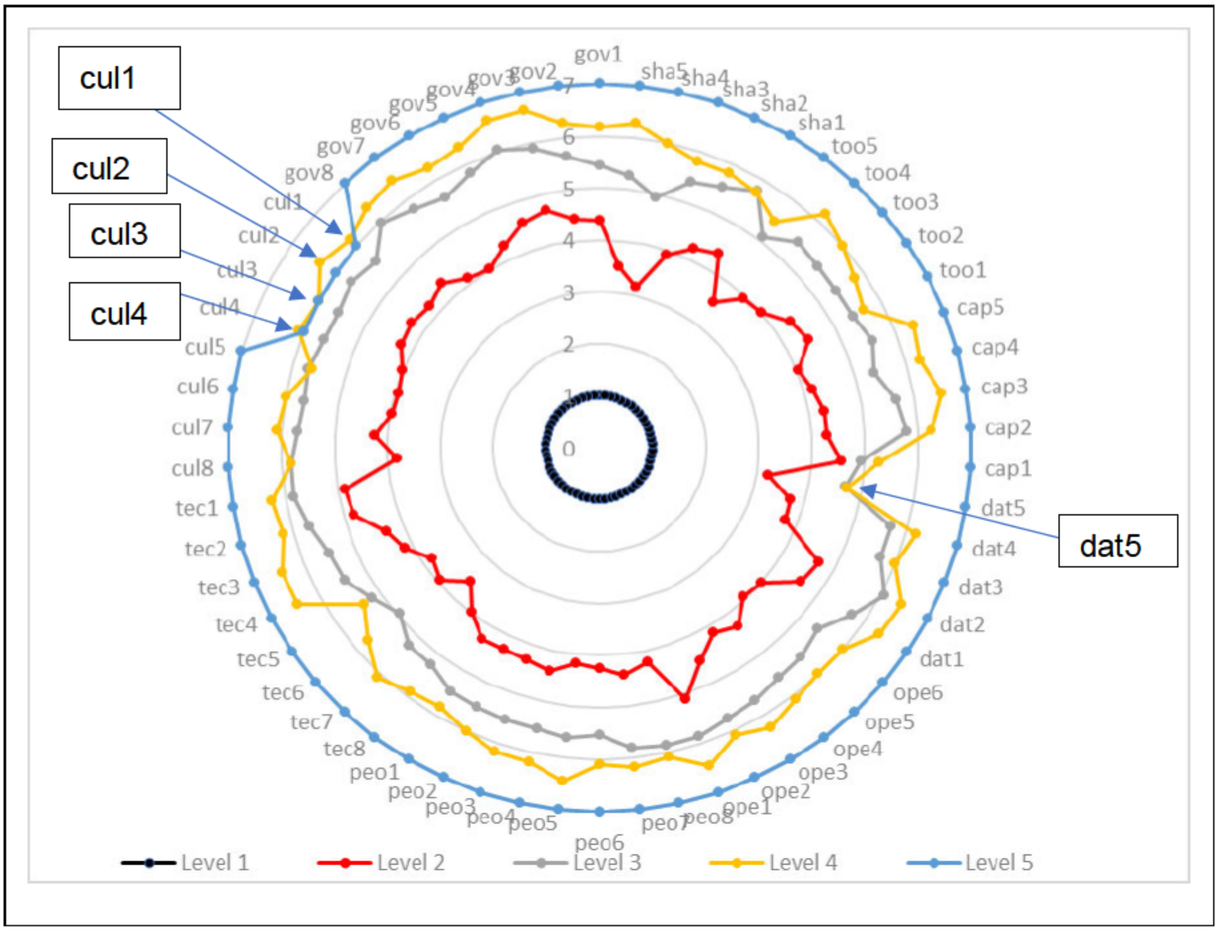

Figure 6.3 Radar Chart Showing the Weighted Average Scores of the Measurement Items for Different Maturity Levels for Survey 2 (cul1, cul2, cul3, cul4, dat5)

The item "cul4" (Employees are willing to accept new things) assesses the willingness of employees to embrace change and innovation. The difficulty value of 0.05 suggests that it is relatively challenging for organisations to ensure that employees are receptive to new ideas and technologies. In Survey 1, this item is classified as Level 3, indicating that, on average, organisations have moderate success in fostering a culture of acceptance for new concepts. The radar chart in Chapter 5, Figure 5.3, shows that even within Level 5 organisations, there are challenges in achieving high scores for the item "cul4", emphasising the importance of change management. The close scores between Levels 3 and 5 indicate that change management is a critical determinant of BA capability and success, and organisations need to actively work on creating a culture of innovation and acceptance.

The item "dat5" (Unstructured data is available in the existing BA platform) assesses the capability of organisations to handle unstructured data in their BA platforms. With a difficulty value of 0.77, it is considered the most challenging item. In Survey 1, this item is classified as Level 5, indicating that organisations, on average, find it very difficult to work with unstructured data. The radar chart in Chapter 5, Figure 5.3, reveals that even organisations at Level 5 have an average score of only 3 out of 7 for this item. This may indicate the difficulty in transforming unstructured data into structured, actionable insights, or it could suggest that these organisations do not make use of unstructured data in their data-driven decision-making, or the description of measurement item "dat5" (Unstructured data is available in the existing BA platform) needs clarification. This item underscores the ongoing challenge organisations face in dealing with unstructured data, despite advancements in AI and machine learning. The potential for analysing unstructured data to enrich business intelligence remains a significant challenge for most organisations.

6.3.7. Discussion of PLS-SEM Results for Surveys 1 and 2

The PLS-SEM model, adapted from Raber et al. (2013a), is specified as a reflective model to test the measurement instruments for assessing the latent (unobservable) variables perceived ERP BA success and perceived BA capability, along with their observed indicators outlined in Chapter 5, Table 5.6. The constructs assessed include BA Maturity, Perceived ERP BA Success, and Perceived BA Capability, with scores ranging from 1 to 5 used for evaluation. BA Maturity is evaluated by its maturity level, determined through Rasch analysis and cluster analysis.

The results of the data analysis are presented to address RQ3.3: "To what extent is BA maturity an indicator of perceived BA capability and Perceived ERP BA success in an organisation?", by testing hypotheses H1 and H2 in Section 5.6 (Comparison of PLS-SEM results). Table 6.5 compares construct reliability and validity results for BA Maturity, Perceived ERP BA Success, and Perceived BA Capability, combining data from Table 5.7 (Survey 1) and Table 5.14 (Survey 2).

Table 6.5 Construct Reliability and Validity Results for BA Maturity, Perceived ERP BA Success, and Perceived BA Capability for Surveys 1 and 2

	Survey 1				Survey 2			
Latent Construct	Cronbach's Alpha	*ρA*	Composite Reliability	AVE	Cronbach's Alpha	*ρA*	Composite Reliability	AVE
BA Maturity	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Perceived ERP BA success	0.912	0.921	0.914	0.682	0.941	0.947	0.958	0.850
Perceived BA Capability	0.958	0.958	0.958	0.851	0.955	0.958	0.965	0.847

ρA (rho_A) is an alternative reliability measure used in PLS-SEM. Similar to Cronbach's alpha, *ρA* values range from 0 to 1, where higher values indicate better reliability. Generally, a *ρA* value above 0.7 is considered acceptable for reliability in PLS-SEM. It assesses internal consistency similarly to Cronbach's alpha but is considered a more accurate measure in certain situations (Kline 2000; Russo & Stol 2021). *ρA* is calculated as the ratio of the sum of the squares of the latent variable scores to the sum of the squares of the measurement residuals. This measure provides insights into the proportion of variance in observed variables due to common factors versus measurement error, aiding in evaluating the reliability of constructs in the PLS-SEM context.

The factor loadings for Perceived BA Capability and Perceived ERP BA success shown in Figure 5.5 (for Survey 1) and Figure 5.8 (for Survey 2) demonstrate adequate reliability with all item loadings meeting the optimal minimum of 0.7 (Nunnally & Bernstein 1994) except for the Perceived ERP BA success item “easy” in Survey 1. The “easy” item in Survey 1 has a loading of 0.669, which is above the minimum of 0.6 (Bradley et al. 2006; Raber et al. 2012). While slightly below the optimal threshold, this minor issue does not undermine the model’s overall validity but may warrant further review in future research. Overall, the factor loadings, reliability scores and AVE values from Survey 1 and Survey 2 confirm that the measurement model is satisfactory and demonstrates acceptable reliability and convergent validity.

The two hypotheses tested in Survey 1 and Survey 2 to answer RQ3.3 in the PLS-SEM path model are stated as (H1) BA maturity level is positively associated with Perceived ERP BA success; and (H2) BA maturity level is positively associated with BA capability.

The primary evaluation criteria for hypothesis testing are R^2, statistical significance and relevance of the path coefficients (Hair et al. 2016). R^2 values represent the proportion of variance of a dependent variable explained by each of the endogenous constructs in the model, and the path coefficients represent the connection strengths between the dependent and independent variables (Chin 2010; Rabaa'i 2021). The path coefficient of (H1) BA Maturity and Perceived ERP BA success indicates a positive and highly significant (0.526* for Survey 1; 0.459* for Survey 2) relationship and the path coefficient of (H2) BA Maturity and Perceived BA Capability indicates a positive and highly significant (0.619*) relationship. The structural model explained 27.7% (R^2=0.277 for Survey 1) and 21.1% (R^2=0.211 for Survey 2) of the variance in the dependent latent variable Perceived ERP BA success and explained 38.3% (R^2=0.383 for Survey 1) and 42.7% (R^2=0.427 for Survey 2) of the variance in the dependent latent variable Perceived BA Capability. The R^2 values show that BA maturity is one of the organisational factors affecting the Perceived ERP BA success and the perceived BA capability in organisations.

6.4. Integration of Findings

This section integrates findings from SLRs 1, 2, and 3 with empirical assessments to highlight CSFs for ERP BA readiness and capability. It focuses on developing and validating the BARCMM and discusses the implications for theory and practice.

6.4.1. Synthesising Findings from SLRs and Empirical Phases

The systematic literature reviews (SLRs 1, 2, and 3), along with empirical assessments, offer complementary insights into ERP BA readiness and capability maturity.

Research Question 1 (RQ1): What are the CSFs that contribute to ERP business analytics (BA) readiness, and how can ERP BA readiness be effectively measured?

In SLR 1 (Chapter 2), RQ1 aimed to identify the CSFs that contribute to ERP BA readiness. This review revealed a necessity for more focused research on CSFs related to BA readiness, particularly in the context of global ERP implementations and the GCR. Despite the growing importance of ERP BA for gaining a competitive edge, there is a limited body of research in this domain. ERP BA facilitates organisations in harnessing valuable insights from data, but many organisations are not adequately prepared, leading to significant failures in BA initiatives (Ariyarathna & Peter 2019).

SLR 1 identified an eight-dimensional CSF classification framework (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services) used to assess ERP BA readiness within the BARCMM. Among these, Governance, Culture, Technology, Operation, and People were selected as measurement items for evaluating ERP BA readiness in organisations using ERP systems. The other dimensions (Project, Performance, and Products/Services) were excluded from the BARCMM assessment questionnaire due to their less direct relevance to BA readiness. For instance, the Project dimension is more related to the implementation phase, Performance involves internal performance metrics that may not be universally applicable, and Products/Services are associated with Industry 4.0 technologies, which may not be relevant to all sectors, particularly in Greater China where some industries have not adopted these technologies.

This approach ensures that the survey remains focused and practical, avoiding overlaps and maintaining high response rates and data quality. It is hypothesised that organisations leveraging ERP systems with integrated business partnerships will enhance their BA capabilities through shared data, potentially leading to increased perceived BA success.

Research Question 2 (RQ2): What are the CSFs that contribute to BA capability, and how can BA capability be measured?

SLR 2 reviews existing methodological approaches for designing, assessing, and validating BAMMs. The review highlights gaps such as the need for enhanced methodological rigour in BAMM design and validation, adaptation to modern ERP systems, and improved transparency in BAMM documentation. Addressing these gaps can improve the precision and reliability of BA maturity assessments within ERP system environments.

SLR 3 builds on this by focusing specifically on RQ2, addressing research gaps related to measuring BA capability. This research aimed to enhance the methodological rigour in designing and validating BAMMs tailored for modern ERP systems. It emphasises the importance of establishing rigorous measurement methods for assessing BA maturity.

These theoretical findings were tested empirically in Phase III. This phase focused on validating the BARCMM model through Rasch and cluster analyses, as well as PLS-SEM evaluations.

The practical contribution lies in applying these findings to the design and development of the BARCMM, ensuring that the model incorporates robust measurement methods and effectively addresses the identified gaps. This approach ensures that BA capability assessments are both rigorous and relevant to modern ERP systems.

Research Question 3 (RQ3): How does ERP business analytics (BA) readiness influence BA capability, and what methods can be employed to test the hypothesis of a maturity model for BA capability in ERP systems?

In Chapters 4 to 6, RQ3 explores the impact of ERP BA readiness on BA capability and proposes methodologies for testing the maturity model hypothesis for BA capability within ERP systems. This phase investigates the CSFs related to ERP BA readiness, which are essential for enhancing BA capability in organisations using ERP systems.

The six key contributions and findings of Research Phase III are as follows:

(1) **Development of BARCMM:** The empirical research introduced a rigorous approach to developing the BARCMM. This model aims to assess both ERP BA readiness and capability systematically, using quantitative evaluation methods to validate the model's effectiveness.

(2) **Methodologies and Validation:** The research employed various methodologies, including Rasch Analysis and hierarchical cluster analysis, to test the maturity model hypothesis. These methods were instrumental in identifying and validating the CSFs related to ERP BA readiness and capability.

(3) **Practical Measurement Instrument:** A practical self-assessment questionnaire was developed as part of the BARCMM. This instrument is adaptable for use by researchers and practitioners, providing a systematic method for evaluating the BA readiness and capability of organisations using ERP systems.

(4) **Application of Item Response Theory (IRT):** IRT was applied to enhance the reliability of measurement items within the BARCMM, ensuring accurate and consistent assessments of BA maturity.

(5) **Testing Hypothesised Relationships:** The hypothesised relationships between BA maturity, perceived BA capability, and perceived ERP BA success were tested using PLS-SEM. the PLS-SEM results validate the proposed relationships, demonstrating that BA maturity is a crucial organisational factor influencing perceived ERP BA success and BA capability. The findings offer a robust empirical basis for evaluating BA maturity and its impact on organisational outcomes.

(6) **Practical Advancements:** The combined contributions of RQ1, RQ2, and RQ3 offer significant practical advancements. They provide a rigorous and quantitative approach to designing and measuring BA maturity, facilitating objective assessments for practitioners and researchers. The BARCMM enables organisations to determine and evaluate their BA maturity levels, supporting performance improvement, strategic decision-making, and benchmarking practices.

6.4.2. Implications for Theory and Practice

Theoretical Implications

The research advances existing knowledge in ERP systems and BA readiness and capability maturity by refining and extending the theoretical frameworks used in these areas. The introduction of the eight-dimensional CSFs framework offers a more comprehensive approach to assessing ERP BA readiness, addressing previously identified gaps, particularly in the context of global ERP implementations in the GCR. This framework provides a structured method for evaluating readiness, thus contributing to a deeper theoretical understanding of how organisations prepare for and implement ERP BA systems.

Furthermore, the development and validation of the BARCMM model through rigorous empirical methods such as Rasch analysis and PLS-SEM enhances the theoretical robustness of BAMMs. By improving the precision and dependability of these models, the research addresses earlier shortcomings related to methodological rigour and transparency. This advancement allows for a more nuanced understanding of BA maturity and its impact on ERP systems, thereby enriching the academic discourse in this field.

Practical Implications

For organisations using ERP systems, the findings provide actionable insights to enhance their BA maturity. The refined CSFs framework and BARCMM model offer practical tools for organisations to evaluate and improve their BA readiness and capability. Specifically:

(1) **Assessment and Improvement**: Organisations can apply the eight-dimensional CSFs framework to assess their ERP BA readiness more comprehensively. By focusing on dimensions such as Governance, Culture, Technology, Operation, and People, organisations can identify key areas needing improvement and implement targeted strategies to enhance their BA capabilities.

(2) **Enhanced Measurement Tools**: The validated BARCMM model, incorporating Rasch analysis and PLS-SEM evaluations, provides organisations with reliable measurement tools to gauge their BA maturity accurately. These tools help in identifying strengths and weaknesses in BA capabilities, enabling organisations to make data-driven decisions to boost their performance.

(3) **Sector-Specific Strategies**: The research highlights varying BA maturity levels across different industry sectors. Organisations should consider sector-specific strategies to address unique challenges and opportunities in their respective fields. For example, the Information Technology and Manufacturing sectors demonstrate higher BA maturity, suggesting that organisations in these sectors may benefit from advanced analytics capabilities and tailored improvements.

(4) **Focus on Key Areas**: The empirical results reveal challenges in data presentation, employee acceptance of change, and handling unstructured data.

Organisations should prioritise these areas to improve their BA maturity. Effective change management practices, enhanced data presentation methods, and better handling of unstructured data are crucial for advancing BA capabilities and achieving greater ERP BA success.

6.5. Contributions of the Study

This section summarises the contributions of the study. These include the development of an eight-dimensional CSF framework, the enhancement of BAMM methodological rigour, and the refinement of measurement techniques. It also provides insights into sector-specific BA maturity and offers empirical validation of theoretical models. Collectively, these contributions advance the understanding of ERP BA readiness and capability for organisations using ERP systems.

6.5.1. Theoretical Contributions

The study significantly advances the theoretical understanding of ERP BA readiness and capability in the context of ERP systems. It achieves this through five key theoretical contributions:

(1) **Development of an Eight-Dimensional CSF Framework**: As informed by SLR 1, it demonstrates significant advancements. It illustrates how CSFs, organised across eight dimensions (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services), can function as foundational measurement items for assessing ERP system success and maturity levels. The study proposes strategies to integrate Industry 4.0 impacts into ERP Maturity Models (ERPMM) assessments using CSFs. It emphasises the need for future studies to establish systematic approaches in selecting context-specific CSFs and adopting rigorous methodologies for designing and evaluating ERPMM maturity levels. The dimensions identified offer insights into the framework and questionnaires related to CSFs used in ERP BA readiness within the BARCMM context. Although SLR 1 identified an eight-dimensional CSF classification framework (Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services), five of these dimensions (Governance, Culture, Technology, Operation, and People) were included in the survey questionnaire for the BARCMM. Governance, Culture, Technology, Operation, and People were selected specifically for evaluating ERP BA readiness in

organisations using ERP systems. Project, Performance, and Products/Services dimensions were omitted due to their lesser direct relevance to BA readiness. The chosen dimensions focus on core elements influencing BA integration and effectiveness for organisations using ERP systems, ensuring practical survey management and maintaining data quality, particularly across diverse industry sectors including Financial, Information Technology, Logistics, Manufacturing, Utilities, and others.

(2) **Enhancement of Methodological Rigour**: The research significantly enhances the theoretical understanding of BA capability by improving the methodological rigour of BAMMs. Through a systematic review of existing approaches in SLR2 and the adaptation of BAMMs to modern ERP systems in SLR3, it addresses significant gaps in methodological transparency and precision. The development of the BARCMM model, validated through Rasch analysis and PLS-SEM (Dekleva & Drehmer 1997; Lahrmann et al. 2011; Raber et al. 2013b, 2013a), provides a more reliable and rigorous approach to measuring BA capability. This advancement is further enriched by the development of a maturity model from the existing literature, specifically for evaluating ERP BA readiness and capability of organisations using ERP systems in the GCR.

(3) **Refinement of Measurement Techniques**: The application of Rasch analysis based on IRT introduces a refined approach to measuring BA maturity. These advanced quantitative techniques contribute to a more nuanced understanding of organisational proficiency and capability. The methodological refinement enhances the theoretical framework for assessing BA maturity. It allows for more accurate and reliable classification of maturity levels across different organisations.

(4) **Insight into Sector-Specific Variations**: The study reveals variations in BA maturity across different industry sectors. This contributes to a deeper theoretical understanding of how sector-specific factors influence BA capabilities. By highlighting differences in BA maturity between sectors such as Information Technology and Manufacturing, the research underscores the need for sector-specific theoretical models and strategies. This insight helps to refine existing theories by incorporating sector-specific considerations into the broader framework of BA readiness and capability.

(5) **Empirical Validation of Theoretical Models**: The empirical validation of the BARCMM model and its components through quantitative methods provides strong support for the theoretical hypotheses related to BA readiness and capability. The findings confirm the practical relevance of the theoretical models by demonstrating that BA maturity significantly influences ERP BA success and capability. Testing the hypotheses that organisations with higher maturity have higher capability and can derive more success or benefit than organisations with lower maturity is crucial in validating a maturity model. This ensures empirical credibility, practical relevance, informed decision-making, justified investments, continuous improvement, and theoretical contributions. This empirical validation strengthens the theoretical framework by providing evidence-based support for the relationships proposed in the model.

6.5.2. Methodological Contributions

The five methodological contributions are as follows:

(1) **Measurement of BA Maturity Using IRT:** Contemporary methods of developing and evaluating measurement instruments suffer from significant issues. Firstly, they often lack specificity, leading to a narrow focus that fails to fully capture the complexity of the concept being measured (Beyera et al. 2020). Secondly, inadequate validation processes undermine the reliability and validity of many instruments, as they lack sufficient conceptual information and rigorous validation procedures (Chan 2014). The research addressed RQ3.1 by developing the BA Readiness and Capability Maturity Model (BARCMM) with a measurement instrument and a rigorous assessment method. This approach utilised Rasch analysis and hierarchical cluster analysis to classify BA maturity levels within organisations using ERP systems. It demonstrated the applicability of the BARCMM in determining the maturity levels of organisations using an ERP system in the GCR. However, the reliability and convergent validity of the measurement instrument need further testing across different geographical regions. The research provided a rigorous method for organisations to assess their BA maturity, potentially leading to improved organisational performance.

(2) **Improving Reliability Through IRT:** RQ3.2 was addressed by reviewing item-fit statistics to identify measurement items with excessive infit and outfit values. The

research also explored the use of the person-item map to determine if survey data fit the Rasch model, contributing to the improvement of the reliability of measurement items in assessing BA maturity levels.

(3) **BA Maturity as an Indicator:** RQ3.3 investigated the extent to which BA maturity serves as an indicator of perceived BA capability that determines perceived BA success within an organisation. The study tested hypotheses (H1 and H2) and found statistically significant positive associations between BA maturity and Perceived ERP BA success and capability.

(4) **Empirical Validation through Advanced Statistical Methods**: The research employed advanced statistical methods, including Rasch analysis and PLS-SEM, to validate the BARCMM model. These methods were used to assess the reliability and validity of the model and to test hypotheses. Rasch analysis provided detailed insights into the distribution of organisational capabilities, while PLS-SEM confirmed the relationships between BA maturity, ERP BA success, and BA capability. This empirical validation strengthens the methodological contributions by demonstrating the practical relevance of the theoretical models.

(5) **Application of Radar Charts for Visual Analysis**: The research utilised radar charts to visually represent ERP BA readiness and capability across different maturity levels. These charts provide a clear and intuitive way to identify strengths and weaknesses in BA readiness and capability. By visually depicting weighted average scores, the radar charts facilitate easier interpretation of complex data and support targeted improvements in BA initiatives.

6.5.3. Practical Contributions

The five practical contributions are as follows:

(1) **Development of a Rigorous BA Maturity Model:** The research question RQ3.1 was addressed by developing a rigorous and quantitative approach to measuring BA maturity within organisations. The research provides researchers and practitioners with a systematic approach to objectively assess the BA maturity of organisations using ERP systems, with potential applicability to other maturity model domains. Employing Rasch analysis and hierarchical cluster analysis ensures a robust evaluation process, enhancing measurement reliability and validity. This is achieved through the creation of the proposed BARCMM, along

with a measurement instrument and a robust assessment method using Rasch analysis and hierarchical cluster analysis. This approach provides researchers and practitioners with a rigorous methodology to determine and assess the BA maturity levels of organisations using ERP systems. Quantitative data collected through surveys and analysed with PLS-SEM is used to evaluate the measurement and significance of individual factors in the BARCMM. The empirical study was conducted in the GCR, although further testing and confirmation with a larger, more diverse sample would be beneficial.

(2) **Enhanced Measurement Reliability with IRT:** In response to RQ3.2, the research uses IRT to enhance the reliability of measurement items used in assessing BA maturity levels. It reviews item-fit statistics to identify problematic items and uses the person-item map to assess data fit to the Rasch model, thus refining the measurement instrument.

(3) **Empirical Validation of BA Maturity Relationships:** RQ3.3 is addressed by empirically testing the relationships between BA maturity, perceived BA capability, and perceived ERP BA success. The study findings support the hypotheses that BA maturity is positively associated with perceived ERP BA success and perceived BA capability. This highlights the practical relevance of assessing and improving BA maturity for organisations using ERP systems.

(4) **Practical Self-Assessment for Enhanced Performance:** The research contributes by offering organisations a practical means to access their BA maturity levels, providing a reality check against their perceived capability and success in BA initiatives. This can aid in performance improvement and strategic decision-making. Additionally, the research outcomes provide a benchmark for organisations within the GCR to compare their BA maturity levels with others in their industry sector, enabling informed benchmarking practices.

(5) **Benchmarking and Comparative Analysis:** The research outcomes enable organisations within the GCR to benchmark their BA maturity levels against industry peers. This comparative analysis provides valuable insights for sector-specific strategies and supports organisations in enhancing their BA performance relative to industry standards.

6.6. Comparison with Previous Research

This section compares the BARCMM with previous maturity models. It highlights the BARCMM's ERP-specific focus and unique features. Additionally, it validates the measurement instrument against prior studies. This validation confirms the credibility and relevance of the BARCMM in assessing ERP BA readiness and capability.

6.6.1. Comparison with Previous Maturity Models

A detailed comparison of the BARCMM with other BAMMs is provided in Chapter 4, Section 4.3.1. The Proposed BARCMM is examined alongside various generic BAMMs such as TDWI (Halper & Stodder 2014), Gartner (Howson & Duncan 2015), INFORMS (The Institute for Operations Research and the Management Sciences 2017), and IIA (International Institute for Analytics n.d.). This comparison highlights its focus on ERP Business Analytics readiness and capability. It also notes the five-level structure of the model and its specific adaptation for the GCR. These features contrast with the broader, less ERP-specific dimensions and methodologies of other models. Chapter 4, Table 4.3 outlines the similarities and differences between the BARCMM and generic BAMMs.

The BARCMM offers several unique features compared to other maturity models such as TDWI, Gartner, INFORMS, and IIA. It specialises in ERP Business Analytics readiness and capability, specifically tailored for ERP systems and the GCR. The model is grounded in the work of Cosic et al. (2012), Hawking et al. (2011), and Halo (2015). Unlike the TDWI model, which focuses on a range of analytics approaches, or the INFORMS model, which centres on benchmarking and operational research, BARCMM features a five-level structure and nine dimensions for a detailed assessment. It employs Rasch analysis and clustering for empirical evaluation, distinguishing itself from the broader, less ERP-specific dimensions and methodologies used by other models.

6.6.2. Validation Against Prior Studies

The findings of the BARCMM measurement instrument are compared with prior studies, highlighting both alignments and divergences. The BARCMM measurement instrument shows strong alignment with previous research, which validates its design and methodology. It utilises established dimensions and consistent methodological approaches while integrating insights from earlier studies. These factors underpin the credibility and relevance of the BARCMM. Additionally, the adaptations and enhancements offer a detailed, well-documented, and comprehensive tool for assessing ERP BA readiness and capability maturity of organisations using ERP systems.

Although Rasch analysis and cluster analysis were adapted by Raber et al. (2013b, 2013a) and Lahrmann et al. (2011) for BIMM, a direct comparison of results is not possible due to the uniqueness of each BAMM's measurement instrument and dimension. Nonetheless, some insights can still be drawn. In the work of Raber et al. (2013b, 2013a), Rasch analysis and cluster analysis are used primarily for classifying organisations into the five levels of BI maturity. In contrast, BARCMM uses Rasch analysis and cluster analysis along with Person-Item Maps and Radar Charts. These additional tools help to identify measurement items that may impact the validity of the results, providing a level of detail not previously published.

The BARCMM measurement instrument was developed through a systematic review of existing literature and methodological approaches, as described in Chapters 4, 5, and 6. The design incorporated insights from previous models and studies, including those by Cosic et al. (2012), Rouhani and Ravasan (2013), Halo (2015), and Rouhani and Mehri (2016). This approach ensured that the BARCMM was grounded in established research. It aligned with previous models, such as the BI Maturity Model by Halo (2015), and adapted methodological rigor from Raber et al. (2013b, 2013a) and Lahrmann et al. (2011).

The BARCMM measurement instrument was validated using empirical data collected from online surveys. Survey items, adapted from sources such as Rouhani and Ravasan (2013) and Halo (2015), were used to assess various dimensions of the model. The validation process involved comparing the BARCMM’s nine dimensions and items with those from similar studies. Established dimensions, including Governance, Culture, Technology, People, and Operations, were incorporated, along with new dimensions like Data Capability and Analytics Capability to address current ERP BA trends. The quantitative survey methodology, aligned with research approaches used by Raber et al. (2013b, 2013a) and

Lahrmann et al. (2011), supported the reliability and validity of the BARCMM. The two-stage survey process and application of PLS-SEM for analysis adhered to best practices in empirical research.

The theoretical framework of the BARCMM builds on existing models and research philosophies. It incorporates applied research and mixed-methods approaches. The development of the model was informed by prior studies, ensuring that the framework is both practical and grounded in existing knowledge.

Five of the nine dimensions of the BARCMM (Governance, Culture, Technology, People, and Operations) were chosen for their relevance and impact on ERP BA readiness. The remaining four dimensions (Data Capability, Analytics Capability, Collaboration Tools Capability, and Sharing Capability) adapted from Halo (2012), focus on the BA capability of organisations. This focused approach contrasts with the broader set of dimensions in earlier models and enables a more targeted assessment. The selective adaptation aligns with the research objectives and supports the practical application of the model.

6.7. Limitations of the Study

This section outlines the limitations of the study. It addresses methodological issues, including perception-based measures, geographic focus, and constraints of quantitative methods. It also highlights practical limitations, such as sample size, geographic applicability, and translation accuracy.

6.7.1. Methodological Limitations

Methodological Limitations refer to flaws or constraints in the design or execution of a study that can affect the validity and reliability of the results (Lundy 1996). There are four methodological limitations related to research design, data collection, and analysis methods in this research on the BARCMM.

(1) **Perception-Based Measures**: Personal perspectives can introduce subjectivity into perception-based measures, as responses are influenced by the viewpoints of the participants in each survey (Kaplan & Pathania 2010; Hatt et al. 2021). This may not fully capture the objective reality of the organisations' maturity levels, affecting the reliability of the data and the accuracy of the maturity assessments.

(2) **Social Desirability Bias**: Social desirability bias occurs when individuals respond in socially acceptable ways, potentially affecting data collection by aligning responses with perceived societal expectations (Grimm 2010; Latkin et al. 2017). This bias can influence maturity level assessments, as participants may provide responses they believe are socially desirable, rather than genuine (Gower et al. 2022). To counteract social desirability bias in quantitative data, anonymity and confidentiality measures are implemented. Qualitative methods, such as in-depth case investigations, can further mitigate social desirability bias by exploring underlying mechanisms and reasons for observed issues, complementing quantitative approaches (Raber et al. 2013b, 2013a).

(3) **Assumptions of Capability Distribution**: Since organisations will be classified into five clusters of maturity levels depending on the capability of each organisation, if the samples of respondents do not have varying capabilities or are biased towards higher or lower capabilities, the Rasch analysis and cluster analysis into five maturity levels will be biased (Lahrmann et al. 2011; Raber et al. 2013a, 2013b). Respondents are assumed to be randomly distributed across the five maturity levels by the BARCMM. If organisations display uniform capabilities or show a bias towards a specific maturity cluster, the survey data may not align with the model's expectations. This assumption may affect the validity of the Rasch analysis and hierarchical clustering results, potentially leading to inaccurate representations of organisational maturity.

(4) **Quantitative Method Limitations**: The use of Rasch analysis and clustering relies heavily on quantitative data, which may not adequately capture qualitative aspects and contextual details of maturity level assessment (Raber et al. 2012). Quantitative methods, such as Rasch analysis and clustering, often overlook qualitative factors such as organisational culture, employee morale, leadership styles, internal communication dynamics, and innovation processes. This limitation necessitates complementary qualitative research for a comprehensive assessment of ERP BA readiness and the capability maturity of organisations using ERP systems.

6.7.2. Practical Limitations

Practical limitations refer to logistical or execution challenges during the research process, such as issues with data collection, sample size, or resource constraints (Eykhoff 1984). There are three practical limitations encountered in this study on the BARCMM, as follows:

(1) **Sample Size and Composition**: The sample size may be a limiting factor in the findings of the study. The actual number of respondents and their characteristics may not fully capture the diversity of ERP system users. Despite efforts to include a representative sample of organisations by randomly inviting participating organisations, this limitation could affect the robustness and generalisability of the findings. A small or non-representative sample may not reflect the broader population of organisations (Hill 1998). Even with random invitations, the voluntary nature of survey participation can result in certain groups being overrepresented or underrepresented. This variation may impact the applicability of the findings to the broader population. For instance, organisations with particular characteristics may be more inclined to participate, which could skew the results. Thus, it is crucial to assess how representative the sample is of the overall population of ERP system users. This assessment will affect the generalisability of the study conclusions (Tipton et al. 2016).

(2) **Geographic Limitations**: The applicability of the research is specifically focused on the GCR, which may restrict the findings to other geographic locations. The cultural, economic, and organisational differences in other regions could mean that the results are not directly transferable or applicable outside the studied area, affecting the external validity of the model (Andrade 2018; Weise et al. 2020).

(3) **Practical Limitation Due to Translation Errors in Bilingual Surveys:** Translation errors pose a practical challenge in the implementation of bilingual surveys. Ensuring accurate translation and consistent understanding across languages requires additional resources and efforts. Any shortcomings in this process can affect the overall effectiveness of the survey. Translation errors can impact the validity and reliability of survey results, emphasising the need for careful translation and validation processes (Chen et al. 2024). Since both Surveys 1 and 2 were available in English and Chinese, potential translation

errors could affect the validity of the survey results, altering the meaning of questions and measurement items and impacting the reliability of the data collected.

6.8. Future Research Directions

This section outlines future research directions. It recommends expanding the geographic scope, increasing sample size and diversity, adopting mixed-methods, and incorporating diverse data sources. Additionally, it identifies key areas for further investigation, including enhanced use of radar charts, clarification of measurement items, and the application of AI and machine learning in smart ERP systems.

6.8.1. Recommendations for Future Studies

Based on the gaps and limitations identified in the current research, seven recommendations for future studies are proposed as follows:

(1) **Expand Geographic Scope:** Future research should expand the proposed BARCMM beyond the GCR to enhance the generalisability of the findings. Conducting similar studies in diverse geographic regions will facilitate comparative analyses, offering valuable insights into regional differences and similarities in BA maturity levels. These comparative studies can enhance understanding of how geographic and cultural contexts influence the adoption and effectiveness of BA readiness and capability within organisations using ERP systems, thus contributing to the global applicability of the research findings. Conducting studies in diverse geographic areas would enhance the generalisability of the findings and allow for comparative analyses. This approach would provide valuable insights into regional differences and similarities in business analytics maturity levels among organisations using ERP systems. It would also contribute to understanding how geographic and cultural contexts impact the adoption and effectiveness of business analytics readiness and capability.

(2) **Increase Sample Size and Diversity:** Future studies should aim to enhance the validity and reliability of the BARCMM by gathering data from a larger and more diverse sample of organisations. It is recommended that this expanded sample

includes organisations from various regions, industries, and sizes. Such an approach would facilitate a comprehensive understanding of BA maturity across different contexts. Moreover, it is imperative to rigorously test the validity and reliability of the BARCMM by collecting and analysing data from a larger and more diverse sample of organisations with varying ERP BA readiness and capability across different regions.

(3) **Adopt Mixed-Methods Approach:** Future research should adopt a mixed-methods approach, combining quantitative methods such as Rasch and clustering analyses with qualitative methods like in-depth interviews, focus groups, and case studies. This approach will provide a comprehensive understanding of ERP BA readiness and capability maturity by capturing both numerical trends and contextual factors that quantitative data alone might overlook. Qualitative investigations can further contextualise and explain quantitative findings. Although self-assessment questionnaires can support anonymous surveys from a large population sample, interviews offer more detailed insights but may require additional resources. Reducing reliance on self-assessment and incorporating longitudinal studies to track changes in BA maturity over time can enhance the accuracy and credibility of findings, advancing BA readiness and capability maturity studies while minimising social desirability bias.

(4) **Incorporate Diverse Data Sources:** Empirical data should integrate additional sources, such as organisational performance metrics, ERP usage logs generated by ERP systems, and employee feedback, to triangulate results. This will enhance the reliability and validity of the assessment, providing deeper insights into how organisations achieve and maintain various maturity levels and offering a fuller picture of BA practices within ERP systems.

(5) **Utilise Longitudinal Studies:** Incorporate longitudinal studies to track changes in BA maturity over time. This will help in understanding the dynamics of BA readiness and capability and provide more accurate and credible findings. Longitudinal studies can offer valuable insights into trends and patterns in BA maturity for organisations using ERP systems. They contribute to a deeper understanding of how organisations develop over time.

(6) **Minimise Social Desirability Bias:** To reduce social desirability bias, future studies should utilise a combination of methods, including online anonymous surveys, as employed in this research, and comprehensive qualitative approaches. These methods are commonly used by practitioners to provide consultancy services aimed at improving organisational maturity. Implementing these techniques will diminish the impact of respondent organisations' tendencies to present themselves in an overly positive manner, thereby improving the reliability of the data gathered.

(7) **Explore Broader Applications:** Apply the methodological approaches used in the BARCMM, such as Rasch and cluster analysis, to other domains beyond ERP systems. This will test the validity and reliability of these methods in different contexts and contribute to a more universal understanding of BA capability and maturity. By using person-item maps, researchers can assess and ensure the effectiveness of these methods in measuring and differentiating BA readiness and capability across various organisations and disciplines.

6.8.2. Potential Areas for Further Investigation

There are five key areas for further investigation to build upon the research findings:

(1) **Enhanced Use of Radar Charts:** Employ radar charts to visualise scores of respondent organisations alongside benchmarking data. This can help identify potential issues with measurement items, such as overlapping average scores between different maturity levels. For instance, items like “cul4” (employee openness to new ideas), and “dat5” (handling unstructured data) require further investigation. Overlapping scores may indicate problems with item clarity or respondent understanding.

(2) **Clarification of Measurement Items:** Address potential ambiguities in measurement items by refining their descriptions. For example, the item “cap1” suggests challenges with static data reports; if scores across maturity levels are closely aligned, this may point to a need for clearer definitions. Similarly, items like “cul4” and “dat5” show that change management and unstructured data capabilities could be areas needing further clarification and improvement.

(3) **Impact of Outliers:** Investigate the effect of outliers, particularly in smaller samples, which may distort average scores and obscure true maturity levels. Outliers can significantly influence results, making higher-level scores appear similar to or lower than those at lower levels. Addressing this issue could involve refining data collection methods or increasing sample sizes.

(4) **Refinement of Survey Instruments:** Investigate the effectiveness of the selected measurement dimensions (Governance, Culture, Technology, Operation, and People). Consider whether including additional dimensions could enhance the survey comprehensiveness without compromising response rates and data quality. Refining the survey instruments to address potential ambiguities and improve clarity will enhance the accuracy and reliability of the assessment.

(5) **Application of AI and Machine Learning in Smart ERP Systems that Support Industry 4.0:** Both Surveys 1 and 2 did not include dimensions for smart ERP systems, which are essential for the manufacturing industry. These surveys overlooked the advanced capabilities of smart ERP systems incorporating AI and machine learning. Integrating technologies such as Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Big Data Analytics, Cloud Computing, Edge Computing, Robotic Process Automation (RPA), Blockchain Technology, Augmented Reality (AR), Virtual Reality (VR), Cyber-Physical Systems (CPS), Advanced Manufacturing Technologies (e.g., 3D Printing), Digital Twins, 5G Connectivity, and Natural Language Processing (NLP) could significantly enhance the processing and analysis of unstructured data. AI and machine learning can improve data processing, predictive analytics, real-time analysis, and automation in smart ERP systems, thereby supporting Industry 4.0 initiatives and boosting decision-making and operational efficiency. Exploring these technologies may offer valuable insights into overcoming challenges in transforming unstructured data into actionable insights.

6.9. Final Remarks

This section summarises the final remarks of the study. It highlights the significant contributions of the study to ERP BA readiness and capability maturity through the BARCMM. Additionally, it reflects on the research journey, noting key insights and challenges, such as collaborative support, methodological rigour, and persistence.

6.9.1. Overall Significance of the Study

This research significantly contributes to the field of ERP BA readiness and capability maturity for organisations using ERP systems by addressing three major high-level research gaps. It advances the understanding of BA readiness and capability through the development of the BARCMM. The six key contributions and implications of this study are summarised as follows:

(1) **Identification and Addressing of CSFs**: The study fills a crucial gap in understanding the CSFs for ERP BA readiness, offering a comprehensive exploration of dimensions essential for assessing ERP BA maturity. By identifying specific CSFs relevant to ERP systems, particularly in the GCR, this research provides valuable insights for organisations looking to enhance their BA readiness and reduce ERP system failures. The findings are particularly relevant for organisations aiming to leverage BA for competitive advantage, helping them better prepare and integrate BA capabilities.

(2) **Development of a Rigorous Measurement Model:** The BARCMM, developed and validated through rigorous methodological approaches such as Rasch analysis and cluster analysis, addresses the limited methodological depth in existing BA maturity models. This research introduces a robust framework for measuring BA capability in organisations using ERP systems, offering a more precise and validated instrument for assessing BA maturity. The model's application demonstrates its effectiveness in evaluating BA maturity levels and provides organisations with actionable benchmarks for performance improvement.

(3) **Advancement of Methodological Approaches:** By incorporating IRT and employing advanced quantitative methods, this study advances the methodological approaches for BA maturity measurement. The use of Rasch analysis and hierarchical cluster analysis contributes to the methodological rigour in developing and validating BA maturity models. This advancement enhances the reliability and validity of maturity assessments, providing a more accurate measure of BA capability and success.

(4) **Insights into Regional and Sector-Specific Variations:** The research highlights the significance of regional and sector-specific variations in BA maturity, emphasising the need for context-specific dimensions in maturity assessments. The comparative analysis across different industry sectors and geographic regions offers valuable insights into how BA practices and readiness differ across contexts. This contributes to a more nuanced understanding of how organisations can tailor their BA strategies to their specific environments.

(5) **Practical Implications for Organisations:** The findings of the study have practical implications for organisations using ERP systems in the GCR. The BARCMM provides a benchmark for assessing BA maturity, allowing organisations to track their progress, compare their performance with industry standards, and identify areas for improvement. The use of radar charts and other visual tools facilitates easy benchmarking and performance tracking, supporting organisations in enhancing their BA capabilities and achieving better business outcomes.

(6) **Contribution to the Global Applicability of Research:** By addressing gaps in the literature and developing a model that can be applied across various regions and sectors, this research contributes to the global applicability of BA maturity assessments. The insights gained from this study can inform future research and practice in different geographic and industry contexts, further advancing the field of ERP and BA maturity.

6.9.2. Reflection on the Research Journey

Reflecting on the research journey undertaken in this study, several key insights and challenges have emerged, shaping the final outcome and personal growth throughout the process. There are four identified insights gained, as follows:

(1) **Value of Collaborative Support:** One of the most profound insights I have gained from this research journey is the value of collaborative support and encouragement. The guidance from my supervisors, Dr. Michael Lane, Dr. Rohan Genrich, Dr. Albert Scott, and Dr. Sophie Cockcroft, has been crucial in refining my research focus. Their support has also ensured methodological rigour. Their diverse perspectives and feedback have greatly enriched both the quality of my research and my academic development.

(2) **Recognition as a Milestone:** Receiving the Best Conference Paper Award for our joint paper titled *Systematic Review of Methodological Approaches for Designing, Assessing and Validating Business Analytics Maturity Models*, co-authored with Dr. Lane and Dr. Cockcroft, and presented at the International Conference on Information Resources Management in 2021 (Wong et al. 2021), was a pivotal moment in my PhD journey (See Appendix K). This recognition not only validated the effort I put into the research but also highlighted the relevance and impact of our study in the field. It reinforced the importance of rigorous research and significantly contributed to my professional growth.

(3) **Critical Role of Rigorous Methodology:** Throughout my research, it became increasingly clear how crucial it was to apply rigorous methodologies, such as Rasch analysis and cluster analysis. These approaches provided a solid foundation for developing and validating the BARCMM. They highlighted the importance of methodological precision in achieving reliable and valid results.

(4) **Adaptation and Persistence:** The journey through my PhD has underscored the vital role of persistence and adaptability. I learned that persistence meant staying focused and motivated despite facing obstacles and setbacks. Adaptability required me to refine my approaches based on feedback and changing circumstances. Initial rejections from journals and conferences were particularly challenging but proved to be valuable learning experiences. With ongoing support and a commitment to refining my research, I was able to overcome these setbacks, ultimately leading to the successful publication of two papers. This experience has reinforced for me that perseverance is crucial in the research process.

There are three identified challenges that have been overcome, as follows:

(1) **Methodological Rigour:** One of the major challenges I encountered was identifying the most suitable methods to ensure methodological rigour in the development and validation of the BARCMM using grounded theory and methodology. Specifically, I faced difficulties in designing the BARCMM, including deciding on the dimensions and questions for the two survey measurement items. Balancing quantitative and qualitative approaches, addressing research gaps,

and integrating various data sources required careful planning and execution. Each step demanded careful consideration to ensure that the framework was robust and reliable. This process involved a thorough examination of both methodological theory and practical application to effectively align the design with the research objectives. Overcoming this challenge involved engaging in rigorous testing, validation, and iterative refinement of my research methods. It was a demanding process, but it ultimately deepened my understanding and strengthened the foundation of my research.

(2) **Publication Process:** Navigating the publication process was another major challenge I faced. Initial rejections from journals highlighted areas where my work needed improvement, requiring multiple revisions and resubmissions. The support from my supervisors and the constructive feedback from reviewers were crucial in overcoming these hurdles. They provided invaluable guidance, helping me refine my research and ultimately achieve successful publication.

(3) **Engaging Participants:** As both Surveys 1 and 2 were anonymous, I sent out invitations without knowing the participants. Recruiting and engaging a diverse and representative sample was challenging and required substantial effort in building and maintaining relationships with organisations and individuals. I found that leveraging my LinkedIn connections was an effective strategy for reaching a large, relevant pool of professionals. My network of 18,000 LinkedIn connections has greatly improved my ability to gather data and connect with key individuals in the field.

6.10. Chapter Summary and Conclusion

6.10.1. Chapter Summary

The findings from SLR 1 related to Research Question 1 (RQ1) aimed to identify the CSFs for ERP BA readiness and effective measurement methods. The review revealed a limited body of research on CSFs, despite the growing importance of ERP BA for organisations seeking a competitive advantage. The study established an eight-dimensional CSF classification framework: Governance, Culture, Technology, Operation, People, Project, Performance, and Products & Services. This framework was used for assessing ERP BA readiness within the BARCMM model. It focused on the first five dimensions, as they are more relevant for evaluating BA readiness in organisations using ERP systems. The remaining dimensions were deemed less directly related or potentially complicating the survey. The study hypothesises that organisations using integrated ERP systems could enhance their BA capabilities through shared data, thereby improving perceived BA success. The practical contribution of this research is the development of the BARCMM, which employs the identified CSFs to measure ERP BA readiness effectively.

Research Question 2 (RQ2) examines the CSFs contributing to BA capability and methods for measuring this capability. SLR 2 explored existing approaches for designing, assessing, and validating BAMMs, highlighting gaps such as the need for enhanced methodological rigour and adaptation to modern ERP systems. It also addressed the importance of improving the transparency and documentation of BAMMs developed by practitioners. Building on this, SLR 3 specifically focused on RQ2, aiming to refine BA capability measurement within BAMMs by enhancing methodological rigour and tailoring assessments for modern ERP systems. The practical significance lies in adapting these rigorous methodologies for effective BA maturity assessments within ERP environments, emphasising the importance of precise and dependable evaluation methods for the proposed BARCMM model.

Research Question 3 (RQ3) explores how ERP BA readiness affects BA capability and proposes methods to test a maturity model hypothesis within ERP systems. The research aims to bridge gaps by investigating CSFs related to ERP BA readiness and their impact on BA capability. High-level contributions from RQ1, RQ2, and RQ3 include the development of a rigorous BARCMM model for assessing ERP BA readiness and capability. This model employs quantitative methods and is validated through empirical assessments, including Rasch and cluster analyses. These assessments revealed that the BARCMM can classify organisations into distinct maturity levels based on their BA capability. Surveys 1 and 2 showed variations in item difficulty and respondent capability, with Survey 2 providing a more balanced item distribution. The analysis also highlighted how correlations between organisational capability and item performance can help identify strengths and areas for improvement. This facilitates better benchmarking and strategic decision-making.

The analysis of industry sector results for Surveys 1 and 2 reveals that approximately 55% of organisations in Survey 1 and 52% in Survey 2 were at maturity level 2. In contrast, 37% in Survey 1 and 47% in Survey 2 reached level 3 or higher. The Information Technology and Manufacturing sectors were notably more BA mature, with a higher proportion of organisations at maturity levels 3 and above. Variations between the surveys were observed, particularly due to regional impacts of COVID-19 lockdowns, which may have affected survey participation and responses. The radar charts highlighted that organisations face challenges in handling unstructured data and in fostering a culture of acceptance for change. The PLS-SEM results showed that BA maturity positively correlates with perceived ERP BA success and BA capability. R^2 values indicated that BA maturity significantly affects these outcomes, underscoring the importance of advancing BA practices across sectors.

The findings from SLRs and empirical assessments are integrated to highlight CSFs for ERP BA readiness and capability. The development and validation of the BARCMM are discussed, along with its theoretical and practical implications. SLRs 1, 2, and 3, combined with empirical research, underscore the need for focused investigation into ERP BA readiness, especially in global implementations and the GCR. SLR 1 identified crucial dimensions for evaluating ERP BA readiness. Meanwhile, SLRs 2 and 3 exposed gaps in methodological rigour and highlighted the necessity for improved measurement methods. The empirical research validated the BARCMM using quantitative methods, such as Rasch and cluster analyses. It demonstrated that the model effectively assesses BA readiness and capability. This research offers actionable insights for organisations by providing tools for comprehensive assessment, targeted improvement strategies, and sector-specific recommendations to advance BA maturity and success in ERP systems.

The study offers several key contributions. Theoretical contributions include the development of an eight-dimensional CSFs framework. This framework enhances the methodological rigour of BAMMs and refines measurement techniques. These advancements provide deeper insights into ERP BA readiness and capability. Methodologically, the study introduces improved measurement techniques using IRT and Rasch analysis. It enhances reliability and validates theoretical models through empirical research. Practically, the research provides a rigorous BA maturity model. It enhances measurement reliability and offers actionable insights for organisations. This includes sector-specific benchmarking and practical self-assessment tools.

Collectively, these contributions advance the understanding and practical application of ERP BA readiness and capability.

The BARCMM is compared with previous maturity models, focusing on its ERP-specific aspects and unique features. It is assessed alongside various generic models such as TDWI, Gartner, INFORMS, and IIA, which highlights its specialisation in ERP Business Analytics readiness and capability, particularly for the GCR. The BARCMM is distinguished by its five-level structure and nine dimensions, setting it apart from other models that may have broader or less ERP-specific dimensions. Validation against previous studies supports the BARCMM's credibility and relevance, showing strong alignment with established research. The model incorporates unique tools like Person-Item Maps and Radar Charts for detailed assessment. It builds on insights from earlier studies and adapts methodologies to provide a comprehensive tool for evaluating ERP BA readiness and capability.

The study acknowledges several limitations. Methodologically, the research faces issues such as reliance on perception-based measures, which introduce subjectivity, and a geographic focus limited to the GCR, affecting generalisability. The use of quantitative methods like Rasch analysis and clustering may overlook qualitative aspects and contextual nuances. Social desirability bias may also influence participant responses. Additionally, the assumption of random distribution across maturity levels could impact the validity of results, and translation accuracy issues in bilingual surveys could affect data reliability. Practically, limitations include sample size and composition, which may not capture the diversity of ERP users, and geographic constraints limiting the applicability of findings outside the GCR.

Future research should address several areas for improvement. The geographic scope is to be expanded beyond the GCR to enhance the generalisability of the research by accounting for diverse economic, cultural, and organisational contexts. The validity and reliability of the findings will be improved through an increased sample size and diversity, which will provide a more representative and varied dataset. A comprehensive understanding of ERP BA readiness and capability maturity will be offered through the adoption of a mixed-methods approach, integrating both quantitative data and qualitative insights for a more robust analysis. Furthermore, incorporating diverse data sources, using longitudinal studies, and reducing social desirability bias will strengthen the research. Future studies should also explore the use of radar charts, clarify measurement items, investigate the impact of outliers, refine survey instruments, and examine the application of AI and machine learning in smart ERP systems to support Industry 4.0.

6.10.2. Chapter Conclusion

The chapter discusses key findings from systematic literature reviews (SLRs 1, 2 and 3) and empirical assessments related to ERP BA readiness and capability. Research Question 1 (RQ1) established an eight-dimensional CSFs framework for assessing ERP BA readiness within the BARCMM model. This framework proved effective in evaluating organisations' readiness. Research Question 2 (RQ2) addressed gaps in existing BAMMs by refining measurement methods and enhancing methodological rigour. Research Question 3 (RQ3) explored the relationship between ERP BA readiness and capability, validating the BARCMM model through quantitative analyses. The study reveals that ERP BA readiness significantly impacts BA capability. It provides sector-specific insights that show variations in maturity levels and challenges related to unstructured data and change management. The BARCMM model's distinct five-level structure and dimensions set it apart from other models, offering a robust tool for assessing ERP BA readiness. The research contributes both theoretically and methodologically by providing improved measurement techniques and practical insights for organisations. Limitations such as geographic focus and methodological constraints are acknowledged. Future research should expand geographic scope, increase sample diversity, and integrate advanced technologies like AI and machine learning for a more comprehensive understanding of ERP BA systems.

CHAPTER 7: CONCLUSION

Chapter 7 summarises the main conclusions and highlights the main contributions of this research. Section 7.1 summarises findings on measuring BA readiness and capability maturity for organisations using ERP systems. It highlights its importance in assessing and enhancing BA initiatives in the GCR, while acknowledging the need for further validation and considering the limitations of perception-based measures. Section 7.2 summarises the thesis by identifying three main research gaps related to BA readiness and capability of organisations using ERP systems in the GCR. It explains the research motivation and outlines the structure of the thesis across seven chapters. Section 7.3 concludes by addressing research questions and highlighting gaps in understanding CSFs for ERP BA readiness and capability measurement. It suggests practical implications for organisations in the GCR and emphasises the need for further validation, considering the limitations of perception-based measures. Section 7.4 outlines five key theoretical contributions: the introduction of an eight-dimensional CSF framework for ERP BA readiness, improvements in BAMM methodological rigour, refinement of measurement techniques through Rasch analysis based on IRT, identification of sector-specific variations in BA maturity, and empirical validation of the BARCMM model. Section 7.5 presents five methodological contributions. These include the development of the BARCMM using Rasch analysis and IRT. The study also enhances reliability through refined item-fit statistics and person-item maps. Additionally, BA maturity is established as a key indicator of perceived capability and success. The empirical validation of the BARCMM model is conducted using Rasch analysis and PLS-SEM. Lastly, radar charts are used for intuitive visual analysis of ERP BA readiness and capability. Section 7.6 outlines five practical contributions. These include the development of a rigorous BA maturity model. The section also covers the enhancement of measurement reliability through IRT. Additionally, it addresses the empirical validation of the relationships between BA maturity and perceived success. Practical self-assessment tools for performance improvement are provided, along with the facilitation of benchmarking and comparative analysis for organisations using ERP systems in the GCR. Section 7.7 outlines the limitations of the study, including issues with perception-based measures, geographic focus, and methodological approaches. It recommends expanding the geographic scope, increasing sample diversity, employing mixed methods, and incorporating diverse data sources. The section also advocates for using longitudinal studies and minimising social desirability bias. Future research should explore broader applications of the BARCMM methodology, investigate radar charts, clarify measurement items, assess the impact of outliers, refine survey instruments, and integrate AI and machine learning in smart ERP systems for Industry 4.0. Finally, Section 7.8 provides a thorough summary and conclusion, outlining the development and evaluation of the BARCMM for ERP systems in the GCR, addressing CSFs in BA readiness and capability, formulating research questions, and utilising rigorous methodologies like Rasch analysis and hierarchical clustering to highlight the positive relationship between BA readiness and capability maturity and perceived success. It offers a structured framework for organisations to enhance their BA maturity, acknowledges limitations in perception-based measures and geographic focus, and suggests the need for broader validation and applicability. Figure 7.1 shows the structure of Chapter 7.

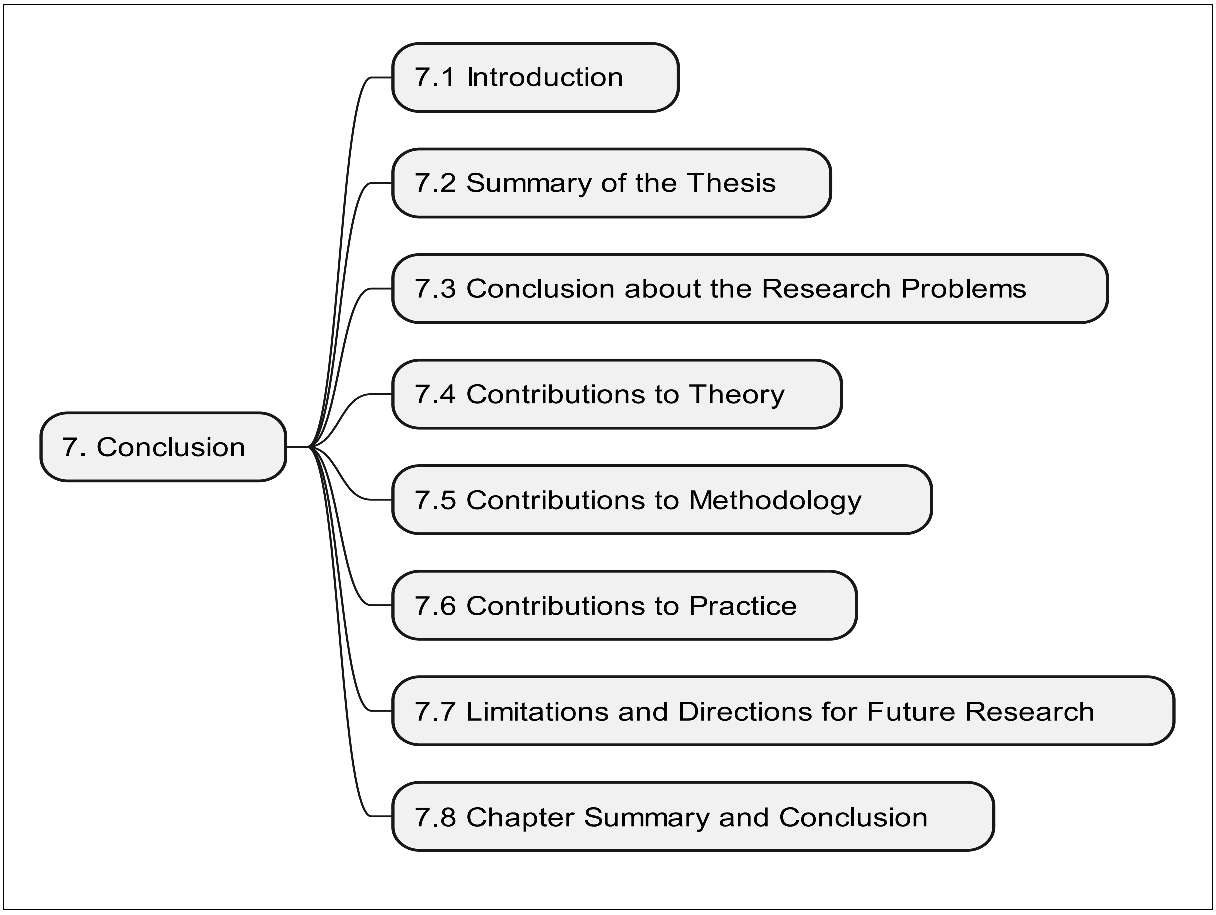

Figure 7.1 Structure of Chapter 7

7.1. Introduction

This research developed and evaluated an instrument to measure BA Readiness maturity and BA Capability maturity of organisations using an ERP system with BA implemented. The BARCMM was designed, developed, and empirically tested. It can be used in future research to determine and evaluate the maturity levels and perceived success of BA readiness and BA capability in organisations using ERP systems. The survey instruments for the maturity of BA readiness maturity and BA capability maturity are provided in Appendix C and Appendix D respectively.

The survey instrument consists of two sections, with the first five dimensions (governance, culture, technology, people, operation) focused on assessing BA readiness for organisations using ERP systems. The last four dimensions (data capability, analytics capability, collaboration tools capability, and sharing capability) are concerned with the BA capability of such organisations. The analysis of the empirical component of this study includes only fully completed survey results for both readiness and capability questions. These dimensions encompass various aspects, such as governance, culture, technology, people, operation, data capability, analytics capability, collaboration tools capability, and sharing capability. Each dimension is further divided into specific items to assess different aspects within the broader construct. A comprehensive evaluation of measurement items in each dimension is achieved by measuring the responses on a seven-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." This structured questionnaire ensures a thorough assessment of BA readiness and capability in organisations using ERP systems

In Survey 1, twenty BA Readiness Maturity items and 20 BA Capability Maturity items were used to calculate the BA Readiness maturity level and BA capability maturity level of an organisation using IRT, Rasch Analysis and Hierarchical Cluster Analysis. In this paper, the applicability and usefulness of the proposed BA Readiness maturity and BA Capability maturity instrument was demonstrated in organisations using ERP systems in GCR. Furthermore, the calculated BA Readiness maturity level and BA Capability maturity level were used as an independent variable in a structural equation model to explain the perceived success of BA Readiness and perceived success of BA Capability (as dependent variables) in organisations using ERP systems. The quality criteria in the PLS analysis were met and the result shows a positive and significant relationship between BA Readiness maturity and BA Capability maturity, and the perceived success of BA Readiness and BA capability in organisations using ERP systems. However, the validity and reliability of the measurement instrument needs to be tested and confirmed by larger sample survey data.

This study relies on subjective, perception-based measures, with the sample consisting of organisations in the GCR using ERP systems with BA experience, which may impact external validity. The measurement instrument was based on the assumption of equidistant maturity increments, offering a systematic, transparent, and rigorous method to determine BA readiness and capability maturity. Organisations can use this instrument for continuous BA maturity improvement, benchmarking against perceived success and assessing actual maturity levels. Ultimately, it aids in monitoring organisational performance against key performance indicators.

7.2. Summary of the Thesis

Three main research gaps of this research were identified: (RG1) Lack of research on CSFs for ERP BA readiness, (RG2) Limited understanding of applying CSFs with methodological rigor for BA capability measurement, and (RG3) Limited exploration and empirical application of CSFs using Item Response Theory to enhance BA capability and success in ERP readiness. These gaps were further detailed into sub-categories and linked to specific research questions to systematically address and explore them, as outlined in Chapter 1, Section 1.5 "Research Gaps", and illustrated in Figure 1.3 and Figure 1.4.

This research was motivated by the need to assess and measure BA readiness and capability within organisations using ERP systems in the GCR. Despite widespread ERP adoption, there is limited research on leveraging BA within ERP systems. This research developed and evaluated a model to assess BA readiness and capability maturity, providing organisations with a benchmark for continuous improvement. Additionally, the study explored perceived success and perceived BA capability, key for evaluating system performance and user satisfaction. By building on existing studies, this research offers valuable insights into the relationship between BA maturity and perceived success, addressing a significant literature gap.

This thesis is organised into seven chapters. Chapter 1 presents the PhD research project, highlighting key research challenges and strategies for addressing them. It contextualises the study within the broader framework of ERP adoption and integration with BA for decision-making. The chapter emphasises the importance of assessing organisational readiness and capability in using BA within ERP systems to achieve business value. It outlines foundational knowledge, research objectives, and questions. The research is justified by highlighting the critical need to integrate ERP systems with BA, varying levels of readiness and capability among organisations, and the impact of maturity levels on BA effectiveness. Specific gaps in existing research are identified, and a structured approach to investigate these gaps through defined objectives and research questions is outlined. The methodology employed is described, and the chapter defines the scope, boundaries, and context of the study. It concludes with a summary of key insights and structural elements.

Chapter 2 lays the groundwork for the thesis, starting with a conventional literature review and advancing to systematic reviews in later chapters, introducing concepts for developing the Business Analytics Readiness and Capability Model (BARCMM) for organisations using ERP systems. It explores CSFs in ERP maturity models, measures Business Analytics Maturity, and reviews methods for designing and validating maturity models. Insights from these reviews guide the development, assessment, and validation of the BARCMM in subsequent chapters. The chapter also discusses the evolution of ERP systems and their integration with advanced Business Analytics, the transition from Business Intelligence to Business Analytics, and the use of maturity models and Item Response Theory in improving organisational capabilities. It concludes with a summary and the importance of these foundational elements.

In Chapter 2, the first systematic literature review (SLR 1) aimed to identify a CSF classification framework applicable to assessing ERP BA readiness and capability in organisations using ERP systems. It is argued that understanding and classifying CSFs specific to ERP systems is crucial. These CSFs are common factors that can be used as measurement items contributing to ERP and BA success. By identifying these CSFs, researchers can assess the maturity of an organisation using ERP systems. The maturity of using ERP systems may influence the BA capability of organisations using ERP systems. This aligns with research goals to pinpoint the dimensions that measure the maturity of organisations using ERP systems and their business analytics capability. SLR 1 outlines a systematic approach to assess ERP system maturity using CSFs and discusses their conceptual definitions, use in maturity models, and the evolution of ERP systems with Industry 4.0 technologies. Through a systematic literature review, the chapter identifies and classifies CSFs into seven dimensions: Governance, Culture, Technology, Operation, People, Project, and Performance. It highlights the dual use of CSFs in predicting ERP success and measuring organisational maturity, proposing an eight-dimensional CSF classification framework to enhance ERP maturity models, especially with Industry 4.0 integration.

In Chapter 2, the second systematic literature review (SLR 2) focuses on the methodological approaches to designing, assessing, and validating BAMMs. It aims to establish a robust framework for the proposed BARCMM by analysing existing methodologies. The chapter highlights the evolution from BI to BA, the importance of systematic research, and the gaps in the theoretical grounding of current models. It compares various BAMMs, noting the lack of documentation in practitioner-developed models. Additionally, it discusses suitable methodological approaches such as Rasch Analysis and Hierarchical Clustering. The chapter emphasises the need for more empirical validation studies to enhance the practical application of BI/BA Maturity Models. It concludes by recommending rigorous methods for comprehensive assessment.

In Chapter 2, the third systematic literature review (SLR 3) presents a comprehensive study on measuring Business Analytics Maturity in ERP systems. It highlights the importance of ERP systems in BI/BA initiatives and identifies gaps in current BAMMs regarding development, empirical validation, and adaptation to new ERP technologies. Using a ten-step systematic literature review methodology, the chapter compares methodologies, measurement items, and focuses to evaluate organisational capabilities and maturity levels. The findings suggest the need for a specialised framework to assess BA maturity within ERP systems. Rigorous methods like Rasch and cluster analysis are proposed for designing and validating BA maturity models. The chapter concludes by recommending adaptations of existing models to incorporate ERP-specific measures, advocating for empirical validation and methodological rigour.

Chapter 3 outlines and justifies the research methodology used in the doctoral research. It provides an overview of the research aims and framework, including the selection of philosophical foundations, analytical methods, survey designs, and research procedures. It aligns with a positivist paradigm, emphasising systematic literature reviews and quantitative methods such as Rasch analysis and hierarchical cluster analysis. The chapter describes the approach for designing and evaluating the BARCMM, covering data collection and analysis strategies, and ensuring validity and reliability. Ethical considerations are addressed according to university guidelines. It concludes with a summary of the key methodological elements, setting the stage for the following chapters.

Chapter 4 presents a structured approach to designing, developing, and evaluating the BARCMM for assessing BA readiness and capability of organisations using ERP systems in the GCR. It starts by outlining the creation of the BARCMM, emphasising its inspiration, design, and methodological framework tailored to the GCR. The chapter specifies the objectives of the BARCMM, with a focus on identifying critical success factors for BA readiness and capability, and investigates how ERP integration influences BA maturity. Balancing theoretical insights and practical applications, it introduces a self-assessment questionnaire to measure BA readiness and capability, advocating for its broader applicability and employing rigorous methodologies such as IRT for reliability. Additionally, the chapter examines previous models, justifies the development of the BARCMM, details its validation through Rasch Analysis and hierarchical clustering, and summarises its contributions to assessing BA capability maturity for organisations using ERP systems.

Chapter 5 presents the results of the empirical application and assessment of the BARCMM for organisations using ERP systems in the GCR. It begins with an overview of the data collection process to assess BA maturity. Following this, it presents key findings that offer a comprehensive view of BA readiness and capability in modern ERP environments. Additional sections delve deeper into these findings, exploring BA maturity through visual representations, industry-specific trends, and alternative data perspectives. A comparative analysis of BARCMM across Surveys 1 and 2 using PLS-SEM investigates how BA maturity correlates with perceived ERP BA success and BA capability, confirming hypotheses and demonstrating the reliability and validity of the results. Finally, the chapter concludes by summarising insights gleaned from this empirical exploration, emphasising the importance of BA readiness and capability in achieving perceived success within ERP systems.

Chapter 6 provides a thorough analysis of findings from three research phases, integrating insights from SLRs and empirical assessments to evaluate ERP BA readiness and capability. It begins with Research Question 1 (RQ1), which focuses on CSFs for ERP BA readiness, developing an eight-dimensional CSF framework with Governance, Culture, Technology, Operation, and People as key elements for the BARCMM. Research Question 2 (RQ2) identifies gaps in BAMMs and suggests improvements in rigor and transparency based on SLR 2 and SLR 3. Research Question 3 (RQ3) evaluates the impact of ERP BA readiness on BA capability, introducing and validating the BARCMM through quantitative methods and offering a self-assessment tool. The chapter highlights major contributions, including the development of the BARCMM, enhanced measurement techniques, and sector-specific insights. It compares the BARCMM with previous models, discusses limitations such as perception-based measures and geographic focus, and recommends future research directions, such as broadening geographic scope, increasing sample size, and incorporating advanced technologies like AI and machine learning into ERP systems.

Chapter 7 summarises the key findings and contributions of the research. It evaluates BA readiness and capability maturity in organisations using ERP systems in the GCR, highlighting impacts on BA initiatives and noting the need for further validation due to perception-based measures. The chapter outlines the thesis structure and motivation, identifies three main research gaps, and introduces a theoretical eight-dimensional CSFs framework for ERP BA readiness, covering Governance, Culture, Technology, Operation, and People. The study enhances BAMMs' methodological rigour and transparency with the BARCMM model, using Rasch and IRT-based cluster analysis to refine measurement techniques. It notes sector-specific variations in BA maturity, suggesting the need for tailored theoretical models. The validated BARCMM model improves understanding of BA readiness and supports strategic decision-making with self-assessment tools and benchmarking capabilities. Limitations include reliance on perception-based measures, a geographically focused sample, and potential biases. Future research should broaden the geographic scope, enhance sample diversity, use mixed methods, incorporate varied data sources, and explore how AI and machine learning might affect the BA readiness and capability of organisations using ERP systems.

7.3. Conclusion about the Research Problems

The mapping of Chapter, Research Gap, Research Question, Focus and Conclusion is given in Table 7.1.

Each of the three high-level main research gaps was identified: (RG1) lack of research on CSFs for ERP BA readiness, (RG2) limited understanding of how to apply CSFs with methodological rigour for BA capability measurement, and (RG3) limited exploration and empirical application of CSFs underpinned by item response theory in ERP BA readiness for enhancing BA capability and success. The corresponding high-level research questions for each of these research gaps were answered through the design and development of the BARCMM and the conduct of Surveys 1 and 2, using rigorous methodological approaches such as Rasch analysis and cluster analysis, as discussed in Chapters 4 to 6.

To address high-level Research Gap 1, the corresponding research question RQ1 was addressed and discussed in Chapters 4 to 6. Low-level research gaps 1.1 and 1.2, along with corresponding research questions RQ1.1 and RQ1.2, were addressed and discussed in SLR 1 in Chapter 2. The conclusion in SLR 1 emphasises the significance of addressing these research gaps to enhance the understanding of CSFs, dimensions, and readiness in the context of ERP and BA. The practical implications of closing these gaps are also highlighted, such as improving the effectiveness of ERP systems, reducing failures, and adapting ERP systems through the use of BA and data-driven decision-making in the rapidly evolving technological landscape. The key findings for each of these research questions are summarised below.

Research Gap 1 (RG1) identified in Chapter 2, Section 2.5: Lack of Research on CSFs for ERP BA Readiness (addressed by RQ1 in Chapter 4, Chapter 5 and Chapter 6): RQ1 aimed to identify CSFs contributing to ERP BA readiness and explore effective measurement methods for ERP BA readiness. This research was prompted by the need for more specific research on CSFs related to BA readiness, particularly in global ERP implementations and the GCR. The study found that limited research has been conducted in this area, despite the increasing importance of ERP BA in gaining a competitive advantage. ERP BA allows organisations to extract valuable insights from their data, but many organisations are not adequately prepared, leading to costly failures (Ariyarathna & Peter 2019).

Research Gap (RG1.1) identified in SLR 1: Limited Understanding of ERPMM Dimensions Enhancing Understanding of ERPMM Dimensions (addressed by RQ1.1 in Chapter 2, SLR 1 in Chapter 2): RQ1.1 focused on improving the understanding of dimensions for assessing ERP maturity models. While existing studies provided some insights, there was a need for a more detailed exploration of dimensions tailored to various industries and organisations. The study revealed that existing ERP maturity models were often too generic and did not account for specific industry needs (Rauch et al. 2020). This research gap emphasised the need for more nuanced dimensions in maturity assessment.

Research Gap (RG1.2) identified in SLR 1: Limited Understanding of CSF Dimensions for Assessing Maturity in New-Generation ERP Systems with BA Features (addressed by RQ1.2 in Chapter 2, SLR 1): RQ1.2 specifically targeted the dimensions required to assess the maturity of organisations using new-generation ERP systems with BA functionalities. The study found that while some research addressed CSFs for ERP implementation, there was a gap in understanding the dimensions relevant to these advanced ERP systems. As technologies evolve and BA functionalities become embedded in modern ERP systems, and with AI continuing to evolve, more ERP vendors are incorporating these capabilities into their products to help organisations streamline operations, improve decision-making, and gain a competitive edge. To address this need, future research could develop a framework to assess these unique dimensions, aiding organisations in making more informed decisions and deriving greater value from their ERP investments (Saade & Nijher 2016).

Research Gap 2 (RG2) identified in Chapter 2, Section 2.5: Limited Understanding on How to Apply CSFs with Methodological Rigour for BA Capability Measurement (addressed by RQ2 in Chapter 4, Chapter 5 and Chapter 6): High-level Research Gap 2 and its corresponding high-level research question

RQ2 were addressed and discussed in Chapters 7, 8, and 9. This gap pertains to understanding the application of CSFs with a methodological approach for measuring ERP BA readiness and BA capability for the design and development of the proposed BARCMM. Low-level Research Gaps 2.1, 2.2, and the corresponding research questions RQ2.1 and RQ2.2, were addressed in SLR 3 in Chapter 2. Additionally, Low-level Research Gap 2.3 and its corresponding low-level research question RQ2.3 were addressed in Chapter 2, SLR 2. High-level research question RQ2 and low-level research questions RQs 2.1, 2.2, and 2.3 address the corresponding research gaps by addressing three significant shortcomings in the literature concerning CSFs for BA capability measurement and the creation of BA capability measurement frameworks. These gaps entail the lack of adequate methodological depth in conceptualising and validating BAMMs, the absence of BAMM constructs designed for new-generation ERP systems, and the lack of rigour in the documentation and reporting of BAMMs advanced by practice. It can be concluded that addressing these gaps may contribute to improving the reliability and validity of BA maturity estimation within the proposed BARCMM. Below are the findings for each of the research questions as outlined.

Research Gap 2.1 (RG2.1) identified in SLR 3: Limited Documentation of Methodological Approaches in Designing, Assessing, and Validating BAMMs (addressed by RQ2.1 in SLR 3 in Chapter 2): To address Research Gap (RG2.1), a systematic literature review (SLR) was conducted to identify methodological approaches available in the design, assessment, and validation of BAMMs. The findings of the SLR showed that the current literature fails to properly address these methodologies and therefore requires a deeper investigation of more methodological BAMMs used in the context of designing, evaluating, and validating the BAMMs (Wong et al. 2021). Some BAMMs are designed using quantitative bottom-up approaches, such as the Rasch analysis supported by cluster analysis, which offers a rigorous methodological approach for assessing maturity levels. However, other practitioners' BAMMs use more qualitative methods, which are subject to bias. This highlights the need for a comprehensive review of the methodologies used in BAMMs to provide valuable insights into best practices and methodological rigour in this domain.

Research Gap 2.2 (RG2.2) identified in SLR 3: Lack of Research on

Adapting BAMMs Underpinned by CSFs for New-Generation ERP Systems (addressed by RQ2.2 in SLR 3 in Chapter 2): Research Gap 2.2 was addressed by exploring the adaptation of existing BAMMs for organisations implementing new-generation ERP systems. The research identified that there is a scarcity of research specifically addressing this adaptation, indicating a notable gap in the literature (Cosic 2020). In a rapidly evolving technological landscape where modern ERP systems are becoming increasingly integrated and advanced, tailored BA maturity models are essential to effectively assess and optimise performance. The significance of adapting existing BAMMs to new-generation ERP systems is emphasised, and valuable insights into addressing this gap can be provided by further research in this area.

Research Gap 2.3 (RG2.3) identified in SLR 2: Limited Documentation and Explanation of BAMMs and Their Empirical Processes (addressed by RQ2.3 in Chapter 2, SLR 2): To address Research Gap 2.3, the research examined the state of research on BAMMs and their empirical design, assessment, and validation. It was found that the current state of research on BAMMs is not well-documented, making it challenging for scholars and practitioners to navigate this specific field (Fedouaki et al. 2013). The study revealed that while BAMMs are an emerging area, there is a need for a comprehensive review of the literature on BAMMs, including empirical design and validation approaches. This review can provide valuable insights into the evolution and best practices within the domain of BAMMs.

Research Gap 3 (RG3) identified in Chapter 2, Section 2.5: Limited Exploration and Empirical Application of CSFs underpinned by Item Response Theory in ERP BA Readiness for Enhancing BA Capability and Success (addressed by RQ3 in Chapter 4, Chapter 5 and Chapter 6): Research question RQ3: "How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?" focuses on understanding the relationship between ERP BA readiness and BA capability, ultimately addressing the inadequately explored CSFs in ERP BA readiness that contribute to enhancing BA capability. RQ3 serves as the core question to bridge the research gap by investigating the factors that play a significant role in the BA capability of organisations. The key findings for each of these research questions are summarised below.

Research Gap 3.1 (RG3.1) identified in Chapter 2, Section 2.5: Limited Exploration of Application of IRT in Quantitatively Measuring BA Maturity (addressed by RQ3.1 in Chapter 4, Chapter 5 and Chapter 6): Research question RQ3.1: "How can BA maturity of an organisation be measured using item response theory as a rigorous and quantitative approach?" has been addressed by developing the proposed BARCMM with a measurement instrument and a rigorous assessment method using Rasch analysis and hierarchical cluster analysis to classify BA maturity levels of organisations using an ERP system. This approach was empirically tested and can be used to determine and assess the BA maturity levels of organisations using ERP systems. The applicability and usefulness of the proposed BA maturity instrument was demonstrated in determining the BA maturity level of organisations using BA tools in ERP systems in the GCR. However, the reliability and convergent validity of the measurement instrument need to be further tested and confirmed by a larger survey sample in different geographical regions.

The measurement using Rasch analysis assumes that (1) item difficulty determines the capability and maturity of organisations, and (2) maturity increases in equidistant steps, which provides a rigorous method to determine the BA maturity level. Organisations can apply the BA maturity measurement instrument to assess their maturity in using BA in ERP systems, thereby providing organisations with the opportunity to improve their BA maturity level, which should lead to improved organisational performance. The BARCMM instruments designed, developed and evaluated in this research provide organisations using BA in their ERP systems with a rigorous way to determine a data derived reality check of their BA maturity against the perceived success and perceived capability of their BA initiatives. The results of BARCMM provides organisations with a benchmark to assess current levels of BA maturity and ultimately assist in monitoring the overall performance of an organisation against its key performance indicators. The result of this empirical study collectively indicates that BA maturity is an indicator of perceived capability and perceived success of BA initiatives. In addition, survey results can be used by organisations in the GCR for benchmarking within their industry sectors. Table 6.2 in Chapter 6, which shows the BA maturity levels of organisations by industry sector for Surveys 1 and 2, can serve as a benchmark for organisations to compare their BA maturity with others in the same industry.

Research Gap 3.2 (RG3.2) identified in Chapter 2, Section 2.5: Limited Exploration of the Potential of IRT to Enhance BA Maturity Measurement in ERP Contexts (addressed by RQ3.2 in Chapter 4, Chapter 5 and Chapter 6): The research question RQ3.2: “How can IRT be used to improve the reliability of the measurement items in assessing BA maturity levels of organisations?” has been addressed by reviewing item-fit statistics to identify measurement items with excessive infit and outfit values, and how the person-item map can be used to determine whether the survey data fits the Rasch model. Research question RQ3.2 has been addressed by (1) designing and developing a measurement instrument and applying a rigorous assessment method using Rasch analysis (a one-parameter IRT model) and hierarchical cluster analysis to measure and classify BA maturity levels of organisations using BA in an ERP system. Secondly (2) item-fit statistics have been reviewed to identify measurement items with excessive infit and outfit values, and the person-item map can be used to determine whether the survey data fits the Rasch model. This approach was empirically tested and can be used to determine and assess the BA maturity levels of organisations using BA in ERP systems. The applicability and usefulness of the proposed BA maturity instrument was demonstrated by determining the BA maturity level of organisations using BA tools in ERP systems in the GCR which is considered to be factory of the World. However, the reliability and convergent validity of the measurement instrument need to be further tested and confirmed by a larger survey sample in different geographical regions. Instrument measurement using Rasch analysis assumes that (1) item difficulty determines the capability and maturity of organisations, and (2) maturity increases in equidistant steps, which provides a rigorous method to determine the BA maturity level.

Research Gap 3.3 (RG3.3) identified in Chapter 2, Section 2.5: Limited Understanding of the Relationships Between BA Maturity, BA Capability, and BA Success (addressed by RQ3.3 in Chapter 4, Chapter 5 and Chapter 6): The research question RQ3.3: "To what extent is BA maturity an indicator of perceived BA capability and Perceived ERP BA success in an organisation?" has been addressed by testing the following two hypotheses:

(H1) BA maturity level is positively associated with perceived ERP BA success.

(H2) BA maturity level is positively associated with perceived BA capability.

The PLS-SEM results show that H1 was found to be statistically significant, and H2 was also found to be statistically significant.

The BARCMM instruments designed, developed and evaluated in this research provide organisations using BA in their ERP systems with a rigorous way to determine a data-derived reality check of their BA maturity against the perceived success and perceived capability of their BA initiatives. The results of BARCMM provide organisations with a benchmark to assess their current levels of BA maturity and ultimately assist in monitoring the overall performance of an organisation against its key performance indicators. The results of this empirical study collectively indicate that BA maturity is an indicator of perceived capability and perceived success of BA initiatives. In addition, survey results can be used by organisations in the GCR for benchmarking in their industry sectors.

In Chapter 6, Table 6.2 shows the BA maturity levels of organisations by industry sector for Surveys 1 and 2, which can be used as a benchmark for organisations to compare their BA maturity with others in the same industry.

In Chapter 5, the radar charts in Figure 5.3 (Survey 1) and Figure 5.7 (Survey 2) enable organisations to compare responses to measurement items across surveys. These charts display multivariate data across multiple dimensions, showing the weighted average scores of BA capability measurement items for five maturity levels (1 to 5). Organisations can use the radar charts to benchmark their BA maturity against industry targets and peers. Participation in multiple surveys allows organisations to track progress over time by comparing radar charts from different iterations.

Table 7.1 Mapping of Chapter, Research Gap, Research Question, Focus and Summarised Conclusion

Chapter (Section)	Research Gap	Research Question	Focus	Summarised Conclusion
2 (2.5) 4, 5, 6	RG1: Lack of Research on CSFs for ERP BA Readiness	RQ1: What are the critical success factors that contribute to ERP BA readiness, and how can ERP BA readiness be effectively measured?	Identify CSFs that contribute to ERP BA readiness and develop effective measurement methods for assessing this readiness.	Limited research exists on CSFs related to BA readiness, highlighting the need for more focused studies, especially in global ERP implementations. ERP BA is crucial for competitive advantage, but many organisations lack preparation, leading to costly failures (Ariyarathna & Peter 2019). This SLR contributes significantly to understanding how CSFs, organised across extended dimensions, can form the basis for measurement items to assess ERP system success and maturity levels.
2 (2.2)	RG1.1: Limited Understanding of ERPMM Dimensions	RQ1.1: What are the main dimensions of critical success factors that can be used as measurement items to assess ERP maturity models?	Identify CSF dimensions for assessing ERP maturity models.	Existing models are too generic; there iss a need for nuanced dimensions tailored to diverse industries (Rauch et al. 2020). It also proposes strategies for incorporating Industry 4.0 impacts into ERPMM assessments using CSFs.

Table 7.1 Mapping of Chapter, Research Gap, Research Question, Focus and Summarised Conclusion

Chapter (Section)	Research Gap	Research Question	Focus	Summarised Conclusion
2 (2.2)	RG1.2: Limited Understanding of CSF Dimensions for Assessing Maturity in New-Generation ERP Systems with BA Features	RQ1.2: What are the additional dimensions of critical success factors that can be used as measurement items to assess the maturity of organisations using new generation ERP systems?	Identify additional dimensions for assessing maturity in new generation ERP systems with BA functionalities.	Lack of understanding regarding dimensions specific to advanced ERP systems. Future research could develop frameworks for assessing these unique dimensions, aiding better decision-making (Saade & Nijher 2016). Future studies are recommended to establish systematic approaches for selecting context-specific CSFs and to adopt rigorous methodologies for designing and assessing ERPMM maturity levels.
2 (2.5) 4, 5, 6	RG2: Limited Understanding on How to Apply CSFs with Methodological Rigour for BA Capability Measurement	RQ2: What are the CSFs that contribute to BA capability, and how can BA capability be measured?	Identify specific CSFs that contribute to BA capability and develop rigorous measurement methods for assessing BA capability.	Limited literature on CSFs contributing significantly to BA capability (Wong et al. 2021).
2 (2.4)	RG2.1: Limited Documentation of Methodological Approaches in Designing, Assessing, and Validating BAMMs	RQ2.1: What are the main methodological approaches used to design, assess, and validate BA maturity models?	Investigate methodological approaches in designing BAMMs.	Lack of detailed examination in existing literature. Some BAMMs use quantitative approaches like Rasch analysis, ensuring rigorous assessment, while others are qualitative, leading to bias. Need for comprehensive review of methodologies used in BAMMs (Wong et al. 2021).

Table 7.1 Mapping of Chapter, Research Gap, Research Question, Focus and Summarised Conclusion

Chapter (Section)	Research Gap	Research Question	Focus	Summarised Conclusion
2 (2.4)	RG2.2: Lack of Research on Adapting BAMMs Underpinned by CSFs for New-Generation ERP Systems	RQ2.2: How can the BA maturity level of organisations using a new generation of ERP system be determined by adapting existing BA maturity models?	Address adaptation of BA maturity models for new generation ERP systems.	Scarcity of research addressing this adaptation, crucial in the evolving technological landscape. Tailored BA maturity models necessary for assessing and optimising performance (Cosic 2020).
2 (2.3)	RG2.3: Limited Documentation and Explanation of BAMMs and Their Empirical Processes	RQ2.3: What is the state of research on BAMMs, and how can they be empirically designed, assessed, and validated?	Examine documentation of BAMMs and their empirical processes.	Current research on BAMMs and their empirical design, assessment, and validation not well-documented, posing challenges for scholars and practitioners. Need for a comprehensive review of literature in this area (Fedouaki et al. 2013).
2 (2.5) 4, 5, 6	RG3: Limited Exploration and Empirical Application of CSFs underpinned by Item Response Theory in ERP BA Readiness for Enhancing BA Capability and Success	RQ3: How does ERP BA readiness determine BA capability, and how can a maturity model for BA capability in ERP systems be tested?	Explore CSFs in ERP BA readiness and their impact on BA capability and success, using IRT to understand and empirically validate the relationship between ERP BA readiness, BA capability, and BA success.	Limited exploration of CSFs in ERP BA readiness affecting BA capability. It provides valuable insights into the relationship between ERP BA readiness, BA capability, and BA success.

Table 7.1 Mapping of Chapter, Research Gap, Research Question, Focus and Summarised Conclusion

Chapter (Section)	Research Gap	Research Question	Focus	Summarised Conclusion
2 (2.5) 4, 5, 6	RG3.1: Limited Exploration of Application of IRT in Quantitatively Measuring BA Maturity	RQ3.1: How can the BA maturity of an organisation be measured using item response theory (IRT) as a rigorous and quantitative approach?	Investigate using IRT for quantitative BA maturity assessment.	Lack of studies applying IRT for BA maturity assessment. Need for development of IRT-based tools tailored to multidimensional nature of BA maturity.
2 (2.5) 4, 5, 6	RG3.2: Limited Exploration of the Potential of IRT to Enhance BA Maturity Measurement in ERP Contexts	RQ3.2: How can IRT be used to improve the reliability of the measurement items in assessing BA maturity levels of organisations?	Explore the potential of IRT to enhance the reliability of measuring BA maturity levels in ERP contexts.	Limited exploration of IRT in improving reliability and validity of BA maturity assessments. Need to refine methodologies and techniques for robust measurements in ERP BA maturity.
2 (2.5) 4, 5, 6	RG3.3: Limited Understanding of the Relationships Between BA Maturity, BA Capability, and BA Success	RQ3.3: To what extent is BA maturity an indicator of perceived BA capability and Perceived ERP BA success in an organisation?	Examine relationships between BA maturity, perceived BA capability, and ERP BA success to understand their correlations and implications for BA initiatives in organisations using ERP systems.	Need for examination on how BA maturity correlates with perceived capability and actual success in BA. It concludes by highlighting the importance of further exploring and validating the application of the BARCMM in organisations using ERP systems, which could offer valuable insights for assessing and improving BA capability to enhance the overall success of business analytics initiatives within the ERP environment.

7.4. Contributions to Theory

Based on the theoretical contributions discussed in Section 6.5.1 of Chapter 6, the study advances five theoretical contributions by (1) introducing an eight-dimensional CSF framework for ERP BA readiness, (2) enhancing the methodological rigour of BAMMs, (3) refining measurement techniques with Rasch analysis and IRT, (4) revealing sector-specific variations in BA maturity, and (5) empirically validating the BARCMM model.

The first theoretical contribution is the development of an eight-dimensional CSF framework. The introduction of this framework marks a notable theoretical advancement. This framework integrates Governance, Culture, Technology, Operation, and People as core dimensions for assessing ERP BA readiness. It addresses previously identified gaps, particularly in the context of global ERP implementations. Consequently, this framework provides a more comprehensive theoretical basis for evaluating BA readiness. It refines existing models by offering a structured and practical approach to assessing readiness. This, in turn, enriches the theoretical discourse on ERP BA systems.

The second theoretical contribution is the enhancement of methodological rigour. The research contributes to the theoretical understanding of BA capability by improving the methodological rigour of BAMMs. It involves a systematic review of existing approaches and the adaptation of BAMMs to modern ERP systems. The study addresses significant gaps in methodological transparency and precision. The development of the BARCMM model, including its validation through Rasch analysis and PLS-SEM, improves the theoretical foundation of BAMMs. This development provides a more reliable and rigorous approach to measuring BA capability.

The third theoretical contribution is the refinement of measurement techniques. The use of Rasch analysis and cluster analysis based on IRT introduces a more precise approach to measuring BA maturity. These advanced quantitative methods enhance the theoretical framework by providing a more accurate and reliable classification of maturity levels across different organisations.

The fourth theoretical contribution is that the research uncovers variations in BA maturity across different industry sectors. This deepens the theoretical understanding of how sector-specific factors influence BA capabilities. Consequently, it necessitates the development of sector-specific theoretical models and strategies. By incorporating these considerations into the broader framework of BA readiness and capability, existing theories are refined.

Finally, the fifth theoretical contribution is the empirical validation of theoretical models. The quantitative validation of the BARCMM model supports the theoretical hypotheses concerning BA readiness and capability. It demonstrates that BA maturity significantly impacts ERP BA success and capability, enhancing empirical credibility, practical relevance, informed decision-making, justified investments, continuous improvement, and theoretical contributions. This validation strengthens the theoretical framework by providing evidence-based support for the model's proposed relationships.

7.5. Contributions to Methodology

The research contributes to the development and demonstration of a rigorous methodological approach for measuring BA maturity in organisations using ERP systems. Based on the discussion of methodological contributions in Section 6.5.2 of Chapter 6, the study advances five methodological contributions: (1) using Rasch analysis and hierarchical cluster analysis based on IRT to develop the BARCMM for assessing BA maturity, with further regional validation needed; (2) enhancing reliability through IRT by refining item-fit statistics and person-item maps; (3) establishing BA maturity as a key indicator of perceived capability and success; (4) employing Rasch analysis and PLS-SEM for empirical validation of the BARCMM model; and (5) using radar charts for intuitive visual analysis of ERP BA readiness and capability.

The first methodological contribution is the measurement of BA maturity using IRT. The development of the BARCMM addressed issues in contemporary measurement methods by employing Rasch analysis and hierarchical cluster analysis. This approach provided a rigorous method for assessing BA maturity in organisations using ERP systems in the GCR. Further testing of the reliability and convergent validity of the measurement instrument is needed across different regions.

The second methodological contribution is improving the reliability of measurement items in assessing BA maturity levels through IRT. This involved reviewing item-fit statistics to identify measurement items with excessive infit and outfit values. Additionally, the person-item map was used to determine if survey data fit the Rasch model. These actions collectively enhanced the reliability of the measurement items.

The third methodological contribution is BA maturity as an indicator. The research investigated whether BA maturity serves as an indicator of perceived BA capability and success within an organisation. It found statistically significant positive associations between BA maturity and perceived ERP BA success and capability.

The fourth methodological contribution is empirical validation through advanced statistical methods. The study employed Rasch analysis and PLS-SEM to validate the BARCMM model. These methods assessed the reliability and validity of the model. Additionally, they confirmed the relationships between BA maturity, ERP success, and capability. This validation reinforces the practical relevance of the model.

Finally, the fifth methodological contribution is the application of radar charts for visual analysis. Radar charts were employed to visually represent ERP BA readiness and capability across maturity levels. These charts provided a clear and intuitive way to identify the strengths and weaknesses in the responses of respondent organisations to each measurement item. They also facilitated targeted improvements in BA initiatives.

7.6. Contributions to Practice

Based on the discussion of practical contributions in Section 6.5.3 of Chapter 6, the five practical contributions include: (1) developing a rigorous BA maturity model; (2) enhancing measurement reliability through IRT; (3) empirically validating the relationships between BA maturity and perceived success; (4) offering practical self-assessment tools for performance improvement; and (5) enabling benchmarking and comparative analysis for organisations using ERP systems in the GCR.

The first practical contribution is the development of a rigorous BA maturity model. The research addresses RQ3.1 by creating a systematic and quantitative approach for measuring BA maturity within organisations using ERP systems. The BARCMM model, validated through Rasch analysis and hierarchical cluster analysis, provides a robust framework for assessing BA maturity and is applicable to various maturity model domains.

The second practical contribution is enhanced measurement reliability with IRT. In response to RQ3.2, the research uses IRT to improve the reliability of measurement items for assessing BA maturity. This involves reviewing item-fit statistics and using the person-item map to refine the measurement instrument, thereby enhancing the accuracy and reliability of BA assessments.

The third practical contribution is the empirical validation of BA maturity relationships. The study addresses RQ3.3 by empirically testing the relationships between BA maturity, perceived BA capability, and perceived ERP BA success. The findings support that higher BA maturity is positively linked with greater perceived ERP BA success and BA capability, demonstrating the importance of assessing and improving BA maturity for organisations using ERP systems.

The fourth practical contribution is practical self-assessment for enhanced performance. The research provides organisations with a practical tool for assessing their BA maturity levels, offering a reality check against perceived capabilities and success in BA initiatives. This tool supports performance improvement and strategic decision-making and serves as a benchmark for comparing BA maturity levels in the GCR.

Finally, the fifth practical contribution is benchmarking and comparative analysis. The research outcomes enable organisations in the GCR to benchmark their BA maturity levels against industry peers. This comparative analysis provides valuable insights for sector-specific strategies and supports organisations in enhancing their BA performance relative to industry standards.

7.7. Limitations and Directions for Future Research

The limitations of this study are noted. Using perception-based measures in the BARCMM survey instrument and the sample size obtained from organisations using ERP systems with BA experience in the GCR may affect the external validity of this research. The results of Surveys 1 and 2 demonstrated that the assessment method rigorously classified organisations into five maturity levels using different versions of the questionnaire in each survey.

7.7.1. Methodological Limitations

Based on the methodological limitations discussed in Section 6.7.1 of Chapter 6, the research on the BARCMM faces four issues with (1) perception-based measures; (2) social desirability bias; (3) assumptions of capability distribution; and (4) quantitative method limitations, each of which can impact the validity and reliability of the findings.

The first methodological limitation is perception-based measures. Personal perspectives can introduce subjectivity, with responses influenced by the viewpoints of the participants in each survey (Kaplan & Pathania 2010; Hatt et al. 2021). This may not fully capture the objective reality of the BA readiness and capability maturity levels of organisations using ERP systems. Consequently, the reliability of the data and the accuracy of the maturity assessments may be affected.

The second methodological limitation is social desirability bias. Social desirability bias occurs when individuals respond in socially acceptable ways, potentially affecting data collection by aligning responses with perceived societal expectations (Grimm 2010; Latkin et al. 2017). This bias skews the accuracy of the results. Responses may be shaped by participants' perceptions of what is socially acceptable, potentially affecting the reliability of the data. Despite implementing anonymity and confidentiality measures, this bias remains a concern. Using qualitative methods, such as in-depth case studies, alongside quantitative data, can offer deeper insights into the reasons behind the observed responses (Raber et al. 2013b, 2013a).

The third methodological limitation is assumptions of capability distribution. Since organisations are classified into five maturity levels based on their capabilities, any bias in respondent samples, such as a lack of variation in capabilities or skew towards higher or lower levels, will result in biased Rasch and cluster analysis outcomes (Lahrmann et al. 2011; Raber et al. 2013a, 2013b). Respondents are assumed to be randomly distributed across the five maturity levels by the BARCMM. If organisations display uniform capabilities or show a bias towards a specific maturity cluster, the survey data may not align with the expected distribution. This assumption may affect the validity of the Rasch analysis and hierarchical clustering results, potentially leading to inaccurate representations of organisational maturity.

Finally, the fourth practical limitation is quantitative method limitations. The use of Rasch analysis and clustering methods in this research, which are based on quantitative data, may not fully capture the qualitative aspects and contextual nuances of maturity levels (Raber et al. 2012). Some important factors influencing maturity might be overlooked or inadequately addressed by the quantitative approach alone due to this practical limitation.

7.7.2. *Practical Limitations*

Based on the practical limitations discussed in Section 6.7.2 of Chapter 6, the study faces three issues. These include (1) sample size and composition; (2) geographic limitations; and (3) translation errors. Each of these factors has the potential to impact the robustness, generalisability, and external validity of the findings.

The first practical limitation is sample size and composition. The sample size may be a limiting factor in the findings of the study. The actual number of respondents and their characteristics might not fully capture the diversity of ERP system users. Despite efforts to include a representative sample of organisations by randomly inviting participating organisations, this limitation could affect the robustness and generalisability of the findings (Tipton et al. 2016). A small or non-representative sample may not reflect the broader population of organisations.

The second practical limitation is geographic limitations. The applicability of the research is specifically focused on the GCR, which may restrict the findings to other geographic locations. The cultural, economic, and organisational differences in other regions could mean that the results are not directly transferable or applicable outside the studied area, affecting the external validity of the model (Andrade 2018; Weise et al. 2020).

Finally, the third practical limitation concerns translation errors in bilingual surveys. Such errors present a challenge in implementing these surveys effectively. Accurate translation and consistent understanding across languages demand extra resources and effort. Any deficiencies in this process can impact the overall effectiveness of the survey. Translation errors can affect survey validity and reliability, highlighting the importance of thorough translation and validation (Chen et al. 2024).

7.7.3. Recommendations for Future Studies

Based on the recommendations for future studies discussed in Section 6.8.1 of Chapter 6, future research should: (1) expand the geographic scope of the BARCMM; (2) increase sample size and diversity; (3) adopt a mixed-methods approach; (4) incorporate diverse data sources; (5) utilise longitudinal studies; (6) minimise social desirability bias; and (7) explore broader applications of the methodological approaches to enhance the understanding and generalisability of BA capability and maturity across various contexts.

The first recommendation for future research is to expand the BARCMM beyond the GCR. Investigating other geographic regions will improve the generalisability of the research findings and support comparative analyses. This approach will provide valuable insights into regional and cultural variations in business analytics maturity and enhance our understanding of how geographic and cultural contexts affect the business analytics readiness and capability maturity of organisations using ERP systems in various regions.

The second recommendation for future research is to increase both the size and diversity of the sample for empirical data collection from organisations with varied industry sectors, types, and sizes. To strengthen the validity and reliability of the BARCMM, future studies should focus on collecting data from a more extensive and diverse range of organisations across various industry sectors, with significant variations in ERP business analytics readiness and capability. It is suggested that this wider sample include organisations across various regions, industries, and sizes. Since the BARCMM assumes organisations with varying BA capabilities using ERP systems, including organisations from different industry sectors will enhance the analytical foundation and improve the generalisability of the research findings. This approach will also facilitate a deeper understanding of business analytics maturity across diverse types and sizes of organisations using ERP systems.

The third recommendation for future research is to employ a mixed-methods approach. By combining quantitative techniques, such as Rasch and clustering analyses, with qualitative methods like in-depth interviews, focus groups, and case studies, a more thorough understanding of ERP BA readiness and capability maturity among organisations using ERP systems can be achieved. This approach will capture both numerical trends and contextual factors that might be overlooked by quantitative data alone, facilitating a more detailed analysis of maturity levels.

The fourth recommendation for future studies is to incorporate diverse data sources. Empirical data and findings should include additional sources, such as organisational performance metrics, ERP usage logs directly extracted from the systems, and employee feedback from various positions within the organisations. These sources will help to triangulate the results. This approach will improve the reliability and validity of the assessment and provide deeper insights into how organisations achieve and maintain different levels of maturity.

The fifth recommendation for future studies is to utilise longitudinal studies. Incorporate longitudinal studies to track changes in BA maturity over time. This will help in understanding the dynamics of BA readiness and capability and provide more accurate and credible findings. Longitudinal studies can offer valuable insights into trends and patterns in BA maturity for organisations using ERP systems, contributing to a deeper understanding of how organisations develop over time.

The sixth recommendation for future studies is to minimise social desirability bias. To achieve this, future studies should utilise a combination of methods. These methods should include online anonymous surveys, as employed in this research, as well as comprehensive qualitative approaches. Such methods are commonly used by practitioners to provide consultancy services aimed at improving organisational maturity. By implementing these techniques, the impact of respondent organisations' tendencies to present themselves in an overly positive manner will be diminished. This will, in turn, improve the reliability of the data gathered.

Finally, the seventh recommendation for future studies is to explore broader applications. Apply the methodological approaches used in the BARCMM, such as Rasch analysis and cluster analysis, to other domains beyond ERP systems. This will test the validity and reliability of these methods in different contexts and help in developing a more universal understanding of BA capability and maturity.

7.7.4. Potential Areas for Further Investigation

Based on Section 6.8.2 of Chapter 6, potential areas for further investigation include: (1) employing radar charts to visualise and benchmark data; (2) clarifying ambiguous measurement items; (3) assessing the impact of outliers; (4) refining survey instruments; and (5) exploring the integration of AI and machine learning in smart ERP systems to enhance data processing and analysis for Industry 4.0.

The first potential area for further investigation is the enhanced use of radar charts. Employing radar charts to visualise scores of respondent organisations alongside benchmarking data can help identify potential issues with measurement items, such as overlapping average scores between different maturity levels. For instance, items like “cul4” (employee openness to new ideas) and “dat5” (handling unstructured data) may require further investigation. Overlapping scores could indicate problems with item clarity or respondent understanding.

The second potential area for further investigation is the clarification of measurement items. Addressing potential ambiguities in measurement items by refining their descriptions is crucial. For example, the item “cap1” suggests challenges with static data reports; if scores across maturity levels are closely aligned, this may indicate a need for clearer definitions. Similarly, items like “cul4” and “dat5” suggest that change management and unstructured data capabilities could be areas requiring further clarification and improvement.

The third potential area for further investigation is the impact of outliers. Investigating the effect of outliers, particularly in smaller samples, is essential as they may distort average scores and obscure true maturity levels. Outliers can significantly influence results, making higher-level scores appear similar to or lower than those at lower levels. Addressing this issue could involve refining data collection methods or increasing sample sizes.

The fourth potential area for further investigation is the refinement of survey instruments. Investigating the effectiveness of the selected measurement dimensions (Governance, Culture, Technology, Operation, and People) is essential. Consider whether including additional dimensions could enhance the comprehensiveness of the survey without compromising response rates and data quality. Refining the survey instruments to clarify ambiguities and improve the descriptions of the measurement items will increase the accuracy and reliability of the assessment.

Finally, the fifth potential area for further investigation is the application of AI and machine learning in smart ERP systems that support Industry 4.0. Both Surveys 1 and 2 did not include dimensions for smart ERP systems, which are crucial for the manufacturing industry. These surveys overlooked the advanced capabilities of smart ERP systems incorporating AI and machine learning. Incorporating new Industry 4.0 dimensions as measurement items, which assess technologies like Artificial Intelligence, Machine Learning, Internet of Things, Big Data Analytics, Cloud Computing, Edge Computing, Robotic Process Automation, Advanced Manufacturing Technologies, Digital Twins, 5G Connectivity, and Natural Language Processing, could significantly enhance the processing and analysis of unstructured data. This integration could improve data processing, predictive analytics, real-time analysis, and automation within smart ERP systems, thus supporting Industry 4.0 initiatives and boosting operational efficiency. Exploring these technologies may provide valuable insights into overcoming challenges in transforming unstructured data into actionable insights.

7.8. Chapter Summary and Conclusion

7.8.1. Chapter Summary

This study developed and evaluated a Business Analytics Readiness and Capability Maturity Model (BARCMM) to assess the BA readiness and capability levels of organisations using ERP systems, particularly in the GCR. It provided a rigorous methodology for constructing the maturity model using Rasch analysis and hierarchical clustering and examined perceived ERP BA success and BA capability as key metrics.

The study was motivated by the critical need to understand and effectively measure BA readiness and capability maturity of organisations using ERP systems in the GCR. The aim was to develop and evaluate the BARCMM to assess ERP BA readiness and capability levels, providing a benchmark for continuous improvement and more effective capture of business value.

Key research gaps were identified at both high and low levels. The high-level gaps were:

(1) (RG1) Lack of research on CSFs for ERP BA readiness

(2) (RG2) Limited understanding of how to apply CSFs with methodological rigour for BA capability measurement

(3) (RG3) Limited exploration and empirical application of CSFs underpinned by Item Response Theory in ERP BA readiness for enhancing BA capability and success.

These high-level gaps were broken down into corresponding low-level sub-categories and mapped to specific research questions. Low-level gaps addressed the theoretical and practical aspects necessary to support the design, development, and evaluation of the BARCMM. This included identifying key CSF dimensions for ERP maturity models, adapting existing BA maturity models, and examining the state of BAMM research. Low-level questions investigated using Item Response Theory to measure BA maturity, enhance reliability, and explore the relationships between BA maturity, perceived capability, and perceived ERP BA success. This structured approach addressed the identified gaps comprehensively through the design, development, and evaluation of the BARCMM across three research phases. Figures 1.3 and 1.4 in Chapter 1 illustrate the mapping of high-level and low-level research gaps to the corresponding research questions.

The research was divided into three phases:

(1) Research Phase I involved the first systematic literature review (SLR 1) to create a CSF classification framework for evaluating the maturity of organisations using ERP systems.

(2) Research Phases I and II involved systematic literature reviews to inform the development and implementation of the BARCMM.

(3) Research Phase III focused on the design, assessment, and validation of the BARCMM and presented the empirical study results of applying the validated BARCMM model to organisations in the GCR.

Justification for this research was grounded in four key factors:

(1) The pressing need to address the critical challenges in integrating ERP systems and Business Analytics.

(2) The varied levels of ERP readiness and BA capability across organisations.

(3) The significant impact of organisational maturity on BA readiness and capability within ERP systems.

(4) The requirement for a tailored maturity model to effectively assess ERP BA readiness and capability.

The research methodology adapted the Business Intelligence Maturity Model by Raber et al. (2013a) and applied it to BAMMs. Surveys were used to collect empirical data on BA readiness and capability maturity within organisations that have implemented ERP systems with BA tools. Maturity levels were assessed using ideal maturity profiles and the Euclidean metric, following a three-phase process. The research applied a positivist paradigm and quantitative methods to provide a rigorous and repeatable approach for constructing and evaluating the BARCMM.

The scope of this research focused on developing and evaluating the BARCMM for organisations using ERP Systems in the GCR. A two-stage survey approach was employed, with Survey 1 as a pilot and Survey 2 as a full study, targeting diverse organisations in different industry sectors in the GCR.

The study addresses three sets of research questions (RQs), each targeting a specific aspect of the research focus.

In the first set of research questions (RQ1) related to ERP BA readiness, the study aims to uncover the CSFs that contribute to ERP BA readiness and explore effective measurement approaches for ERP BA readiness (RQ1). To further expand on these findings, the study delves into the key dimensions of CSFs that can serve as measurement items to assess the maturity of ERP systems (RQ1.1 in SLR 1). Additionally, it investigates the additional dimensions of CSFs applicable to assessing the maturity of organisations implementing new-generation ERP systems, particularly those incorporating BA functionalities (RQ1.2 in SLR 1).

In the second set of research questions (RQ2), there is a concern about the lack of understanding of applying CSFs with methodological rigour for BA capability measurement, addressed by formulating research question RQ2 and its sub-questions (RQ2.1 and RQ2.2 in SLR 3 in Chapter 2, and RQ2.3 in SLR 2 in Chapter 2) to bridge gaps in CSF application, identify rigorous BA capability measurement methods, and enhance the reliability and validity of BA maturity assessments in ERP systems. This set of questions also explores the methodological approaches used in designing, assessing, and validating BAMMs (RQ2.1 in SLR 3 in Chapter 2). Furthermore, it investigates how existing BA maturity models can be adapted to determine the BA maturity level of organisations that have adopted new-generation ERP systems (RQ2.2 in SLR 3 in Chapter 2). The study also explores the state of research on BAMMs and the empirical design, assessment, and validation of these models (RQ2.3 in SLR 2 in Chapter 2).

The third set of research questions (RQ3) explored how ERP BA readiness determines BA capability and investigated methods to test the hypotheses that organisations with higher maturity will have higher perceived BA capability and BA success for organisations using ERP systems. RQ3.1 investigates the application of IRT in measuring BA maturity, validating the proposed BA maturity instrument. RQ3.2 focuses on using IRT to enhance the reliability of measurement items for determining BA maturity levels. RQ3.3 examines the relationship between BA maturity, perceived capability, and success, validating the BA capability maturity instrument and providing a data-derived reality check for organisations. These findings contribute both theoretically and practically to understanding and measuring BA capability in ERP systems, although the reliance on perception-based measures and a specific geographic area may limit generalisability.

The development of a BA readiness and capability maturity model for organisations using ERP systems involved the use of a quantitative instrument based on existing literature. The Rasch analysis was used to allocate items measuring capabilities to five maturity levels. Hierarchical Cluster analysis provided a robust method for classifying respondent organisations into different maturity levels. The BA Readiness and BA Capability MM were treated as a single model integrated into a structural equation model to predict perceived success in BA readiness and capability. This assumes that organisations with a higher maturity level will have a higher perceived success.

This study employed two surveys, Survey 1 (Pilot study, April 2017 - September 2018) and Survey 2 (Full study, October 2018 - October 2021), including respondents from Survey 1 and new participants. It introduces a paradigm that employs CSFs to assess maturity levels of BA readiness and capability. The two surveys demonstrated that the maturity model can be adapted to incorporate new measurement dimensions for the latest ERP system features. This flexibility ensures the continued relevance and adaptability of the maturity model to the evolving ERP landscape, making it a more robust and future-proof tool for assessing BA readiness and capability. The use of Rash analysis and clustering analysis in the development of the maturity model provides an objective and rigorous approach to determine the corresponding maturity levels of BA readiness and capability.

The results indicate a positive and significant relationship between BA readiness and capability maturity and the perceived success of BA initiatives within organisations using ERP systems. While the research provides a methodological approach for assessing and improving BA maturity, its focus on perception-based measures and a specific geographic area limits its scope. This research contributes both theoretically and practically by providing organisations in the GCR with a rigorous means to assess BA readiness and BA capability maturity during ERP adoption and usage. Further research is needed to validate the model in diverse geographical regions and minimise biases associated with self-assessment questionnaires.

7.8.2. Chapter Conclusion

This chapter concludes by highlighting the importance of the BARCMM for organisations using ERP systems. The study addressed CSFs impacting BA readiness and capability, particularly in the GCR, and filled significant research gaps in ERP BA readiness and maturity assessment. The BARCMM, validated through rigorous methods like IRT, Rasch analysis, and cluster analysis, provides a strong framework for organisations to measure and improve their BA maturity. It facilitates better decision-making, competitive advantage, and successful outcomes by enabling organisations to benchmark their maturity levels against industry peers. The

BARCMM also serves as a foundation for further enhancements based on survey responses and perceived BA success and capability. Although the research focuses on the GCR, the adaptability of the model makes it relevant to global ERP systems. The framework allows for updates to measurement items and the inclusion of new CSFs to assess features of modern ERP systems. Additional validation in various regions is advised to improve the applicability of the BARCMM and address potential biases.

REFERENCES

Abonyi, J & Feil, B 2007, *Cluster Analysis for Data Mining and System Identification*.

Abu Madi, A, Ayoubi, RM & Alzbaidi, M 2024, 'Spotting the Critical Success Factors of Enterprise Resource Planning Implementation in the Context of Public Higher Education Sector', *International Journal of Public Administration*, vol. 47, no. 2, pp. 73-89.

Ahmad, MO, Ahmad, I, Rana, NP & Khan, IS 2023, 'An Empirical Investigation on Business Analytics in Software and Systems Development Projects', *Information Systems Frontiers*, vol. 25, no. 2, pp. 917-27.

Ahmed, A & Ayman, M 2011, 'The effect of ERP system implementation on business performance: An exploratory case-study', *Communications of the IBIMA*.

Ahmed, W, Najmi, A & Majeed, S 2024, 'Understanding the impact of technological flexibility at different decision levels to reap enterprise resource planning benefits', *Journal of Systems and Information Technology*, vol. 26, no. 1, pp. 115-39.

Ajah, IA & Nweke, HF 2019, 'Big data and business analytics: Trends, platforms, success factors and applications', *Big Data and Cognitive Computing*, vol. 3, no. 2, p. 32.

Al-Mamary, YHS, Al-Nashmi, MM, Shamsuddin, A & Abdulrab, M 2019, 'Development of an integrated model for successful adoption of management information systems in Yemeni telecommunication organizations', *International Journal of Scientific & Technology Research*, vol. 8, no. 11, pp. 3912-39.

Al-Mashari, M, Al-Mudimigh, A & Zairi, M 2003, 'Enterprise resource planning: A taxonomy of critical factors', *European Journal of Operational Research*, vol. 146, no. 2, pp. 352-64.

Ali, F, Rasoolimanesh, SM, Sarstedt, M, Ringle, CM & Ryu, K 2018, 'An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research', *International journal of contemporary hospitality management*, vol. 30, no. 1, pp. 514-38.

Almajali, DA, Masa'deh, R & Tarhini, A 2016, 'Antecedents of ERP systems implementation success: a study on Jordanian healthcare sector', *Journal of Enterprise Information Management*, vol. 29, no. 4, pp. 549-65.

AlMuhayfith, S & Shaiti, H 2020, 'The Impact of Enterprise Resource Planning on Business Performance: With the Discussion on Its Relationship with Open Innovation', *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 3, p. 87.

Ambrosini, V, Bowman, C & Collier, N 2009, 'Dynamic capabilities: An exploration of how firms renew their resource base', *British journal of management*, vol. 20, pp. S9-S24.

Amoako-Gyampah, K & Salam, AF 2004, 'An extension of the technology acceptance model in an ERP implementation environment', *Information & Management*, vol. 41, no. 6, pp. 731-45.

Andersen, EB 1973, 'A goodness of fit test for the Rasch model', *Psychometrika*, vol. 38, pp. 123-40.

Anderson-Lehman, R, Watson, HJ, Wixom, BH & Hoffer, JA 2004, 'Continental airlines flies high with real-time business intelligence', *MIS Quarterly Executive*, vol. 3, no. 4, pp. 163-76.

Andrade, C 2018, 'Internal, external, and ecological validity in research design, conduct, and evaluation', *Indian journal of psychological medicine*, vol. 40, no. 5, pp. 498-9.

Andrich, D & Marais, I 2019, *A Course in Rasch Measurement Theory: Measuring in the Educational, Social and Health Sciences*, Springer.

Angreani, LS, Vijaya, A & Wicaksono, H 2020, 'Systematic Literature Review of Industry 4.0 Maturity Model for Manufacturing and Logistics Sectors', *Procedia Manufacturing*, vol. 52, pp. 337-43.

Aparisi-Torrijo, S, Ribes-Giner, G & Chaves-Vargas, J-C 2023, 'How leadership factors impact different entrepreneurship phases: an analysis with PLS-SEM', *Journal of Business Economics and Management*, vol. 24, no. 1, pp. 136–54-–54.

Appelbaum, D, Kogan, A, Vasarhelyi, M & Yan, Z 2017, 'Impact of business analytics and enterprise systems on managerial accounting', *International Journal of Accounting Information Systems*, vol. 25, pp. 29-44.

Ariyarathna, K & Peter, S 2019, 'Business analytics maturity models: A systematic review of literature', *Focus*, vol. 3, no. 10, p. 4.

Augier, M & Teece, DJ 2007, 'Dynamic capabilities and multinational enterprise: Penrosean insights and omissions', *Management international review*, vol. 47, pp. 175-92.

Aziz, MA, Ragheb, MA, Ragab, AA & El Mokadem, M 2018, 'The impact of enterprise resource planning on supply chain management practices', *The Business & Management Review*, vol. 9, no. 4, pp. 56-69.

Babones, S 2016, 'Interpretive quantitative methods for the social sciences', *Sociology*, vol. 50, no. 3, pp. 453-69.

Backlund, F, Chronéer, D & Sundqvist, E 2015, 'Maturity assessment: towards continuous improvements for project-based organisations?', *International Journal of Managing Projects in Business*, vol. 8.

Badi, S 2024, *Maximizing Business Potential: Harnessing Gamification, AI, and ERP Integration for Unparalleled Performance and Innovation*.

Balić, A, Turulja, L, Kuloglija, E & Pejić-Bach, M 2022, 'ERP Quality and the Organizational Performance: Technical Characteristics vs. Information and Service', *Information*, vol. 13, no. 10, p. 474.

Balparda, K, Herrera-Chalarca, T, Cano-Bustamante, M, Gómez-González, T & Nicholls-Molina, M 2021, 'Rasch development and validation of a new faces scale for measuring pain, and its comparison with a gold standard: the Balparda–Herrera Pain Scale', *Pain Management*, vol. 11.

Bandara, F, Jayawickrama, U, Subasinghage, M, Olan, F, Alamoudi, H & Alharthi, M 2024, 'Enhancing ERP Responsiveness Through Big Data Technologies: An Empirical Investigation', *Information Systems Frontiers*, vol. 26, no. 1, pp. 251-75.

Barney, JB 1996, 'The resource-based theory of the firm', *Organization science*, vol. 7, no. 5, pp. 469-.

Barney, JB & Clark, DN 2007, *Resource-based theory: Creating and sustaining competitive advantage*, OUP Oxford.

Bartlett, R 2013, *A Practitioner's Guide to Business Analytics*, McGraw-Hill, New York, NY.

Batchelder, L, Fox, D, Potter, CM, Peters, M, Jones, K, Forder, JE & Fitzpatrick, R 2020, 'Rasch analysis of the long-term conditions questionnaire (LTCQ) and development of a short-form (LTCQ-8)', *Health and Quality of Life Outcomes*, vol. 18, pp. 1-12.

Bayrak, T 2015, 'A Review of Business Analytics: A Business Enabler or Another Passing Fad', *Procedia - Social and Behavioral Sciences*, vol. 195, pp. 230-9.

Beard, JW & Sumner, M 2004, 'Seeking strategic advantage in the post-net era: viewing ERP systems from the resource-based perspective', *The Journal of Strategic Information Systems*, vol. 13, no. 2, pp. 129-50.

Becker, J-M, Rai, A & Rigdon, E 2013, 'Predictive validity and formative measurement in structural equation modeling: Embracing practical relevance'.

Becker, J, Knackstedt, R & Pöppelbuß, J 2009, 'Developing Maturity Models for IT Management: A Procedure Model and its Application', *Business & Information Systems Engineering*, vol. 1, no. 3, pp. 213-22.

Becker, J, Niehaves, B, Poeppelbuss, J & Simons, A 2010, *Maturity Models in IS Research*.

Bento, F & Costa, CJ 2013, 'ERP measure success model; a new perspective', *Proceedings of the 2013 International Conference on Information Systems and Design of Communication*: *Proceedings of the Proceedings of the 2013 International Conference on Information Systems and Design of Communication* Association for Computing Machinery, Lisboa, Portugal, pp. 16–26.

Beyera, GK, O'Brien, J & Campbell, S 2020, 'The development and validation of a measurement instrument to investigate determinants of health care utilisation for low back pain in Ethiopia', *PloS one*, vol. 15, no. 1, p. e0227801.

Bond, T 2015, *Applying the Rasch Model: Fundamental Measurement in the Human Sciences, Third Edition*, Taylor & Francis.

Boone, W & Noltemeyer, A 2017, 'Rasch Analysis: A Primer for School Psychology Researchers and Practitioners', *Cogent Education*, vol. 4.

Boone, WJ 2016, 'Rasch Analysis for Instrument Development: Why, When, and How?', *CBE—Life Sciences Education*, vol. 15, no. 4, p. rm4.

Boone, WJ & Noltemeyer, A 2017, 'Rasch analysis: A primer for school psychology researchers and practitioners', *Cogent Education*, vol. 4, no. 1, p. 1416898.

Boone, WJ, Staver, JR & Yale, MS 2013, *Rasch analysis in the human sciences*, Springer.

Boone, WJ, Staver, JR & Yale, MS 2014, 'Understanding person measures', in *Rasch analysis in the human sciences*, Springer, pp. 69-92.

Borman, M & Janssen, M 2013, 'Similarities and Differences in Critical Success Factors across Context and Time: An Examination in the Setting of Shared Services', *e-Service Journal*, vol. 9, no. 1, pp. 85-105.

Boughzala, I & de Vreede, G-J 2011, 'A first application of a Collaboration Maturity Model in the automotive industry', *International Conference on Knowledge Management and Information Sharing*, SCITEPRESS, pp. 28-37.

Bozkus, K 2023, 'Organizational Culture Change and Technology: Navigating the Digital Transformation', in.

Bradley, RV, Pridmore, JL & Byrd, TA 2006, 'Information Systems Success in the Context of Different Corporate Cultural Types: An Empirical Investigation', *Journal of Management Information Systems*, vol. 23, no. 2, pp. 267-94.

Brookes, N & Clark, R 2009, 'Using maturity models to improve project management practice', *POMS 20th Annual Conference*, pp. 285-96.

Brooks, P, El-Gayar, O & Sarnikar, S 2015, 'A framework for developing a domain specific business intelligence maturity model: Application to healthcare', *International Journal of Information Management*, vol. 35, no. 3, pp. 337-45.

Butarbutar, ZT, Handayani, PW, Suryono, RR & Wibowo, WS 2023, 'Systematic literature review of Critical success factors on enterprise resource planning post implementation', *Cogent Business & Management*, vol. 10, no. 3, p. 2264001.

Caralli, RA, Stevens, JF, Willke, BJ & Wilson, WR 2004, *The critical success factor method: establishing a foundation for enterprise security management*, Carnegie-Mellon Univ Pittsburgh Pa Software Engineering Inst, https://resources.sei.cmu.edu/asset_files/TechnicalReport/2004_005_001_14393.pdf>.

Castor, N, Damberg, D & Sjöborg, E 2016, *MESA MOM Capability Maturity Level*, https://www.control.lth.se/fileadmin/control/Education/EngineeringProgram/FRTN20/2016/Report-mesa-mom-capability__1_.pdf>.

Chaghooshi, AJ, Moghadam, MM & Etezadi, S 2016, 'Ranking business processes maturity by modified rembrandt technique with considering CMMI dimensions', *Iranian Journal of Management Studies*, vol. 9, no. 3, pp. 559-78A.

Chan, E 2014, 'Standards and Guidelines for Validation Practices: Development and Evaluation of Measurement Instruments', in pp. 9-24.

Chatterjee, S, Rana, NP & Dwivedi, YK 2024, 'How does business analytics contribute to organisational performance and business value? A resource-based view', *Information Technology & People*, vol. 37, no. 2, pp. 874-94.

Chatzoglou, P, Chatzoudes, D & Apostolopoulou, G 2016, 'Antecedents and outcomes of ERP implementation success', *2016 Federated Conference on Computer Science and Information Systems (FedCSIS)*, IEEE, pp. 1253-62.

Chen, H, Chiang, RHL & Storey, VC 2012, 'Business Intelligence and Analytics: From Big Data to Big Impact', *MIS Quarterly*, vol. 36, no. 4, pp. 1165-88.

Chen, Q, Liang, C, Lu, J & Jiang, Z 2024, 'Translation and validation of the Chinese version of the Self-awareness Scale for Nurses', *Frontiers in Public Health*, vol. 12.

Cheung, G 2017, *China factors: political perspectives and economic interactions*, Routledge.

Cheung, GW, Cooper-Thomas, HD, Lau, RS & Wang, LC 2023, 'Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations', *Asia Pacific Journal of Management*, pp. 1-39.

Chevrier, S 2024, 'What we inherit and what we create. Making the case for an interpretive approach to societal cultures', *International Journal of Cross Cultural Management*, p. 14705958241227774.

Chin, WW 1998, 'The partial least squares approach to structural equation modeling', *Modern methods for business research*, vol. 295, no. 2, pp. 295-336.

Chin, WW 2010, 'How to write up and report PLS analyses', in *Handbook of partial least squares*, Springer, pp. 655-90.

Chism, NVN, Douglas, E & Hilson, W 2008, 'Qualitative research basics: A guide for engineering educators', *Rigorous Research in Engineering Education*, pp. 1-65.

Chou, J-S & Hong, J-H 2013, 'Assessing the impact of quality determinants and user characteristics on successful enterprise resource planning project implementation', *Journal of Manufacturing Systems*, vol. 32, no. 4, pp. 792-800.

Chou, SW & Chang, YC 2008, 'The implementation factors that influence the ERP (enterprise resource planning) benefits', *Decision Support Systems*, vol. 46, no. 1, pp. 149-57.

Christensen, KS, Cosci, F, Carrozzino, D & Sensky, T 2024, 'Rasch Analysis and Its Relevance to Psychosomatic Medicine', *Psychotherapy and Psychosomatics*, vol. 93, no. 2, pp. 88-93.

Ciampi, F, Demi, S, Magrini, A, Marzi, G & Papa, A 2021, 'Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation', *Journal of Business Research*, vol. 123, pp. 1-13.

Clark, LA & Watson, D 2019, 'Constructing validity: New developments in creating objective measuring instruments', *Psychological assessment*, vol. 31, no. 12, p. 1412.

Cleven, AK, Winter, R, Wortmann, F & Mettler, T 2014, 'Process management in hospitals: an empirically grounded maturity model', *Business Research*, vol. 7, pp. 191-216.

CMMI Institute 2014, *Data Management Maturity (DMM)*, http://cmmiinstitute.com/data-management-maturity>.

CMMI Institute 2023, *CMMI Release: V3.0, 6 April 2023*, https://cmmiinstitute.com/getattachment/47a7c84e-472c-4f7f-a473-ddc21c6ae045/attachment.aspx>.

Cohen, RJ & Swerdlik, ME 2017, *Psychological Testing and Assessment: An Introduction to Tests and Measurement*, 9th Edition edn, McGraw-Hill Education.

Combrinck, C-M 2018, 'The Use of Rasch Measurement Theory to Address Measurement and Analysis Challenges in Social science Research', Ph.D. thesis, University of Pretoria (South Africa), South Africa.

Combrinck, C 2020, 'Is this a useful instrument? An introduction to Rasch measurement models', in Psychological Society of South Africa.

Combrinck, C, Scherman, V & Maree, D 2017, 'Evaluating anchor items and reframing assessment results through a practical application of the Rasch Measurement Model', *South African Journal of Psychology*, vol. 47, no. 3, pp. 316-29.

Conboy, K, Mikalef, P, Dennehy, D & Krogstie, J 2020, 'Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda', *European Journal of Operational Research*, vol. 281, no. 3, pp. 656-72.

Copper, JF 2003, 'The meaning and significance of Greater China', in *Political Communications in Greater China*, Routledge, pp. 22-50.

Corallo, A, Crespino, AM, Del Vecchio, V, Gervasi, M, Lazoi, M & Marra, M 2023, 'Evaluating maturity level of big data management and analytics in industrial companies', *Technological Forecasting and Social Change*, vol. 196, p. 122826.

Cosic, R 2020, 'Business Analytics: Capability Maturity and Development', Thesis thesis, University of Melbourne, Australia.

Cosic, R, Shanks, G & Maynard, S 2012, 'Towards a business analytics capability maturity model', *ACIS 2012*, Geelong, Vic., pp. 1-11.

Cosic, R, Shanks, G & Maynard, SB 2015, 'A business analytics capability framework', *Australasian Journal of Information Systems*, vol. 19.

Couckuyt, D & Van Looy, A 2021, *Identifying green business process maturity levels by classifying ecolabels*.

da Motta, C, Castilho, P, Pato, MT & Barreto Carvalho, C 2022, 'Rasch model analysis of the Situational Test of Emotional Understanding – brief in a large Portuguese sample', *Current Psychology*, vol. 41, no. 6, pp. 3853-64.

da Silva, ET, Martins, MAF, Moya Rodríguez, JL & Ferreira, AS 2024, 'Evaluation of the influence of distributed generation on the well-being of the rural community using PLS-SEM', *Journal of Cleaner Production*, vol. 442, p. 141023.

Dabaghi, S, Esmaielzadeh, F & Rohani, C 2020, 'Application of rasch analysis for development and psychometric properties of adolescents' quality of life instruments: a systematic review', *Adolescent health, medicine and therapeutics*, pp. 173-97.

Dalmaijer, ES, Nord, CL & Astle, DE 2022, 'Statistical power for cluster analysis', *BMC bioinformatics*, vol. 23, no. 1, p. 205.

Davčik, NS 2013, 'The use and misuse of structural equation modeling in management research', *FCT Strategic Project UI 315 PEst-OE/EGE/UI0315, Working Paper–13*, vol. 7.

Davenport, TH 1998, 'Putting the enterprise into the enterprise system', *Harvard Business Review*, vol. 76, no. 4, pp. 121-31.

Davenport, TH & Harris, JG 2007, *Competing on analytics: The new science of winning*, Harvard Business School Review Press, Boston, MA.

Davenport, TH, Harris, JG & Morison, R 2010, *Analytics at work smarter decisions, better results*, Harvard Business Press, Boston, Mass.

Davis, DR & Boone, W 2021, 'Using Rasch analysis to evaluate the psychometric functioning of the other-directed, lighthearted, intellectual, and whimsical (OLIW) adult playfulness scale', *International Journal of Educational Research Open*, vol. 2, p. 100054.

Davis, EW & Spekman, RE 2004, *The Extended Enterprise: Gaining Competitive advantage through collaborative supply chains*, FT Press.

Day, GS 1994, 'The Capabilities of Market-Driven Organizations', *Journal of marketing*, vol. 58, no. 4, p. 37.

De Battisti, F, Nicolini, G & Salini, S 2005, 'The Rasch model to measure the service quality', *The Journal of Services Marketing*, vol. 3, no. 3, pp. 58-80.

Degerli, M 2020, 'Practical Suggestions to Successfully Adopt the CMMI V2. 0 Development for Better Process, Performance, and Products', *2020 5th International Conference on Computer Science and Engineering (UBMK)*, IEEE, pp. 126-9.

Dekleva, S & Drehmer, D 1997, 'Measuring Software Engineering Evolution: A Rasch Calibration', *Information Systems Research*, vol. 8, no. 1, pp. 95-104.

Deloitte 2017, *Extended Enterprise Risk Management Driving performance through the third-party ecosystem*, https://www2.deloitte.com/content/dam/Deloitte/us/Documents/risk/us-extended-enterprise-risk-management.pdf>.

Díaz-Reza, JR, García-Alcaraz, JL & Martínez-Loya, V 2019, 'Impact Analysis of Total Productive Maintenance', *Springer International Publishing*.

Dikhanbayeva, D, Shaiholla, S, Suleiman, Z & Turkyilmaz, A 2020, 'Assessment of Industry 4.0 Maturity Models by Design Principles', *Sustainability*, vol. 12.

Dominion Dominic, E & Mahamed, DM 2023, 'A Guide on Quantitative Research Paradigms, Theory, and Frameworks in Social Sciences Research', *Mastura, A Guide on Quantitative Research Paradigms, Theory, and Frameworks in Social Sciences Research (April 13, 2023)*.

dos Santos-Neto, JBS & Costa, APCS 2019, 'Enterprise maturity models: a systematic literature review', *Enterprise IS*, vol. 13, no. 5, pp. 719-69.

Dredden, G & Bergdolt, JC 2007, 'Enterprise Resource Planning', *Air Force Journal of Logistics*, vol. 31, no. 2, pp. 48-52.

Drobik, A & Rayner, N 2015, *2015 Strategic Road Map for Postmodern ERP*, Gartner, http://docs.media.bitpipe.com/io_12x/io_128036/item_1242147/2015%20Strategic%20Road%20Map%20for%20Postmodern%20ERP.htm>.

Edelen, MO & Reeve, BB 2007, 'Applying item response theory (IRT) modeling to questionnaire development, evaluation, and refinement', *Quality of Life Research*, vol. 16, no. 1, p. 5.

Ehie, IC & Madsen, M 2005, 'Identifying critical issues in enterprise resource planning (ERP) implementation', *Computers in Industry*, vol. 56, no. 6, pp. 545-57.

Ekstrand, J, Westergren, A, Årestedt, K, Hellström, A & Hagell, P 2022, 'Transformation of Rasch model logits for enhanced interpretability', *BMC Medical Research Methodology*, vol. 22, no. 1, p. 332.

Elbashir, MZ, Collier, PA & Davern, MJ 2008, 'Measuring the effects of business intelligence systems: The relationship between business process and organizational performance', *International Journal of Accounting Information Systems*, vol. 9, no. 3, pp. 135-53.

Elgendy, N, Elragal, A & Päivärinta, T 2022, 'DECAS: a modern data-driven decision theory for big data and analytics', *Journal of Decision Systems*, vol. 31, no. 4, pp. 337-73.

Elhan, AH, Küçükdeveci, A & Tennant, A 2010, 'The Rasch measurement model', *Advances in Rehabilitation. Research Issues in Physical & Rehabilitation Medicine*, pp. 89-102.

Elragal, A & Hassanien, HE-D 2019, 'Augmenting Advanced Analytics into Enterprise Systems: A Focus on Post-Implementation Activities', *Systems*, vol. 7, no. 2, p. 31.

Eykhoff, P 1984, 'Identification theory: Practical implications and limitations', *Measurement*, vol. 2, no. 2, pp. 75-85.

Fariz, AA, Raharjo, T & Genia, V 2023, 'ISO 9001: 2015 and Capability Maturity Model Integration 3.0 in Software Development Project', *Indonesian Journal of Computer Science*, vol. 12, no. 6.

Fauzi, TH 2022, 'Impact of enterprise resource planning systems on management control systems and firm performance', *Uncertain Supply Chain Management*, pp. 745-54.

Fedouaki, F, Okar, C & El Alami, S 2013, 'A maturity model for Business Intelligence System project in Small and Medium-sized Enterprises: an empirical investigation', *International Journal of Computer Science Issues (IJCSI)*, vol. 10, no. 6, p. 61.

Felt, JM, Castaneda, R, Tiemensma, J & Depaoli, S 2017, 'Using Person Fit Statistics to Detect Outliers in Survey Research', *Frontiers in Psychology*, vol. 8, pp. 863-.

Fertig, T, Schütz, A & Weber, K 2023, *Developing a Maturity Model for Information Security Awareness Using a Polytomous Extension of the Rasch Model*.

Findley, MG, Kikuta, K & Denly, M 2021, 'External validity', *Annual Review of Political Science*, vol. 24, no. 1, pp. 365-93.

Fosso Wamba, S, Queiroz, MM, Wu, L & Sivarajah, U 2024, 'Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture', *Annals of Operations Research*, vol. 333, no. 2, pp. 559-78.

Fox, CM & Jones, JA 1998, 'Uses of Rasch Modeling in Counseling Psychology Research', *Journal of counseling psychology*, vol. 45, no. 1, pp. 30-45.

Frank, AG, Dalenogare, LS & Ayala, NF 2019, 'Industry 4.0 technologies: Implementation patterns in manufacturing companies', *International Journal of Production Economics*, vol. 210, pp. 15-26.

Friesen, MC, Shortreed, SM, Wheeler, DC, Burstyn, I, Vermeulen, R, Pronk, A, Colt, JS, Baris, D, Karagas, MR, Schwenn, M, Johnson, A, Armenti, KR, Silverman, DT & Yu, K 2014, 'Using Hierarchical Cluster Models to Systematically Identify Groups of Jobs With Similar Occupational Questionnaire Response Patterns to Assist Rule-Based Expert Exposure Assessment in Population-Based Studies', *The Annals of Occupational Hygiene*, vol. 59, no. 4, pp. 455-66.

Gaardboe, R, Sandalgaard, N & Nyvang, T 2017, 'An assessment of business intelligence in public hospitals', *International Journal of Information Systems and Project Management*, vol. 5, no. 4, pp. 5-18.

Gašpar, D, Ćorić, I & Mabić, M 2023, 'Composable ERP–New Generation of Intelligent ERP', *International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies*, Springer, pp. 359-75.

Gehlbach, H & Brinkworth, ME 2011, 'Measure Twice, Cut down Error: A Process for Enhancing the Validity of Survey Scales', *Review of General Psychology*, vol. 15, no. 4, pp. 380-7.

Geissbauer, R, Vedso, J & Schrauf, S 2016, *Industry 4.0: Building the digital enterprise*, https://www.pwc.com/gx/en/industries/industries-4.0/landing-page/industry-4.0-building-your-digital-enterprise-april-2016.pdf>.

Geneste, L & Weber, P 2011, 'BUSINESS PERCEIVED SUCCESS AND GROWTH INTENTIONS', *Journal of Asia Entrepreneurship and Sustainability, suppl. Special Issue Editors and Review Board*, vol. 7, no. 2, pp. 72-90.

Gërvalla, M 2020, 'A maturity model for implementation and application of Enterprise Resource Planning systems and ERP utilization to Industry 4.0', Corvinus University of Budapest.

Gessa, A, Jiménez, A & Sancha, P 2023, 'Exploring ERP systems adoption in challenging times. Insights of SMEs stories', *Technological Forecasting and Social Change*, vol. 195, p. 122795.

Ghadge, A, Er Kara, M, Moradlou, H & Goswami, M 2020, 'The impact of Industry 4.0 implementation on supply chains', *Journal of Manufacturing Technology Management*, vol. 31, no. 4, pp. 669-86.

Ghazal, T, Soomro, TR & Shaalan, K 2013, 'Integration of project management maturity (PMM) based on capability maturity model integration (CMMI)', *Eur. J. Sci. Res*, vol. 99, pp. 418-28.

Ghosh, S & Skibniewski, MJ 2010, 'Enterprise resource planning systems implementation as a complex project: a conceptual framework', *Journal of Business Economics and Management*, vol. 11, no. 4, pp. 533-49.

Gómez, LE, Arias, B, Verdugo, MÁ & Navas, P 2012, 'Application of the Rasch rating scale model to the assessment of quality of life of persons with intellectual disability', *Journal of Intellectual and Developmental Disability*, vol. 37, no. 2, pp. 141-50.

Gomm, R 2018, 'A positivist orientation: Hypothesis testing and the ‘scientific method'', *The SAGE encyclopedia of educational research, measurement, and evaluation*, pp. 213-40.

Gorman, MF & Klimberg, RK 2014, 'Benchmarking academic programs in business analytics', *Interfaces*, vol. 44, no. 3, pp. 329-41.

Gower, T, Pham, J, Jouriles, EN, Rosenfield, D & Bowen, HJ 2022, 'Cognitive biases in perceptions of posttraumatic growth: A systematic review and meta-analysis', *Clinical Psychology Review*, vol. 94, p. 102159.

Grimm, P 2010, 'Social desirability bias', *Wiley international encyclopedia of marketing*.

Gröger, C 2018, 'Building an industry 4.0 analytics platform', *Datenbank-Spektrum*, vol. 18, no. 1, pp. 5-14.

Grube, M & Wynn, M 2018, 'The Impact of SAP on the Utilisation of Business Process Management (BPM) Maturity Models in ERP projects', *eKNOW 2018, The Tenth International Conference on Information, Process, and Knowledge Management*: *Proceedings of the eKNOW 2018, The Tenth International Conference on Information, Process, and Knowledge Management* Rome, Italy, pp. 115-21.

Guo, X, Zhong, S, Wu, Y, Zhang, Y & Wang, Z 2022, 'The impact of lockdown in Wuhan on residents confidence in controlling COVID-19 outbreak at the destination cities', *Frontiers in Public Health*, vol. 10, p. 902455.

Gupta, M & Kohli, A 2006, 'Enterprise resource planning systems and its implications for operations function', *Technovation*, vol. 26, no. 5, pp. 687-96.

Gürdür, D, El-khoury, J & Törngren, M 2019, 'Digitalizing Swedish industry: What is next?: Data analytics readiness assessment of Swedish industry, according to survey results', *Computers in Industry*, vol. 105, pp. 153-63.

Hagquist, C, Bruce, M & Gustavsson, JP 2009, 'Using the Rasch model in nursing research: An introduction and illustrative example', *International Journal of Nursing Studies*, vol. 46, no. 3, pp. 380-93.

Hair, JF, Hult, GTM, Ringle, C & Sarstedt, M 2016, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd edn, SAGE Publications.

Hair, JF, Risher, JJ, Sarstedt, M & Ringle, CM 2019, 'When to use and how to report the results of PLS-SEM', *European Business Review*, vol. 31, no. 1, pp. 2-24.

Hair, JF, Hult, GTM, Ringle, CM, Sarstedt, M, Danks, NP & Ray, S 2021, 'An Introduction to Structural Equation Modeling', in JF Hair Jr, et al. (eds), *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*, Springer International Publishing, Cham, pp. 1-29.

Hair Jr, JF, Hult, GTM, Ringle, CM, Sarstedt, M, Danks, NP & Ray, S 2021, *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*, Springer Nature.

Hairech, OE & Lyhyaoui, A 2020, 'The new generation of ERP in the era of artificial intelligence and industry 4.0', *International Conference on Advanced Intelligent Systems for Sustainable Development*, Springer, pp. 1086-94.

Halo 2015, *Halo Business Intelligence Maturity Model*, viewed 6 Dec, <http://halobi.com/solutions/halo-bi-maturity-model/ >.

Halper, F & Stodder, D 2014, *TDWI Analytics Maturity Model Guide*, The Data Warehousing Institute, https://tdwi.org/whitepapers/2014/10/tdwi-analytics-maturity-model-guide.aspx>.

Hammer, M 2007, 'The process audit', *Harvard Business Review*, vol. 85, no. 4, p. 111.

Hanafiah, MH 2020, 'Formative vs. reflective measurement model: Guidelines for structural equation modeling research', *International Journal of Analysis and Applications*, vol. 18, no. 5, pp. 876-89.

Hatt, CR, Brydges, CR, Mogle, JA, Sliwinski, MJ & Bielak, AA 2021, 'Evaluating the consistency of subjective activity assessments and their relation to cognition in older adults', *Geriatrics*, vol. 6, no. 3, p. 74.

Hawking, P & Sellitto, C 2010, 'Critical Success Factors of Business Intelligence (BI) in an ERP Systems Environment', *CONFENIS*, Natal, Brazil.

Hawking, P, Jovanovic, R & Sellitto, C 2011, 'Business Intelligence Maturity in Australia', *Americas Conference of Information Systems (AMCIS)*, Detroit, USA.

Haynes, SN, Richard, D & Kubany, ES 1995, 'Content validity in psychological assessment: A functional approach to concepts and methods', *Psychological assessment*, vol. 7, no. 3, p. 238.

Helfrich, CD, Blevins, D, Smith, JL, Kelly, PA, Hogan, TP, Hagedorn, H, Dubbert, PM & Sales, AE 2011, 'Predicting implementation from organizational readiness for change: a study protocol', *Implementation science : IS*, vol. 6, no. 1, pp. 76-.

Hill, R 1998, 'What sample size is “enough” in internet survey research', *Interpersonal Computing and Technology: An electronic journal for the 21st century*, vol. 6, no. 3-4, pp. 1-12.

Hittleman, DR & Simon, AJ 1997, *Interpreting educational research : an introduction for consumers of research*, Merrill, Upper Saddle River, N.J.

Hmoud, H, Al-Adwan, AS, Horani, O, Yaseen, H & Zoubi, JZA 2023, 'Factors influencing business intelligence adoption by higher education institutions', *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 3, p. 100111.

Holland, C & Light, B 2001, 'A stage maturity model for enterprise resource planning systems use', *The data base for advances in information systems*, vol. 32, no. 2, pp. 34-45.

Holsapple, C, Sena, M & Wagner, W 2019, 'The perceived success of ERP systems for decision support', *Inf. Technol. and Management*, vol. 20, no. 1, pp. 1–7.

Hong, KK & Kim, YG 2002, 'The critical success factors for ERP implementation: an organizational fit perspective', *Information & Management*, vol. 40, no. 1, pp. 25-40.

Hopkins, EG, Lyndon, MP, Henning, MA & Medvedev, ON 2021, 'Applying Rasch analysis to evaluate and enhance the Academic Motivation Scale', *Australian Journal of Psychology*, vol. 73, no. 3, pp. 348-56.

Hornick, M 2020, *A Data Science Maturity Model for Enterprise Assessment*, Oracle, viewed 23 Dec, <https://www.oracle.com/a/devo/docs/data-science-maturity-model.pdf>.

Howson, C & Duncan, A 2015, *Gartner's ITScore for BI and Analytics Maturity Model*, Gartner.

Hwang, Y & Grant, D 2014, 'An empirical study of enterprise resource planning integration: global and local perspectives', *Information Development*, vol. 32, no. 3, pp. 260-70.

Ifinedo, P, Rapp, B, Ifinedo, A & Sundberg, K 2010, 'Relationships among ERP post-implementation success constructs: An analysis at the organizational level', *Computers in Human Behavior*, vol. 26, no. 5, pp. 1136-48.

International Institute for Analytics n.d., *Analytics Maturity Assessment*, https://iianalytics.com/services/benchmarking>.

Ismail, M, Din, MH & Jusoh, M 2021, 'Predictive modelling using Rasch’s person-item map: Intrepreting and assessing in Malaysia manufacturing firms', *AIP Conference Proceedings*, AIP Publishing LLC, p. 020288.

Izah, SC, Sylva, L & Hait, M 2023, 'Cronbach's Alpha: A Cornerstone in Ensuring Reliability and Validity in Environmental Health Assessment', *ES Energy & Environment*, vol. 23, p. 1057.

Jarrar, YF, Al-Mudimigh, A & Zairi, M 2000, 'ERP implementation critical success factors-the role and impact of business process management', *Proceedings of the 2000 IEEE International Conference on Management of Innovation and Technology. ICMIT 2000. 'Management in the 21st Century' (Cat. No.00EX457)*, pp. 122-7 vol.1.

Jo, H & Park, D-H 2023, 'Mechanisms for successful management of enterprise resource planning from user information processing and system quality perspective', *Scientific Reports*, vol. 13, no. 1, p. 12678.

Joachim, N, Beimborn, D & Weitzel, T 2011, 'An instrument for measuring SOA maturity', *ICIS 2011 Proceedings. 3.*

Kaplan, DS & Pathania, V 2010, 'What influences firms' perceptions?', *Journal of Comparative Economics*, vol. 38, no. 4, pp. 419-31.

Keskin, FD, Kabasakal, İ, Kaymaz, Y & Soyuer, H 2018, 'An assessment model for organizational adoption of industry 4.0 based on multi-criteria decision techniques', *The International Symposium for Production Research*, Springer, pp. 85-100.

Khorsan, R & Crawford, C 2014, 'External validity and model validity: a conceptual approach for systematic review methodology', *Evidence-Based Complementary and Alternative Medicine*, vol. 2014, no. 1, p. 694804.

Kitchenham, B 2007, *Guidelines for performing Systematic Literature Reviews in software engineering. EBSE Technical Report EBSE-2007-01*.

Kuhfeld, M & Soland, J 2020, 'Using assessment metadata to quantify the impact of test disengagement on estimates of educational effectiveness', *Journal of Research on Educational Effectiveness*, vol. 13, no. 1, pp. 147-75.

Laaber, F, Florack, A, Koch, T & Hubert, M 2023, 'Digital maturity: Development and validation of the Digital Maturity Inventory (DIMI)', *Computers in Human Behavior*, vol. 143, p. 107709.

Lahrmann, G, Marx, F, Mettler, T, Winter, R & Wortmann, F 2011, 'Inductive design of maturity models: applying the Rasch algorithm for design science research', *International Conference on Design Science Research in Information Systems*, Springer, pp. 176-91.

Lameijer, BA, Boer, H, Antony, J & Does, RJMM 2023, 'Continuous improvement implementation models: a reconciliation and holistic metamodel', *Production Planning & Control*, vol. 34, no. 11, pp. 1062-81.

Lamoureux, EL, Pallant, JF, Pesudovs, K, Tennant, A, Rees, G, O'Connor, PM & Keeffe, JE 2008, 'Assessing Participation in Daily Living and the Effectiveness of Rehabiliation in Age Related Macular Degeneration Patients Using the Impact of Vision Impairment Scale', *Ophthalmic Epidemiology*, vol. 15, no. 2, pp. 105-13.

Lara-Pérez, JA, Canibe-Cruz, F & Duréndez, A 2024, 'How the interaction of innovation and ERP systems on business intelligence affects the performance of Mexican manufacturing companies', *Information Technology & People*.

Lasrado, LA 2018, *Set-Theoretic Approach to Maturity Models*, Frederiksberg: Copenhagen Business School (CBS).

Lasrado, LA, Vatrapu, R & Andersen, KN 2015, 'Maturity Models Development in IS Research: A Literature Review', *IRIS: Selected Papers of the Information Systems*

Research Seminar in Scandinavia, Scandinavian Chapter of the Association for Information Systems (AIS …, p. 6.

Lasrado, LA, Vatrapu, R & Mukkamala, RR 2017, 'Whose maturity is it anyway? The influence of different quantitative methods on the design and assessment of maturity models', *Twenty-Fifth European Conference on Information Systems (ECIS), Guimarães, Portugal, 2017*.

Latkin, CA, Edwards, C, Davey-Rothwell, MA & Tobin, KE 2017, 'The relationship between social desirability bias and self-reports of health, substance use, and social network factors among urban substance users in Baltimore, Maryland', *Addictive behaviors*, vol. 73, pp. 133-6.

Laudon, KC & Laudon, JP 2019, *Management information systems: Managing the digital firm*, 16th edition edn, Pearson Educación.

Laudon, KC & Laudon, JP 2020, *Management information systems : managing the digital firm*, Sixteenth edition. edn, Pearson, New York, NY.

LaValle, S, Lesser, E, Shockley, R, Hopkins, MS & Kruschwitz, N 2010, 'Big data, analytics and the path from insights to value', *MIT sloan management review*.

Law, CCH, Chen, CC & Wu, BJP 2010, 'Managing the full ERP life-cycle: Considerations of maintenance and support requirements and IT governance practice as integral elements of the formula for successful ERP adoption', *Computers in Industry*, vol. 61, no. 3, pp. 297-308.

Lazarova-Molnar, S, Mohamed, N & Al-Jaroodi, J 2018, 'Collaborative data analytics for industry 4.0: challenges, opportunities and models', *2018 sixth international conference on enterprise systems (ES)*, IEEE, pp. 100-7.

Leso, BH, Cortimiglia, MN & Ghezzi, A 2023, 'The contribution of organizational culture, structure, and leadership factors in the digital transformation of SMEs: a mixed-methods approach', *Cognition, Technology & Work*, vol. 25, no. 1, pp. 151-79.

Li, W & Lay, YF 2024, 'Examining the Reliability and Validity of Measuring Scales related to Informatization Instructional Leadership Using PLS-SEM Approach', *Dinamika Jurnal Ilmiah Pendidikan Dasar*, vol. 16, no. 1, pp. 12-32.

Liberatore, MJ, Pollack-Johnson, B & Clain, SH 2017, 'Analytics capabilities and the decision to invest in analytics', *Journal of Computer Information Systems*, vol. 57, no. 4, pp. 364-73.

Lichtblau, K, Stich, V, Bertenrath, R, Blum, M, Bleider, M, Millack, A, Schmitt, K, Schmitz, E & Schröter, M 2015, *Impuls: Industrie 4.0 Readiness*, VDMA: Aachen, Cologne, Germany, http://industrie40.vdma.org/documents/4214230/5356229/Industrie%204.0%20Readiness%20Study%20English.pdf/f6de92c1-74ed-4790-b6a4-74b30b1e83f0>.

Linacre, JM 2002, *What do infit and outfit, mean-square and standardized mean? Rasch Measurement Transactions, 16 (2), 878*.

Liu, DT, Mueller, CA & Sedaghat, AR 2024, 'A scoping review of Rasch analysis and item response theory in otolaryngology: Implications and future possibilities', *Laryngoscope Investigative Otolaryngology*, vol. 9, no. 1, p. e1208.

Lowry, PB & Gaskin, J 2014, 'Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it', *IEEE transactions on professional communication*, vol. 57, no. 2, pp. 123-46.

Lukman, T, Hackney, R, Popovič, A, Jaklič, J & Irani, Z 2011, 'Business intelligence maturity: the economic transitional context within Slovenia', *Information systems management*, vol. 28, no. 3, pp. 211-22.

Lundy, P 1996, 'Limitations of quantitative research in the study of structural adjustment', *Social Science & Medicine*, vol. 42, no. 3, pp. 313-24.

Makota, J, Kabote, F & Nharo, T 2023, 'Exploring the Motivations and Critical Factors of Successful Enterprise Resource Planning Implementation in Organisations in Zimbabwe'.

Markus, ML & Tanis, C 2000, 'The enterprise systems experience-from adoption to success', *Framing the domains of IT research: Glimpsing the future through the past*, vol. 173, no. 2000, pp. 207-173.

McCreary, LL, Conrad, KM, Conrad, KJ, Scott, CK, Funk, RR & Dennis, ML 2013, 'Using the Rasch measurement model in psychometric analysis of the Family Effectiveness Measure', *Nursing research*, vol. 62, no. 3, pp. 149-59.

Meijer, RR 2002, 'Outlier Detection in High-Stakes Certification Testing', *Journal of Educational Measurement*, vol. 39, no. 3, pp. 219-33.

Merkus, J, Helms, R & Kusters, R 2020, *Reference Model for Generic Capabilities in Maturity Models*.

Meyer, JP 2014, *Applied measurement with jMetrik*, Routledge, New York; London.

Mezmir, EA 2020, 'Qualitative data analysis: An overview of data reduction, data display, and interpretation', *Research on humanities and social sciences*, vol. 10, no. 21, pp. 15-27.

Mikalef, P, Boura, M, Lekakos, G & Krogstie, J 2019, 'Big data analytics and firm performance: Findings from a mixed-method approach', *Journal of Business Research*, vol. 98, pp. 261-76.

Mittal, P 2020, 'Impact of Digital Capabilities and Technology Skills on Effectiveness of Government in Public Services', *2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)*, pp. 1-5.

Monkwe, F & Prinsloo, T 2016, 'Assessing the correlation between ERP system implementation and business process maturity', *CONF-IRM*, p. 61.

Müller, M 2020, 'Item fit statistics for Rasch analysis: can we trust them?', *Journal of Statistical Distributions and Applications*, vol. 7, no. 1, p. 5.

Muntean, M, Bologa, A-R, Corbea, AMI & Bologa, R 2019, 'A Framework for Evaluating the Business Analytics Maturity of University Programmes', *Sustainability (Basel, Switzerland)*, vol. 11, no. 3, p. 853.

Myers, MD 2019, *Qualitative research in business and management*, Sage, Los Angeles.

Nah, F & Delgado, S 2006, 'Critical success factors for enterprise resource planning implementation and upgrade', *Journal of Computer Information Systems*, vol. 46.

Nah, FFH, Lau, JLS & Kuang, J 2001, 'Critical factors for successful implementation of enterprise systems', *Business Process Management Journal*.

Negash, S 2004, 'Business Intelligence', *Communications of the Association of Information Systems*, vol. 13, pp. 177–95.

Ngai, EWT, Law, CCH & Wat, FKT 2008, 'Examining the critical success factors in the adoption of enterprise resource planning', *Computers in Industry*, vol. 59, no. 6, pp. 548-64.

Nofal, MI & Yusof, ZM 2013, 'Integration of Business Intelligence and Enterprise Resource Planning within Organizations', *Procedia Technology*, vol. 11, pp. 658-65.

Nour, M 2023, 'The Impact of ERP Systems on Organizational Performance: The Role of Antecedents and Moderators', *International journal of enterprise information systems*, vol. 19, pp. 1-29.

Nunnally, JC & Bernstein, IH 1994, *Psychometric theory*, McGraw-Hill, New York.

O'Neill, M & Brabazon, A 2019, 'Business analytics capability, organisational value and competitive advantage', *Journal of Business Analytics*, vol. 2, no. 2, pp. 160-73.

Obaid, T & Abu-Naser, SS 2023, 'Big Data Analytics in Project Management: A Key to Success'.

Oh, M & Choi, S 2020, 'The Competence of Project Team Members and Success Factors with Open Innovation', *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, p. 51.

Olaoye, G & Samon, D 2024, 'Role of Enterprise Resource Planning (ERP) in Digital Transformation'.

Olszak, CM & Mach-Król, M 2018, 'A conceptual framework for assessing an organization's readiness to adopt big data', *Sustainability*, vol. 10, no. 10, p. 3734.

Pancić, M, Ćućić, D & Serdarušić, H 2023, 'Business intelligence (BI) in firm performance: Role of big data analytics and blockchain technology', *Economies*, vol. 11, no. 3, p. 99.

Park, JH, Suh, HJ & Yang, HD 2007, 'Perceived absorptive capacity of individual users in performance of Enterprise Resource Planning (ERP) usage: The case for Korean firms', *Information & Management*, vol. 44, no. 3, pp. 300-12.

Park, YS, Konge, L & Artino, ARJ 2020, 'The Positivism Paradigm of Research', *Academic medicine*, vol. 95, no. 5, pp. 690-4.

Park, YS, Konge, L & Artino Jr, AR 2020, 'The positivism paradigm of research', *Academic medicine*, vol. 95, no. 5, pp. 690-4.

Parthasarathy, S & Ramachandran, M 2008, 'Requirements Engineering Method and Maturity Model for ERP Projects', *International journal of enterprise information systems*, vol. 4, no. 4, pp. 1-14.

Paulk, MC, Curtis, B, Chrissis, MB & Weber, CV 1993, 'Capability maturity model, version 1.1', *IEEE software*, vol. 10, no. 4, pp. 18-27.

Paulk, MC, Weber, CV, Curtis, B & Chrissis, MB 1995, *The Capability maturity model : guidelines for improving the software process*, Addison-Wesley Pub. Co., Reading, Mass.

Peter, C, Schulenberg, S, Buchanan, E, Prodinger, B & Geyh, S 2016, 'Rasch analysis of measurement instruments capturing psychological personal factors in persons with spinal cord injury', *Journal of Rehabilitation Medicine*, vol. 48, pp. 175-88.

Popoola, OA, Adama, HE, Okeke, CD & Akinoso, AE 2024, 'The strategic value of business analysts in enhancing organizational efficiency and operations', *International Journal of Management & Entrepreneurship Research*, vol. 6, no. 4, pp. 1288-303.

Ptak, CA & Schragenheim, E 2004, *ERP: tools, techniques, and applications for integrating the supply chain*, 2nd edn, Crc Press.

Pulkkinen, A, Anttila, J-P & Leino, S-P 2019, 'Assessing the maturity and benefits of digital extended enterprise', *Procedia Manufacturing*, vol. 38, pp. 1417-26.

Purcell, B 2012, 'Emergence of "Big Data" technology and analytics', *Journal of Technology Research*, vol. 4.

Putri, A, Lubis, M & Azizah, A 2020, *Analysis of Critical Success Factors (CSF) in Enterprise Resource Planning (ERP) Implementation using Extended Technology Acceptance Model (TAM) at Trading and Distribution Company*.

Rabaa'i, A 2021, 'Students' Continuance Intention to Use Moodle: An Expectation-Confirmation Model Approach', *Interdisciplinary Journal of Information, Knowledge, and Management*, vol. 16, pp. 397-434.

Raber, D, Winter, R & Wortmann, F 2012, 'Using quantitative analyses to construct a capability maturity model for business intelligence', *2012 45th Hawaii International Conference on System Sciences*, IEEE, pp. 4219-28.

Raber, D, Wortmann, F & Winter, R 2013a, 'Situational Business Intelligence Maturity Models: An Exploratory Analysis', *System Sciences (HICSS), 2013 46th Hawaii International Conference on System Sciences*, pp. 3797-806.

Raber, D, Wortmann, F & Winter, R 2013b, 'Towards The Measurement Of Business Intelligence Maturity', *ECIS 2013 Completed Research. 95*, p. 95, <https://aisel.aisnet.org/ecis2013_cr/95>.

Rafael, LD, Jaione, GE, Cristina, L & Ibon, SL 2020, 'An Industry 4.0 maturity model for machine tool companies', *Technological Forecasting and Social Change*, vol. 159, p. 120203.

Rajan, CA & Baral, R 2015, 'Adoption of ERP system: An empirical study of factors influencing the usage of ERP and its impact on end user', *IIMB Management Review*, vol. 27, no. 2, pp. 105-17.

Rajterič, IH 2010, 'Overview of Business Intelligence maturity Models', *Management*, vol. 15, no. 1, pp. 47-67.

Ram, J & Corkindale, D 2014, 'How "critical" are the critical success factors (CSFs)?: Examining the role of CSFs for ERP', *Business Process Management Journal*, vol. 20, no. 1, pp. 151-74.

Ray, S & Ramakrishnan, K 2006, 'Resources, Competences and Capabilities Conundrum: A Back-To-Basics Call', *Decision (0304-0941)*, vol. 33, no. 2.

Raykov, T & Marcoulides, GA 2011, *Introduction to psychometric theory*, Routledge.

Reise, SP & Revicki, DA 2014, *Handbook of item response theory modeling*, Taylor & Francis New York, NY.

Ribeiro, J, Lima, R, Eckhardt, T & Paiva, S 2021, 'Robotic Process Automation and Artificial Intelligence in Industry 4.0–A Literature review', *Procedia Computer Science*, vol. 181, pp. 51-8.

Ridder, A-K 2012, 'External dynamic capabilities: creating competitive advantage in innovation via external resource renewal', *Academy Management Proceeding*, pp. 1-48.

Ringle, CM, Wende, S & Becker, J-M 2015, *SmartPLS 3*, Bönningstedt: SmartPLS, http://www.smartpls.com >.

Rios, JA & Soland, J 2021, 'Parameter estimation accuracy of the Effort-Moderated Item Response Theory Model under multiple assumption violations', *Educational and Psychological Measurement*, vol. 81, no. 3, pp. 569-94.

Rockart, JF 1979, 'Chief executives define their own data needs', *Harvard Business Review*, vol. 57, no. 2, pp. 81-93.

Rockwell Automation 2014, *The Connected Enterprise Maturity Model*, https://literature.rockwellautomation.com/idc/groups/literature/documents/wp/cie-wp002_-en-p.pdf>.

Rogers, EM 2003, *Diffusion of innovations*, 5th ed. edn, Free Press, New York.

Röglinger, M, Pöppelbuß, J & Becker, J 2012, 'Maturity models in business process management', *Business Process Management Journal*, vol. 18, no. 2, pp. 328-46.

Romero, JA & Abad, C 2022, 'Cloud-based big data analytics integration with ERP platforms', *Management Decision*, vol. 60, no. 12, pp. 3416-37.

Rouhani, S & Ravasan, AZ 2013, 'ERP success prediction: An artificial neural network approach', *Scientia Iranica, Transactions E: Industrial Engineering*, vol. 20, no. 3, pp. 992–1001.

Rouhani, S & Mehri, M 2016, 'Does ERP have benefits on the business intelligence readiness? An empirical study', vol. 8, pp. 81-105.

Rusticus, S 2014, 'Content validity', *Encyclopedia of quality of life and well-being research*, vol. 1261.

Ryan, WG, Fenton, A, Ahmed, W & Scarf, P 2020, 'Recognizing events 4.0: The digital maturity of events', *International Journal of Event and Festival Management*, vol. 11, no. 1, pp. 47-68.

Sabherwal, R & Chan, YE 2001, 'Alignment between business and IS strategies: A study of prospectors, analyzers, and defenders', *Information Systems Research*, vol. 12, no. 1, pp. 11-33.

Salih, S, Hamdan, M, Abdelmaboud, A, Abdelaziz, A, Abdelsalam, S, Althobaiti, MM, Cheikhrouhou, O, Hamam, H & Alotaibi, F 2021, 'Prioritising organisational factors impacting cloud ERP adoption and the critical issues related to security, usability, and vendors: A systematic literature review', *Sensors*, vol. 21, no. 24, p. 8391.

Sarker, IH 2021, 'Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective', *SN Computer Science*, vol. 2, no. 5, p. 377.

Schniederjans, D & Yadav, S 2013, 'Successful ERP implementation: An integrative model', *Business Process Management Journal*, vol. 19, no. 2, pp. 364-98.

Schniederjans, MJ, Schniederjans, DG & Starkey, CM 2014, *Business Analytics Principles, Concepts, and Applications: What, Why, and How*, Pearson, New Jersey.

Schumacher, A, Erol, S & Sihn, W 2016, 'A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises', *Procedia CIRP*, vol. 52, pp. 161-6.

Schwade, F & Schubert, P 2017, 'Social collaboration analytics for enterprise collaboration systems: Providing business intelligence on collaboration activities'.

Seal, KC, Leon, LA, Przasnyski, ZH & Lontok, G 2020, 'Delivering business analytics competencies and skills: A supply side assessment', *INFORMS Journal on Applied Analytics*, vol. 50, no. 4, pp. 239-54.

Seamon, BA, Kautz, SA & Velozo, CA 2019, 'Rasch analysis of the Activities-Specific Balance Confidence Scale in individuals poststroke', *Archives of rehabilitation research and clinical translation*, vol. 1, no. 3-4, p. 100028.

Senna, PP, Barros, AC, Roca, JB & Azevedo, A 2023, 'Development of a digital maturity model for Industry 4.0 based on the technology-organization-environment framework', *Computers & Industrial Engineering*, vol. 185, p. 109645.

Shatat, AS & Dana, N 2016, 'Critical success factors across the stages of ERP system implementation in Sohar University: A case study', *International journal of management and applied research*, vol. 3, no. 1, pp. 30-47.

Shaul, L & Tauber, D 2013, 'Critical success factors in enterprise resource planning systems: Review of the last decade', *ACM Comput. Surv.*, vol. 45, no. 4, p. Article 55.

Shen, Y-C, Chen, P-S & Wang, C-H 2016, 'A study of enterprise resource planning (ERP) system performance measurement using the quantitative balanced scorecard approach', *Computers in Industry*, vol. 75, pp. 127-39.

Shi, Z & Wang, G 2018, 'Integration of big-data ERP and business analytics (BA)', *Journal of high technology management research*, vol. 29, no. 2, pp. 141-50.

Snabe, JH, Rosenberg, A, Møller, C & Scavillo, M 2008, *Business process management: The sap roadmap*, Galileo Press.

Spanos, Y & Prastacos, G 2004, 'Understanding Organizational Capabilities: Towards a Conceptual Framework', *J. Knowledge Management*, vol. 8, pp. 31-43.

Srivastava, G, Venkataraman, R, V, K & N, P 2022, 'A review of the state of the art in business intelligence software', *Enterprise Information Systems*, vol. 16, no. 1, pp. 1-28.

Stemler, SE & Naples, A 2021, 'Rasch measurement v. Item response theory: knowing when to cross the line', *Practical Assessment, Research & Evaluation*, vol. 26, p. 11.

Strauss, ME & Smith, GT 2009, 'Construct validity: Advances in theory and methodology', *Annual review of clinical psychology*, vol. 5, pp. 1-25.

Streukens, S & Leroi-Werelds, S 2016, 'Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results', *European Management Journal*, vol. 34, no. 6, pp. 618-32.

Subramaniam, SAP, Salamzadeh, Y & Mujtaba, BG 2023, 'The Mediating Role of Dynamic Capability on the Relationship between E-Leadership Qualities and

Innovation Management: Insights from Malaysia’s Medical Device Industry', *Sustainability*, vol. 15, no. 24, p. 16778.

Sudweeks, RR, Reeve, S & Bradshaw, WS 2004, 'A comparison of generalizability theory and many-facet Rasch measurement in an analysis of college sophomore writing', *Assessing Writing*, vol. 9, no. 3, pp. 239-61.

Tarhan, A, Turetken, O & Reijers, HA 2016, 'Business process maturity models: A systematic literature review', *Information and Software Technology*, vol. 75, pp. 122-34.

Tavakol, M & Dennick, R 2013, 'Psychometric evaluation of a knowledge based examination using Rasch analysis: An illustrative guide: AMEE Guide No. 72', *Medical teacher*, vol. 35, no. 1, pp. e838-e48.

Teah, HY, Pee, LG & KANKANHALLi, A 2006, 'Development and application of a general knowledge management maturity model', *PACIS 2006 Proceedings*, p. 12.

Templier, M & Pare, G 2018, 'Transparency in literature reviews: an assessment of reporting practices across review types and genres in top IS journals', *European Journal of Information Systems*, vol. 27, no. 5, pp. 503-50.

Tennant, A & Küçükdeveci, AA 2023, 'Application of the Rasch measurement model in rehabilitation research and practice: Early developments, current practice, and future challenges', *Frontiers in Rehabilitation Sciences*, vol. 4.

Tesio, L, Caronni, A, Kumbhare, D & Scarano, S 2024, 'Interpreting results from Rasch analysis 1. The “most likely” measures coming from the model', *Disability and Rehabilitation*, vol. 46, no. 3, pp. 591-603.

Thamir, A & Theodoulidis, B 2013, 'Business Intelligence Maturity Models: Information Management Perspective', *Information and Software Technologies*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 198-221.

Thanh, NC & Thanh, T 2015, 'The interconnection between interpretivist paradigm and qualitative methods in education', *American journal of educational science*, vol. 1, no. 2, pp. 24-7.

The Institute for Operations Research and the Management Sciences 2017, *INFORMS Analytics Maturity Model User Guide*, viewed 17 Oct 2017, <https://analyticsmaturity.informs.org/AMMUserGuide.php>.

Tibshirani, RJ & Efron, B 1993, 'An introduction to the bootstrap', *Monographs on statistics and applied probability*, vol. 57, no. 1, pp. 1-436.

Tipton, E, Hallberg, K, Hedges, L & Chan, W 2016, 'Implications of Small Samples for Generalization: Adjustments and Rules of Thumb', *Evaluation Review*, vol. 41.

Tladi, LS 2017, 'Perceived ability and success: which self-efficacy measures matter? A distance learning perspective', *Open Learning: The Journal of Open, Distance and e-Learning*, vol. 32, no. 3, pp. 243-61.

Tripathi, A, Bagga, T & Aggarwal, R 2020, 'Strategic Impact of Business Intelligence : A Review of Literature', *Prabandhan: Indian Journal of Management*, vol. 13, p. 35.

Trkman, P, McCormack, K, de Oliveira, MPV & Ladeira, MB 2010, 'The impact of business analytics on supply chain performance', *Decision Support Systems*, vol. 49, no. 3, pp. 318-27.

Ulrich, D & Smallwood, N 2004, 'Capitalizing on capabilities', *Harvard Business Review*, pp. 119-28.

Valentin, JB, Mainz, J, Johnsen, SP, Kristensen, K & Kristensen, S 2024, 'Rasch analysis of a patient-reported outcome measure for self-perceived health among psychiatric patients in Denmark', *BMJ Open Quality*, vol. 13, no. 1, p. e002519.

Van der Linden, WJ & Hambleton, R 1997, 'Handbook of item response theory', *Taylor & Francis Group. Citado na pág*, vol. 1, no. 7, p. 8.

van Hillegersberg, J 2019, 'The Need for a Maturity Model for Maturity Modeling', in *The Art of Structuring*, Springer, pp. 145-51.

Van Steenbergen, M, Bos, R, Brinkkemper, S, Van De Weerd, I & Bekkers, W 2010, 'The design of focus area maturity models', *International Conference on Design Science Research in Information Systems*, Springer, pp. 317-32.

Van Steenbergen, M, Bos, R, Brinkkemper, S, Van de Weerd, I & Bekkers, W 2013, 'Improving IS Functions Step by Step: The use of focus area maturity models', *Scandinavian Journal of Information Systems*, vol. 25, pp. 35-56.

Venkatesh, V, Morris, MG, Davis, GB & Davis, FD 2003, 'User Acceptance of Information Technology: Toward a Unified View', *MIS Quarterly*, vol. 27, no. 3, pp. 425-78.

Venturini, S & Mehmetoglu, M 2019, 'plssem: A Stata Package for Structural Equation Modeling with Partial Least Squares', *Journal of Statistical Software*, vol. 88.

Vishnubhotla, S, Mendes, E & Lundberg, L 2021, *Understanding the Perceived Relevance of Capability Measures: A Survey of Agile Software Development Practitioners*.

Wagire, AA, Joshi, R, Rathore, APS & Jain, R 2021, 'Development of maturity model for assessing the implementation of Industry 4.0: learning from theory and practice', *Production Planning & Control*, vol. 32, no. 8, pp. 603-22.

Wang, CH 2016, 'A novel approach to conduct the importance-satisfaction analysis for acquiring typical user groups in business-intelligence systems', *Computers in Human Behavior*, vol. 54, pp. 673-81.

Wang, Y, Kung, L & Byrd, TA 2018, 'Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations', *Technological Forecasting and Social Change*, vol. 126, pp. 3-13.

Warner, KS & Wäger, M 2019, 'Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal', *Long range planning*, vol. 52, no. 3, pp. 326-49.

Weise, A, Büchter, R, Pieper, D & Mathes, T 2020, 'Assessing context suitability (generalizability, external validity, applicability or transferability) of findings in evidence syntheses in healthcare—An integrative review of methodological guidance', *Research Synthesis Methods*, vol. 11, no. 6, pp. 760-79.

Wendler, R 2012, 'The maturity of maturity model research: A systematic mapping study', *Information and Software Technology*, vol. 54, no. 12, pp. 1317-39.

Wendt, H, Bos, W & Goy, M 2011, 'On applications of Rasch models in international comparative large-scale assessments: A historical review', *Educational Research and Evaluation*, vol. 17, no. 6, pp. 419-46.

Wilson, M 2005, *Constructing measures: An item response modeling approach*, Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US.

Wixom, BH & Todd, PA 2005, 'A theoretical integration of user satisfaction and technology acceptance', *Information Systems Research*, vol. 16, no. 1, pp. 85-102.

Wong, WYF & Lane, M 2023, 'Critical Success Factors Classification Framework for Measuring Maturity of Organisations using New Generation ERP Systems: A Systematic Literature Review', *Forty-Fourth International Conference on Information Systems*: *Proceedings of the Forty-Fourth International Conference on Information Systems* Hyderabad, India.

Wong, WYF, Lane, M & Cockcroft, S 2021, 'Systematic review of methodological approaches for designing, assessing and validating business analytics maturity models', *International Conference on Information Resources Management*: *Proceedings of the International Conference on Information Resources Management* Johannes Kepler University Linz, Austria.

Wright, B & Linacre, J 1989, 'Observations are always ordinal; measurements, however, must be interval', *Archives of physical medicine and rehabilitation*, vol. 70, pp. 857-60.

Wright, BD 1977, 'Solving measurement problems with the Rasch model', *Journal of Educational Measurement*, pp. 97-116.

Yahaya, J, Abai, NHZ, Deraman, A & Jusoh, YY 2019, 'The implementation of business intelligence and analytics integration for organizational performance management: A case study in public sector', *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 11, pp. 292-9.

Yeoh, W & Koronios, A 2010, 'Critical success factors for business intelligence systems', *Journal of Computer Information Systems*, vol. 50, no. 3, pp. 23-32.

Yu, CH 2020, 'Objective Measurement: How Rasch Modeling Can Simplify and Enhance Your Assessment', in MS Khine (ed.), *Rasch Measurement: Applications in Quantitative Educational Research*, Springer Singapore, Singapore, pp. 47-73.

Yuan, Z, Xiao, Y, Dai, Z, Huang, J, Zhang, Z & Chen, Y 2020, 'Modelling the effects of Wuhan's lockdown during COVID-19, China', *Bulletin of the World Health Organization*, vol. 98, no. 7, p. 484.

Zeba, G, Lucić, J & Čičak, M 2019, 'ERP systems in croatian enterprises and industry 4.0', *Industry 4.0*, vol. 4, no. 6, pp. 313-6.

Zhang, B, Cao, M, Tay, L, Luo, J & Drasgow, F 2020, 'Examining the item response process to personality measures in high-stakes situations: Issues of measurement validity and predictive validity', *Personnel Psychology*, vol. 73, no. 2, pp. 305-32.

APPENDIX A: ETHICS DOCUMENTS

A-1 ETHICS APPROVAL FOR THE QUESTIONNAIRE SURVEY

OFFICE OF RESEARCH
Human Research Ethics Committee
PHONE +61 7 4687 5703| FAX +61 7 4631 5555
EMAIL ethics@usq.edu.au

UNIVERSITY OF SOUTHERN QUEENSLAND AUSTRALIA

9 December 2016

Mr Freddy Wong
Flat D, 2/F, Tower 1
Dragons Range Court B
33 Lai Ping Road
Shatin NT
Hong Kong

Dear Freddy

The USQ Human Research Ethics Committee has recently reviewed your responses to the conditions placed upon the ethical approval for the project outlined below. Your proposal is now deemed to meet the requirements of the *National Statement on Ethical Conduct in Human Research (2007)* and full ethical approval has been granted.

Approval No.	**H16REA180**
Project Title	A maturiy model for evaluating business analytics implementations in ERP systems: An empirical study of Greater China region
Approval date	9 December 2016
Expiry date	9 December 2019
HREC Decision	**Approved**

The standard conditions of this approval are:

(a) conduct the project strictly in accordance with the proposal submitted and granted ethics approval, including any amendments made to the proposal required by the HREC
(b) advise (email: ethics@usq.edu.au) immediately of any complaints or other issues in relation to the project which may warrant review of the ethical approval of the project
(c) make submission for approval of amendments to the approved project before implementing such changes
(d) provide a 'progress report' for every year of approval
(e) provide a 'final report' when the project is complete

(f) advise in writing if the project has been discontinued, using a 'final report'

For (c) to (f) forms are available on the USQ ethics website:
http://www.usq.edu.au/research/support-development/research-services/research-integrity-ethics/human/forms

Please note that failure to comply with the conditions of approval and the *National Statement (2007)* may result in withdrawal of approval for the project.

You may now commence your project. I wish you all the best for the conduct of the project.

[redacted]
Ethics Officer

Copies to: wywong@vtc.edu.hk

A-2 ETHICS RENEWAL APPROVAL (V1) FOR THE QUESTIONNAIRE SURVEY

UniSQ

Freddy Wong <u1065347@umail.usq.edu.au>

[RIMS] USQ HRE Amendment - H16REA180 (v1) - Expedited review outcome - Approved
2 messages

human.ethics@usq.edu.au <human.ethics@usq.edu.au> Wed, Jan 22, 2020 at 9:27 AM

[redacted]

Dear Freddy

The revisions outlined in your HRE Amendment have been deemed by the USQ Human Research Ethics Expedited Review process to meet the requirements of the National Statement on Ethical Conduct in Human Research (2007). Your project is now granted full ethical approval as follows.

USQ HREC ID: H16REA180 (v1)
Project title: A maturity model for evaluating business analytics utilisation in ERP systems: An empirical study of the Greater China Region
Approval date: 22/01/2020
Expiry date: 31/12/2020
Project status: Approved with conditions.

The standard conditions of this approval are:

(a) conduct the project strictly in accordance with the proposal submitted and ethics approval, including any amendments made to the proposal required by the USQ HREC, or affiliated University ethical review processes;

(b) advise the USQ HREC (via human.ethics@usq.edu.au) immediately of any complaint or other issue in relation to the conduct of this project which may warrant review of the ethical approval of the project;

(c) make submission for ethical review and approval of any amendments or revision to the approved project prior to implementing any changes;

(d) complete and submit a milestone (progress) report as requested, and at least for every year of approval; and

(e) complete and submit a milestone (final) report when the project does not commence within the first 12 months of approval, is abandoned at any stage, or is completed (whichever is sooner).

Additional conditions of this approval are:

(a)

Failure to comply with the conditions of approval or the requirements of the National Statement on Ethical Conduct in Human Research (2007) may result in withdrawal of ethical approval for this project.

If you have any questions or concerns, please contact an Ethics Officer.

Kind regards

Human Research Ethics

University of Southern Queensland
Toowoomba – Queensland – 4350 – Australia
Phone: (07) 4631 2690
Email: human.ethics@usq.edu.au

Freddy Wong <u1065347@umail.usq.edu.au> Tue, Jan 28, 2020 at 4:58 AM
To: WONG WAI YIP FREDDY <wywong@vic.edu.hk>, freddy wong <wyfwong@gmail.com>

[Quoted text hidden]

A-3 ETHICS RENEWAL APPROVAL (V2) FOR THE QUESTIONNAIRE SURVEY

UniSQ

Freddy Wong <u1065347@umail.usq.edu.au>

[RIMS] USQ HRE Amendment - H16REA180 (v2) - Expedited review outcome - Approved

1 message

human.ethics@usq.edu.au <human.ethics@usq.edu.au> Mon, Dec 14, 2020 at 1:40 PM

[redacted]

Dear Freddy

The revisions outlined in your HRE Amendment have been deemed by the USQ Human Research Ethics Expedited Review process to meet the requirements of the National Statement on Ethical Conduct in Human Research (2007). Your project is now granted full ethical approval as follows.

USQ HREC ID: H16REA180 (v2)
Project title: A maturity model for evaluating business analytics utilisation in ERP systems: An empirical study of the Greater China Region
Approval date: 14/12/2020
Expiry date: 29/10/2021
Project status: Approved with conditions.

The standard conditions of this approval are:

(a) conduct the project strictly in accordance with the proposal submitted and ethics approval, including any amendments made to the proposal required by the USQ HREC, or affiliated University ethical review processes;

(b) advise the USQ HREC (via human.ethics@usq.edu.au) immediately of any complaint or other issue in relation to the conduct of this project which may warrant review of the ethical approval of the project;

(c) make submission for ethical review and approval of any amendments or revision to the approved project prior to implementing any changes;

(d) complete and submit a milestone (progress) report as requested, and at least for every year of approval; and

(e) complete and submit a milestone (final) report when the project does not commence within the first 12 months of approval, is abandoned at any stage, or is completed (whichever is sooner).

Additional conditions of this approval are:

(a)

Failure to comply with the conditions of approval or the requirements of the National Statement on Ethical Conduct in Human Research (2007) may result in withdrawal of ethical approval for this project.

If you have any questions or concerns, please contact an Ethics Officer.

Kind regards

Human Research Ethics

University of Southern Queensland
Toowoomba – Queensland – 4350 – Australia
Phone: (07) 4631 2690
Email: human.ethics@usq.edu.au

A-4 ETHICS RENEWAL APPROVAL (V3) FOR THE QUESTIONNAIRE SURVEY

UniSQ

Freddy Wong <u1065347@umail.usq.edu.au>

[RIMS] USQ HRE Amendment - H16REA180 (v3) - Expedited review outcome - Approved

Human Ethics <Human.Ethics@usq.edu.au> Thu, Nov 4, 2021 at 9:33 AM
To: Human Ethics <Human.Ethics@usq.edu.au>, [redacted]
Cc: Michael Lan[redacted]

Dear Freddy

The revisions outlined in your HRE Amendment have been deemed by the USQ Human Research Ethics Expedited Review process to meet the requirements of the National Statement on Ethical Conduct in Human Research (2007). Your project is now granted full ethical approval as follows.

USQ HREC ID: H16REA180 (v3)
Project title: A maturity model for evaluating business analytics utilisation in ERP systems: An empirical study of the Greater China Region
Approval date: 03/11/2021
Expiry date: 18/03/2022
Project status: Approved with conditions.

The standard conditions of this approval are:

(a) conduct the project strictly in accordance with the proposal submitted and ethics approval, including any amendments made to the proposal required by the USQ HREC, or affiliated University ethical review processes;

(b) advise the USQ HREC (via human.ethics@usq.edu.au) immediately of any complaint or other issue in relation to the conduct of this project which may warrant review of the ethical approval of the project;

(c) make submission for ethical review and approval of any amendments or revision to the approved project prior to implementing any changes;

(d) complete and submit a milestone (progress) report as requested, and at least for every year of approval; and

(e) complete and submit a milestone (final) report when the project does not commence within the first 12 months of approval, is abandoned at any stage, or is completed (whichever is sooner).

Additional conditions of this approval are:

(a)

Failure to comply with the conditions of approval or the requirements of the National Statement on Ethical Conduct in Human Research (2007) may result in withdrawal of ethical approval for this project.

If you have any questions or concerns, please contact an Ethics Officer.

Kind regards

Human Research Ethics

University of Southern Queensland
Toowoomba – Queensland – 4350 – Australia
Email: human.ethics@usq.edu.au

A-5 SURVEY 1 PARTICIPANT INFORMATION SHEET

University of Southern Queensland

Participant Information for USQ Research Project Questionnaire

Project Details	
Title of Project:	A maturity model for evaluating Business Analytics implementations in ERP systems: An Empirical Study of Greater China Region
Human Research Ethics Approval Number:	H16REA180

Research Team Contact Details

Principal Investigator Details

Ir Freddy Wong
PhD Research Student, School of Commerce,
University of Southern Queensland
[redacted]

Supervisor Details

Dr. Albert SCOTT
[redacted]

Dr. Michael LANE
[redacted]

Description

This project is being undertaken as part of a PhD research.

The purpose of this project is to examine the critical success factors of successful Enterprise Resource Planning (ERP) and Business Analytics (BA) implementation and to explore the impact of ERP and Business Analytics on technological, operational, managerial and strategic performance measures.

The research team requests your assistance because you have valuable experience in the ERP and Business Analytics implementation in your organisation which is important to the data collection for this research.

Participation

Your participation will involve completion of a questionnaire that will take approximately 20 minutes of your time.

Questions will include questions of the overall experience by giving an appropriate score for the question that you will be asking.

Your participation in this project is entirely voluntary. If you do not wish to take part you are not obliged to. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. Please note, that if you wish to withdraw from the project after you have submitted your responses, the Research Team are unable to remove your data from the project (unless identifiable information has been collected). If you do wish to withdraw from this project, please contact the Research Team (contact details at the top of this form).

Your decision whether you take part, do not take part, or to take part and then withdraw, will in no way impact your current or future relationship with the University of Southern Queensland.

Expected Benefits

It is expected that this project will directly benefit you because you can have an initial self-evaluation of the ERP Business Analytics practices of your organization which will act as a baseline for further improvement.

At the end of the survey, you will be given a Web Page address so that you can access a summary of the research results. You can also opt for receiving the research results by sending the investigator an email requesting this.

Risks

There are low anticipated risks beyond the time it will take to complete the survey associated with your participation in this project.

Privacy and Confidentiality

All comments and responses will be treated confidentially unless required by law.

The names of individual persons are not required in any of the responses.

Any data collected as a part of this project will be stored securely as per University of Southern Queensland's Research Data Management policy.

Data may be used for future studies as per University of Southern Queensland's Research Data Management policy.

Consent to Participate

Either the return of the completed questionnaire or clicking on the 'Submit' button at the conclusion of the questionnaire is accepted as an indication of your consent to participate in this project.

Questions or Further Information about the Project

Please refer to the Research Team Contact Details at the top of the form to have any questions answered or to request further information about this project.

Concerns or Complaints Regarding the Conduct of the Project

If you have any concerns or complaints about the ethical conduct of the project you may contact the University of Southern Queensland Ethics Coordinator on (07) 4631 2690 or email ethics@usq.edu.au. The Ethics Coordinator is not connected with the research project and can facilitate a resolution to your concern in an unbiased manner.

Thank you for taking the time to help with this research project. Please keep this sheet for your information.

A-6 SURVEY 2 PARTICIPANT INFORMATION SHEET

UNIVERSITY OF SOUTHERN QUEENSLAND AUSTRALIA

University of Southern Queensland

Participant Information for USQ Research Project Questionnaire

Project Details

Title of Project:	A maturity model for evaluating Business Analytics implementations in ERP systems: An Empirical Study of Greater China Region (Second Survey)
Human Research Ethics Approval Number:	H16REA180

Research Team Contact Details

Principal Investigator Details

Ir Freddy Wong
PhD Research Student, School of Commerce,
University of Southern Queensland
[redacted]

Supervisor Details

Dr. Albert SCOTT
[redacted]

Dr. Michael LANE
[redacted]

Description

This project is being undertaken as part of a PhD research.

The purpose of this project is to examine the critical success factors of successful Enterprise Resource Planning (ERP) and Business Analytics (BA) implementation and to explore the impact of ERP and Business Analytics on technological, operational, managerial and strategic performance measures.

The research team requests your assistance because you have valuable experience in the ERP and Business Analytics implementation in your organisation which is important to the data collection for this research.

Participation

For new participants, your participation will involve completion of both Part A and B of the questionnaire that will take approximately 30 minutes of your time.

For participants who have participated in the First Survey, your participation will involve completion of only Part B of the questionnaire that will take approximately 10 minutes of your time.

Questions will include questions of the overall experience by giving an appropriate score for the question that you will be asking.

Your participation in this project is entirely voluntary. If you do not wish to take part you are not obliged to. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. Please note, that if you wish to withdraw from the project after you have submitted your responses, the Research Team are unable to remove your data from the project (unless identifiable information has been collected). If you do wish to withdraw from this project, please contact the Research Team (contact details at the top of this form).

Your decision whether you take part, do not take part, or to take part and then withdraw, will in no way impact your current or future relationship with the University of Southern Queensland.

Expected Benefits

It is expected that this project will directly benefit you because you can have an initial self-evaluation of the ERP Business Analytics practices of your organization which will act as a baseline for further improvement.
At the end of the survey, you will be given a Web Page address so that you can access a summary of the research results. You can also opt for receiving the research results by sending the investigator an email requesting this.

Risks

There are low anticipated risks beyond the time it will take to complete the survey associated with your participation in this project.

Privacy and Confidentiality

All comments and responses will be treated confidentially unless required by law.
The names of individual persons are not required in any of the responses.
Any data collected as a part of this project will be stored securely as per University of Southern Queensland's Research Data Management policy.
Data may be used for future studies as per University of Southern Queensland's Research Data Management policy.

Consent to Participate

Either the return of the completed questionnaire or clicking on the 'Submit' button at the conclusion of the questionnaire is accepted as an indication of your consent to participate in this project.

Questions or Further Information about the Project

Please refer to the Research Team Contact Details at the top of the form to have any questions answered or to request further information about this project.

Concerns or Complaints Regarding the Conduct of the Project

If you have any concerns or complaints about the ethical conduct of the project you may contact the University of Southern Queensland Ethics Coordinator on (07) 4631 2690 or email ethics@usq.edu.au. The Ethics Coordinator is not connected with the research project and can facilitate a resolution to your concern in an unbiased manner.

Thank you for taking the time to help with this research project. Please keep this sheet for your information.

APPENDIX B: SURVEY QUESTIONNAIRES

B-1 SURVEY 1 RESEARCH QUESTIONNAIRES

Survey 1 Research Questionnaire

Survey 1 Research Questionnaire

*Required

Demographics

1. **(LOCATION) What is the location of your organisation? ***
   - Taiwan
   - Hong Kong
   - Macau
   - China (Please specify the city/district/province):

2. **(TYPE) What type of business organisation does your organisation belong to? ***
   - Domestic Private Enterprises
   - Foreign Invested Companies
   - State-Owned Enterprises
   - Other:

3. **(INDUSTRY) What is your organisation's industry? ***
   - Manufacturing
   - Information technology/Telecommunications
   - Logistics/Courier services
   - Governmental agencies/Nonprofits
   - Financial
   - Utilities
   - Wholesale/Retail
   - Other:

About yourself

4. (POSITION) What is your position in the organisation?
   - IT senior management
   - IT middle management
   - Non-IT senior management
   - Non-IT middle management
   - Other:

5. (INTERACTION) What is your role involved in the use of Business Analytics in your ERP system?
   - User of Business Analytics in the ERP system
   - Developer of Business Analytics in the ERP system
   - Administrator of Business Analytics in the ERP system
   - Other:

Page **1** of **7**

General ERP Business Analytics questions

6. (MATURITY) What is the usage of ERP Business Analytics (BA) in your organisation? *

- Focused on data collection and data organisation having the beginning of a BA system in place
- Requirements are driven from a limited executive group
- KPI's and analytics are identified, but not well used
- KPI's and analytics are identified and effectively used
- KPI's and analytics are used to manage the full value chain

7. (STRATEGY) What was your ERP and Business Analytics implementation strategy? *

- No ERP system implemented but Business Analytics Tools were used to analyse enterprise data
- Single ERP package without Business Analytics features
- Single ERP package with Business Analytics features
- Multiple ERP packages without Business Analytics features
- Multiple ERP packages with Business Analytics features
- ERP system without Business Analytics features developed in-house
- ERP system with Business Analytics features developed in-house

8. (TOOLS) Please specify the products/vendors of ERP/ Business Analytics tools

9. (IMPTIME) Please select number of months of implementation of ERP/ Business Analytics tools from start to first production operation.

(IMPTIME1) Number of months of implementation of ERP system from start to first production operation	(IMPTIME2) Number of months of implementation of Business Analytics tools from start to first production operation
Less than 6 months 6 months to less than 12 months 12 months to less than 18 months Over 18 months	Less than 6 months 6 months to less than 12 months 12 months to less than 18 months Over 18 months

10. Self-assessment of critical success factors in the successful implementation of the ERP system in your organisation *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Governance	1	2	3	4	5	6	7
(GOV1) The vision and mission are well understood by employees across the organisation	○	○	○	○	○	○	○
(GOV2) The goals and objectives of the ERP system are well understood by employees across the organisation	○	○	○	○	○	○	○
(GOV3) IT plans and activities are integrated with business plans and activities supported and involved by top management	○	○	○	○	○	○	○
(GOV4) There is enough support from senior management in the ERP Business Analytics project	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Culture	1	2	3	4	5	6	7
(CUL1) Majority of staff recognised the need for change	○	○	○	○	○	○	○
(CUL2) There is a culture that encourages open communication	○	○	○	○	○	○	○
(CUL3) Employees at different levels are motivated to participate in generating new ideas	○	○	○	○	○	○	○
(CUL4) Employees are willing to accept new things	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Technology	1	2	3	4	5	6	7
(TEC1) There is a standardised IT infrastructure	○	○	○	○	○	○	○
(TEC2) There was a stable and successful business supported by IT legacy systems	○	○	○	○	○	○	○
(TEC3) There is good integration of Business Analytics between the ERP system and other systems in the organisation to share and transfer information	○	○	○	○	○	○	○
(TEC4) There is good integration of Business Analytics between the ERP system and other ERP systems in the supply chain to share and transfer information	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

People	1	2	3	4	5	6	7
(PEO1) There is a high level of morale and motivation among employees	○	○	○	○	○	○	○
(PEO2) There is a well-documented education and training strategy to support effective user training	○	○	○	○	○	○	○
(PEO3) The management has good communication, controlling, leadership skills, planning and IT management skills	○	○	○	○	○	○	○
(PEO4) The IT staff has good communication, IT management, planning and technical skills	○	○	○	○	○	○	○
(PEO5) Project team has prior experience in large IT projects and good domain knowledge of the ERP Business Analytics	○	○	○	○	○	○	○
(PEO6) Staff expectations are effectively communicated at all levels	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Operation	1	2	3	4	5	6	7
(OPE1) The ERP system was customised according to the organisation's needs to fit its existing business process	○	○	○	○	○	○	○
(OPE2) Processes, procedures and functions are regularly audited for efficiency and effectiveness	○	○	○	○	○	○	○

11. The level of ERP success achieved in your organisation *

From your perspective, please indicate to what extent do you rank the level of ERP success achieved in your organisation for each of the following:

1 = Unsuccessful; 2 = Minimally Successful; 3 = Fully Successful;

4 = Exceeds Fully Successful; 5 = Outstanding

Level of ERP success achieved	1	2	3	4	5
(ACCURACY) Data accuracy	○	○	○	○	○
(EASY) Easy to learn	○	○	○	○	○
(INTEGRATION) Data integration	○	○	○	○	○
(EFFICIENCY) Efficiency	○	○	○	○	○
(PRODUCTIVITY) Improving individual productivity	○	○	○	○	○

Do you have business analytics experience in your organisation?

- ○ Yes, please answer business analytics profile questionnaire from Question 12 to 16.
- ○ No, please go directly to Question 17

12. Business analytics (BA) profile questionnaire regarding your organisation's data sources *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Data sources capabilities	1	2	3	4	5	6	7
(DAT1) The existing BA system extracts from at least one data source.	○	○	○	○	○	○	○
(DAT2) The existing BA system extracts data from multiple data sources.	○	○	○	○	○	○	○
(DAT3) Data quality tools are integrated into the existing BA platform.	○	○	○	○	○	○	○
(DAT4) The existing BA platform is updated in real time as new data becomes available.	○	○	○	○	○	○	○
(DAT5) Unstructured data such as machine sensors, weather and social media feeds, is available in the existing BA platform.	○	○	○	○	○	○	○

13. Business analytics (BA) profile questionnaire regarding your organisation's reporting and business analytics capabilities. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Reporting and business analytics capabilities	1	2	3	4	5	6	7
(CAP1) Data is presented in static reports often raising more questions than answers.	○	○	○	○	○	○	○
(CAP2) Using dashboards and other interactive tools, users can ask and answer their questions regarding historical data series and learn from past performance.	○	○	○	○	○	○	○
(CAP3) Real-time data can be used to monitor actionable metrics such as key performance indicators (KPIs).	○	○	○	○	○	○	○
(CAP4) Using historical data and forecasting models, users can see what might happen next month or next quarter and take actions today that impact future	○	○	○	○	○	○	○

Reporting and business analytics capabilities	1	2	3	4	5	6	7
events.							
(CAP5) Business intelligence is leveraged to optimise the future performance of the organisation such as inventory levels and which products customers are most likely to buy.	○	○	○	○	○	○	○

14. Business analytics (BA) profile questionnaire regarding your organisation's collaboration tools. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Collaboration tools capabilities	1	2	3	4	5	6	7
(TOO1) Users access specific data they need to make the decisions that drive the part of the business for which they are responsible. Data is usually not formally shared between employees.	○	○	○	○	○	○	○
(TOO2) Data is extracted from the BA system on an ad-hoc, as-needed basis with or without the assistance of IT.	○	○	○	○	○	○	○
(TOO3) Scheduled emails push relevant data to key stakeholders on a pre-set schedule.	○	○	○	○	○	○	○
(TOO4) Decision-makers are automatically notified of changes in key metrics anytime, anywhere.	○	○	○	○	○	○	○
(TOO5) Individuals inside and outside the organisation can access data, share views, ask questions and track progress within the BA platform.	○	○	○	○	○	○	○

15. Business analytics (BA) profile questionnaire regarding your organisation's sharing capabilities. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Sharing capabilities	1	2	3	4	5	6	7
(SHA1) Users can access data and track key metrics specific to their job function only.	○	○	○	○	○	○	○
(SHA2) Users can access data and track key	○	○	○	○	○	○	○

Sharing capabilities	1	2	3	4	5	6	7
performance metrics at the departmental level.							
(SHA3) Users can access data and track key metrics across multiple departments within the organisation.	○	○	○	○	○	○	○
(SHA4) Access to BA extends beyond the organisation's boundaries to the suppliers and distributors.	○	○	○	○	○	○	○
(SHA5) Customers can access self-service BA metrics and data empowering them to make better business decisions.	○	○	○	○	○	○	○

16. The level of Business Analytics (BA) success achieved in your organisation *

From your perspective, please indicate to what extent do you rank the level of Business Analytics (BA) success achieved in your organisation for each of the following capabilities:

1 = Unsuccessful; 2 = Minimally Successful; 3 = Fully Successful;

4 = Exceeds Fully Successful; 5 = Outstanding

Level of Business Analytics (BA) success achieved	1	2	3	4	5
(BAS1) Data capabilities	○	○	○	○	○
(BAS2) Analytics capabilities	○	○	○	○	○
(BAS3) Collaboration capabilities	○	○	○	○	○
(BAS4) Dissemination capabilities	○	○	○	○	○

Concluding questions

17. Write details of any success factor not mentioned in the above survey and why it is critical to your organisation here:

18. Would you be interested in participating in the second stage of the survey and receiving the results of this survey? *

If you do not wish to reveal the organisation that you work for, you can give your private emails such as gmail, hotmail or yahoo.

○ No

○ Yes, please give your email:

Submit

B-2 SURVEY 2 RESEARCH QUESTIONNAIRES

Survey 2 Research Questionnaire

Survey 2 Research Questionnaire

Have you participated in the Pilot Study of the First Survey?

- ○ Yes, please go directly to Part B (Second Survey, expected to be completed in 10 minutes)
- ○ No, please go directly to Question 17 please answer Question 1 to 16 (expected to be completed in 20 minutes)

If you have participated in the First Survey and would like to link the First Survey results with the Second Survey, please enter the Reference Code assigned by the system ___________

If you forgot the Reference Code, please enter your email that you have given in the First Survey.

Research Questionnaire (PART A) for new participants

*Required

Demographics

1. (LOCATION) What is the location of your organisation? *

- ○ Taiwan
- ○ Hong Kong
- ○ Macau
- ○ China (Please specify the city/district/province):

2. (TYPE) What type of business organisation does your organisation belong to? *

- ○ Domestic Private Enterprises
- ○ Foreign Invested Companies
- ○ State-Owned Enterprises
- ○ Other:

3. (INDUSTRY) What is your organisation's industry? *

- ○ Manufacturing
- ○ Information technology/Telecommunications
- ○ Logistics/Courier services
- ○ Governmental agencies/Nonprofits
- ○ Financial
- ○ Utilities
- ○ Wholesale/Retail
- ○ Other:

About yourself

4. (POSITION) What is your position in the organisation?
   - IT senior management
   - IT middle management
   - Non-IT senior management
   - Non-IT middle management
   - Other:
5. (INTERACTION) What is your role involved in the use of Business Analytics in your ERP system?
   - User of Business Analytics in the ERP system
   - Developer of Business Analytics in the ERP system
   - Administrator of Business Analytics in the ERP system
   - Other:

General ERP Business Analytics questions

6. **(MATURITY) What is the usage of ERP Business Analytics (BA) in your organisation? ***
   - Focused on data collection and data organisation having the beginning of a BA system in place
   - Requirements are driven from a limited executive group
   - KPI's and analytics are identified, but not well used
   - KPI's and analytics are identified and effectively used
   - KPI's and analytics are used to manage the full value chain
7. **(STRATEGY) What was your ERP and Business Analytics implementation strategy? ***
   - No ERP system implemented but Business Analytics Tools were used to analyse enterprise data
   - Single ERP package without Business Analytics features
   - Single ERP package with Business Analytics features
   - Multiple ERP packages without Business Analytics features
   - Multiple ERP packages with Business Analytics features
   - ERP system without Business Analytics features developed in-house
   - ERP system with Business Analytics features developed in-house
8. **(TOOLS) Please specify the products/vendors of ERP/ Business Analytics tools**

9. **(IMPTIME) Please select number of months of implementation of ERP/ Business Analytics tools from start to first production operation.**

(IMPTIME1) Number of months of implementation of ERP system from start to first production operation	(IMPTIME2) Number of months of implementation of Business Analytics tools from start to first production operation
○ Less than 6 months ○ 6 months to less than 12 months ○ 12 months to less than 18 months ○ Over 18 months	○ Less than 6 months ○ 6 months to less than 12 months ○ 12 months to less than 18 months ○ Over 18 months

10. Self-assessment of critical success factors in the successful implementation of the ERP system in your organisation *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Governance	1	2	3	4	5	6	7
(GOV1) The vision and mission are well understood by employees across the organisation	○	○	○	○	○	○	○
(GOV2) The goals and objectives of the ERP system are well understood by employees across the organisation	○	○	○	○	○	○	○
(GOV3) IT plans and activities are integrated with business plans and activities supported and involved by top management	○	○	○	○	○	○	○
(GOV4) There is enough support from senior management in the ERP Business Analytics project	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Culture	1	2	3	4	5	6	7
(CUL1) Majority of staff recognised the need for change	○	○	○	○	○	○	○
(CUL2) There is a culture that encourages open communication	○	○	○	○	○	○	○
(CUL3) Employees at different levels are motivated to participate in generating new ideas	○	○	○	○	○	○	○
(CUL4) Employees are willing to accept new things	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Technology	1	2	3	4	5	6	7
(TEC1) There is a standardised IT infrastructure	○	○	○	○	○	○	○
(TEC2) There was a stable and successful business supported by IT legacy systems	○	○	○	○	○	○	○
(TEC3) There is good integration of Business Analytics between the ERP system and other systems in the organisation to share and transfer information	○	○	○	○	○	○	○
(TEC4) There is good integration of Business Analytics between the ERP system and other ERP systems in the supply chain to share and transfer information	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

People	1	2	3	4	5	6	7
(PEO1) There is a high level of morale and motivation among employees	○	○	○	○	○	○	○
(PEO2) There is a well-documented education and training strategy to support effective user training	○	○	○	○	○	○	○
(PEO3) The management has good communication, controlling, leadership skills, planning and IT management skills	○	○	○	○	○	○	○
(PEO4) The IT staff has good communication, IT management, planning and technical skills	○	○	○	○	○	○	○
(PEO5) Project team has prior experience in large IT projects and good domain knowledge of the ERP Business Analytics	○	○	○	○	○	○	○
(PEO6) Staff expectations are effectively communicated at all levels	○	○	○	○	○	○	○

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Operation	1	2	3	4	5	6	7
(OPE1) The ERP system was customised according to the organisation's needs to fit its existing business process	○	○	○	○	○	○	○
(OPE2) Processes, procedures and functions are regularly audited for efficiency and effectiveness	○	○	○	○	○	○	○

11. The level of ERP success achieved in your organisation *

From your perspective, please indicate to what extent do you rank the level of ERP success achieved in your organisation for each of the following:

1 = Unsuccessful; 2 = Minimally Successful; 3 = Fully Successful;

4 = Exceeds Fully Successful; 5 = Outstanding

Level of ERP success achieved	1	2	3	4	5
(ACCURACY) Data accuracy	○	○	○	○	○
(EASY) Easy to learn	○	○	○	○	○
(INTEGRATION) Data integration	○	○	○	○	○
(EFFICIENCY) Efficiency	○	○	○	○	○
(PRODUCTIVITY) Improving individual productivity	○	○	○	○	○

Do you have business analytics experience in your organisation?

○ Yes, please answer business analytics profile questionnaire from Question 12 to 16.

○ No, please go directly to Question 17

12. Business analytics (BA) profile questionnaire regarding your organisation's data sources *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Data sources capabilities	1	2	3	4	5	6	7
(DAT1) The existing BA system extracts from at least one data source.	○	○	○	○	○	○	○
(DAT2) The existing BA system extracts data from multiple data sources.	○	○	○	○	○	○	○
(DAT3) Data quality tools are integrated into the existing BA platform.	○	○	○	○	○	○	○
(DAT4) The existing BA platform is updated in real time as new data becomes available.	○	○	○	○	○	○	○
(DAT5) Unstructured data such as machine sensors, weather and social media feeds, is available in the existing BA platform.	○	○	○	○	○	○	○

13. Business analytics (BA) profile questionnaire regarding your organisation's reporting and business analytics capabilities. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Reporting and business analytics capabilities	1	2	3	4	5	6	7
(CAP1) Data is presented in static reports often raising more questions than answers.	○	○	○	○	○	○	○
(CAP2) Using dashboards and other interactive tools, users can ask and answer their questions regarding historical data series and learn from past performance.	○	○	○	○	○	○	○
(CAP3) Real-time data can be used to monitor actionable metrics such as key performance indicators (KPIs).	○	○	○	○	○	○	○
(CAP4) Using historical data and forecasting models, users can see what might happen next month or next quarter and take actions today that impact future events.	○	○	○	○	○	○	○
(CAP5) Business intelligence is leveraged to optimise the future performance of the organisation such as inventory levels and which products customers are most likely to buy.	○	○	○	○	○	○	○

14. Business analytics (BA) profile questionnaire regarding your organisation's collaboration tools. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Collaboration tools capabilities	1	2	3	4	5	6	7
(TOO1) Users access specific data they need to make the decisions that drive the part of the business for which they are responsible. Data is usually not formally shared between employees.	○	○	○	○	○	○	○
(TOO2) Data is extracted from the BA system on an ad-hoc, as-needed basis with or without the assistance of IT.	○	○	○	○	○	○	○
(TOO3) Scheduled emails push relevant data to key stakeholders on a pre-set schedule.	○	○	○	○	○	○	○
(TOO4) Decision-makers are automatically notified of changes in key metrics anytime, anywhere.	○	○	○	○	○	○	○

(TOO5) Individuals inside and outside the organisation can access data, share views, ask questions and track progress within the BA platform.	○	○	○	○	○	○	○

15. Business analytics (BA) profile questionnaire regarding your organisation's sharing capabilities. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Sharing capabilities	1	2	3	4	5	6	7
(SHA1) Users can access data and track key metrics specific to their job function only.	○	○	○	○	○	○	○
(SHA2) Users can access data and track key performance metrics at the departmental level.	○	○	○	○	○	○	○
(SHA3) Users can access data and track key metrics across multiple departments within the organisation.	○	○	○	○	○	○	○
(SHA4) Access to BA extends beyond the organisation's boundaries to the suppliers and distributors.	○	○	○	○	○	○	○
(SHA5) Customers can access self-service BA metrics and data empowering them to make better business decisions.	○	○	○	○	○	○	○

16. The level of Business Analytics (BA) success achieved in your organisation *

From your perspective, please indicate to what extent do you rank the level of Business Analytics (BA) success achieved in your organisation for each of the following capabilities:

1 = Unsuccessful; 2 = Minimally Successful; 3 = Fully Successful;

4 = Exceeds Fully Successful; 5 = Outstanding

Level of Business Analytics (BA) success achieved	1	2	3	4	5
(BAS1) Data capabilities	○	○	○	○	○
(BAS2) Analytics capabilities	○	○	○	○	○
(BAS3) Collaboration capabilities	○	○	○	○	○
(BAS4) Dissemination capabilities	○	○	○	○	○

Concluding questions

17. Write details of any success factor not mentioned in the above survey and why it is critical to your organisation here:

18. Would you be interested in participating in the second stage of the survey and receiving the results of this survey? *

If you do not wish to reveal the organisation that you work for, you can give your private emails such as gmail, hotmail or yahoo.

- No
- Yes, please give your email:

Submit

Research Questionnaire (PART B): Second Survey for all participants

B1. From your perspective, please enter the percentage of the contribution of each of the following capabilities that leads the overall success of Business Analytics implemented in your organisation. *

Capabilities	Percentage
Data sources capabilities	
Reporting and business analytics capabilities	
Collaboration tools capabilities	
Sharing capabilities	
Other capabilities	
Total	100

Governance

B2. Business analytics (BA) profile questionnaire regarding the governance aspects of your organisation. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Governance	1	2	3	4	5	6	7
(GOV5) Data management and ownership policies are in place and documented in my organisation.	○	○	○	○	○	○	○
(GOV6) A business analytics governance team is in place with key business stakeholders from other departments of the organisation.	○	○	○	○	○	○	○
(GOV7) The roles and responsibilities of the business analytics governance team are clearly identified and defined.	○	○	○	○	○	○	○
(GOV8) Security policies are in place and enforced for all sensitive data in my organisation.	○	○	○	○	○	○	○

Culture

B3. Business analytics (BA) profile questionnaire regarding the culture aspects of your organisation. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Culture	1	2	3	4	5	6	7
(CUL5) A well-established funding process is in place for business analytics initiatives driven by both business and IT.	○	○	○	○	○	○	○
(CUL6) A business analytics road map is in place and is clearly defined.	○	○	○	○	○	○	○
(CUL7) Business processes are refined or improved which are driven by the findings from business analytics.	○	○	○	○	○	○	○
(CUL8) There are existing staff in my organisation with skills in advanced business analytics to support the needs of the business.	○	○	○	○	○	○	○

Technology

B4. Business analytics (BA) profile questionnaire regarding the technology aspects of your organisation. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Technology	1	2	3	4	5	6	7
(TEC5) Mobile applications are adopted for end-users to view summary results of business analytics.	○	○	○	○	○	○	○
(TEC6) A public, private or hybrid cloud platform is adopted for business analytics.	○	○	○	○	○	○	○
(TEC7) A big data analytics infrasturture is implemented in the organisation.	○	○	○	○	○	○	○
(TEC8) An in-memory computing platform is adopted in the organisation.	○	○	○	○	○	○	○

People

B5. Business analytics (BA) profile questionnaire regarding the people aspects of your organisation. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

People	1	2	3	4	5	6	7
(PEO7) There are staff in my organisation with technical skills in advanced business analytics.	○	○	○	○	○	○	○
(PEO8) Some staff in my organisation with business analytics skills can easily be involved across produce, consume and enable activities.	○	○	○	○	○	○	○

Operation

B5. Business analytics (BA) profile questionnaire regarding the operation aspects of your organisation. *

From your perspective, please indicate to what extent do you AGREE or DISAGREE for each of the following:

1=Strongly Disagree; 2=Disagree; 3= Somewhat Disagree; 4=Neutral; 5=Somewhat Agree; 6=Agree; 7=Strongly Agree

Operation	1	2	3	4	5	6	7
(OPE3) There are existing standards and processes defined for use of business analytics in the organisation.	○	○	○	○	○	○	○
(OPE4) Real-time business analytics is available for key users to access integrated summary information from the production system.	○	○	○	○	○	○	○
(OPE5) Operational process intelligence is available for managers to create real-time process visibility and propose line-of-business workers appropriate actions to respond immediately on critical business situations.	○	○	○	○	○	○	○
(OPE6) Multichannel analytics are available for key users to create and access their desired presentation formats for data-driven decision making.	○	○	○	○	○	○	○

B6. Would you be interested in receiving the detailed results of this survey? *

If you do not wish to reveal the organisation that you work for, you can give your private emails such as Gmail, Hotmail or yahoo.

○ No (A web site will be given to you to access the summary results of this survey)

○ Yes, please give your email:

Submit

B-3 SURVEY 1 SAMPLE INVITATION LETTER

UNIVERSITY OF SOUTHERN QUEENSLAND

Survey 1 Invitation Letter Sample

Dear Sir/Madam,

I am a PhD research student at the School of Commerce, University of Southern Queensland (USQ), Australia. I am conducting an online survey as an essential part of my PhD research titled "A maturity model for evaluating Business Analytics implementations in ERP systems: An Empirical Study of Greater China Region".

The purpose of this research is to examine the critical success factors for a successful Enterprise Resource Planning (ERP) and Business Analytics (BA) implementation and to explore the impact of ERP and Business Analytics on technological, operational, managerial and strategic performance measures in organisations. The research team requests your assistance because you have valuable experience in the ERP and Business Analytics implementation in your organisation which is important to the data collection for this research.

I would be very much appreciated if you could forward this email to two persons in your organisation who have involvement in the implementation and/or operation of either an ERP system or Business Analytics.

It is expected that this project will directly benefit you because you can have access to an initial self-evaluation of the ERP Business Analytics practices of your organization on completing this survey which will act as a baseline for further improvement in your organisation. At the end of the survey, you will be given a Web Page address so that you can access your results of this self-evaluation of the ERP business Analytics practices in your organization with a summary of the research results from other participants.

Please could you help my research by completing the online survey which should take less than 20 minutes at http://108.167.182.152/LIMESURVEY/index.php/144421 or by scanning QR Code at the bottom of this page you complete this survey online with your mobile device using any QR Code Scanner app which can be downloaded from Apple Apps Store or Google Play Store.

This survey has been approved by the USQ Ethics Committee of University of Southern Queensland. There are no risks associated with participating in this study other the time constraint of 20 minutes to complete this survey. All of the responses to the survey will be recorded anonymously. The information you provide will only be used in this research. Please feel free to contact me at [redacted] if you have any other questions.

QR Code for accessing an online survey

Thanks for your participation.

Yours faithfully,

Ir. Freddy Wong
PhD research student, School of Commerce,
University of Southern Queensland, Australia

Survey 1 Invitation Letter Sample

(Chinese Invitation Letter)

敬启者

本人是澳大利亚南昆士兰大学商学院的博士研究生。现正进行一项网上调查，作为博士研究的一部分，题为“评估大中华地区的企业资源规划系统中业务分析实施成功的成熟度模型之实证研究”。

本研究的目的旨在探讨**企业资源规划系统**的成功和**数据业务分析**实施成功的关键因素及其对技术、运营、管理及策略绩效措施的影响。研究团队诚邀你的帮忙，因为你机构中的员工具有宝贵的**企业资源规划系统**及**数据业务分析**实施经验，这对本研究的数据收集是极为重要的。

请你将此电邮转发给你机构中曾参与有关**企业资源规划系统**或**数据业务分析**的实施或操作的两位同事参与此问卷调查。

参与此问卷调查将会获益良多，参与者可自我评估贵机构的企业资源规划系统之数据业务分析的操作，用作改善现有的数据业务分析。在调查结束时，你将获得一个调查结果网址，以便你日后可以查阅研究结果。

完成此网上调查只需 20 分钟，请到以下网址
http://108.167.182.152/LIMESURVEY/index.php/144421
或使用手机扫描此页面底部的 QR 码，便可在手机上完成此调查。

这项调查已获澳大利亚南昆士兰大学的道德委员会批准并将风险评估列为低风险。此调查将以匿名方式记录，并只限用于此研究用途。如有任何问题，欢迎用电邮联络本人
[redacted]

感谢你的参与。

敬祝安康

手机扫描 QR 码

澳大利亚南昆士兰大学商学院博士研究生
王伟业敬上

B-4 SURVEY 2 SAMPLE INVITATION LETTER

UNIVERSITY OF SOUTHERN QUEENSLAND

Survey 2 Invitation Letter Sample

Dear Sir/Madam,

I am a PhD research student at the School of Commerce, University of Southern Queensland (USQ), Australia. I am conducting an online survey as an essential part of my PhD research titled "A maturity model for evaluating Business Analytics implementations in ERP systems: An Empirical Study of Greater China Region".

The purpose of this research is to examine the critical success factors for a successful Enterprise Resource Planning (ERP) and Business Analytics (BA) implementation and to explore the impact of ERP and Business Analytics on technological, operational, managerial and strategic performance measures in organisations. The research team requests your assistance because you have valuable experience in the ERP and Business Analytics implementation in your organisation which is important to the data collection for this research.

I would be very much appreciated if you could forward this email to two persons in your organisation who have involvement in the implementation and/or operation of either an ERP system or Business Analytics.

It is expected that this project will directly benefit you because you can have access to an initial self-evaluation of the ERP Business Analytics practices of your organization on completing this survey which will act as a baseline for further improvement in your organisation. At the end of the survey, you will be given a Web Page address so that you can access your results of this self-evaluation of the ERP business Analytics practices in your organization with a summary of the research results from other participants.

Please could you help my research by completing the online survey which should take less than 30 minutes at http://108.167.182.152/LIMESURVEY/index.php/235586/ or by scanning QR Code at the bottom of this page you complete this survey online with your mobile device using any QR Code Scanner app which can be downloaded from Apple Apps Store or Google Play Store.

This survey has been approved by the USQ Ethics Committee of University of Southern Queensland. There are no risks associated with participating in this study other the time constraint of 30 minutes to complete this survey. All of the responses to the survey will be recorded anonymously. The information you provide will only be used in this research. Please feel free to contact me at [redacted] if you have any other questions.

QR Code for accessing an online survey

Thanks for your participation.

Yours faithfully,

Ir. Freddy Wong
PhD research student, School of Commerce,
University of Southern Queensland, Australia

Survey 2 Invitation Letter Sample

(Chinese Invitation Letter)

敬启者

本人是澳大利亚南昆士兰大学商学院的博士研究生。现正进行一项网上调查，作为博士研究的一部分，题为“评估大中华地区的企业资源规划系统中业务分析实施成功的成熟度模型之实证研究”。

本研究的目的旨在探讨**企业资源规划系统**的成功和**数据业务分析**实施成功的关键因素及其对技术、运营、管理及策略绩效措施的影响。研究团队诚邀你的帮忙，因为你机构中的员工具有宝贵的**企业资源规划系统**及**数据业务分析**实施经验，这对本研究的数据收集是极为重要的。

请你将此电邮转发给你机构中曾参与有关**企业资源规划系统**或**数据业务分析**的实施或操作的两位同事参与此问卷调查。

参与此问卷调查将会获益良多，参与者可自我评估贵机构的企业资源规划系统之数据业务分析的操作，用作改善现有的数据业务分析。在调查结束时，你将获得一个调查结果网址，以便你日后可以查阅研究结果。

完成此网上调查只需 30 分钟，请到以下网址
http://108.167.182.152/LIMESURVEY/index.php/235586/lang-zh-Hans
或使用手机扫描此页面底部的 QR 码，便可在手机上完成此调查。

这项调查已获澳大利亚南昆士兰大学的道德委员会批准并将风险评估列为低风险。此调查将以匿名方式记录，并只限用于此研究用途。如有任何问题，欢迎用电邮联络本人

[redacted]

感谢你的参与。

敬祝安康

手机扫描 QR 码

澳大利亚南昆士兰大学商学院博士研究生
王伟业敬上

APPENDIX C: OVERALL ESSENTIAL CHARACTERISTICS OF THE FIVE-LEVEL BARCMM FOR ORGANISATIONS USING ERP SYSTEMS

Maturity Level	**Characteristics of BA readiness and capability in ERP Systems**
1 Initial	Organisations primarily focus on collecting and organising data at the start of an ERP system implementation. They decided to invest in ERP and BA, and have implemented or are starting to implement ERP systems, data collection systems and data warehousing solutions.
2 Repeatable	Organisations have implemented ERP and data systems and have the ability to derive some ERP and BA value from basic analytics, producing historical reports for key personnel only.
3 Defined	Organisations have standardised ERP systems and derive strategic value from the ERP system. Organisations are focusing most efforts on cleaning up data, formalising KPIs and metrics, and increasing the distribution and use of data across the organisation. Organisations are deriving value from BA, and also exploring predictive analytics capabilities.
4 Managed	Organisations perceive information as critical for business and have formal processes around data and metrics using ERP systems to make and support key decisions. Senior management is fully engaged in ERP and BA, focused on rapid decision making, cost reduction, and empowerment through distributed collaboration. They see ERP and BA as a differentiator between their competitors.
5 Optimising	Organisations can facilitate optimal metric-driven decisions with people, processes and technology aligned. They provide their customers, distributors and suppliers with key performance data through collaborative work across the entire supply chain through their ERP and BA systems to improve products, services and business performance.

APPENDIX D: A SUMMARY OF THE MEASUREMENT INSTRUMENTS IN SURVEYS 1 AND 2

Dimension	Item Description	Survey 1 Code	Survey 2 Code	Scale
Governance	The vision and mission are well understood by employees	gov1	gov1	1 - 7
	The goals and objectives of the ERP system are well understood by employees	gov2	gov2	1 - 7
	IT plans and activities are integrated and supported by top management	gov3	gov3	1 - 7
	There is enough support from senior management in the ERP BA project	gov4	gov4	1 - 7
	Data management and ownership policies are in place and documented in my organisation		gov5	1 - 7
	A business analytics governance team is in place with key business stakeholders from other departments of the organisation		gov6	1 - 7
	The roles and responsibilities of the business analytics governance team are clearly identified and defined		gov7	1 - 7
	Security policies are in place and enforced for all sensitive data in my organisation		gov8	1 - 7
Culture	Majority of staff recognised the need for change	cul1	cul1	1 - 7
	There is a culture that encourages open communication	cul2	cul2	1 - 7
	Employees are motivated to participate in generating new ideas	cul3	cul3	1 - 7
	Employees are willing to accept new things	cul4	cul4	1 - 7
	A well-established funding process is in place for business analytics initiatives driven by both business and IT		cul5	1 - 7
	A business analytics road map is in place and is clearly defined		cul6	1 - 7
	Business processes are refined or improved which are driven by the findings from business analytics		cul7	1 - 7
	A strong training culture has been developed in my organisation to provide adequate training to staff in order to acquire with the required skills in advanced business analytics to support the needs of the business		cul8	1 - 7

Dimension	Item Description	Survey 1 Code	Survey 2 Code	Scale
Technology	There is a standardised IT infrastructure	tec1	tec1	1 - 7
	There was a stable and successful business supported by IT legacy systems	tec2	tec2	1 - 7
	There is good integration of Business Analytics between the ERP system and other systems in the organisation to share and transfer information	tec3	tec3	1 - 7
	There is good integration of Business Analytics between the ERP system and other ERP systems in the supply chain to share and transfer information	tec4	tec4	1 - 7
	Mobile applications are adopted for end-users to view summary results of business analytics		tec5	1 - 7
	A public, private or hybrid cloud platform is adopted for business analytics		tec6	1 - 7
	A big data analytics infrastructure is implemented in the organisation		tec7	1 - 7
	An in-memory computing platform is adopted in the organisation		tec8	1 - 7
People	There is a high level of morale and motivation among employees	peo1	peo1	1 - 7
	There are a well-documented education and training strategy to support effective user training	peo2	peo2	1 - 7
	The management has good communication, controlling, leadership skills, planning and IT management skills	peo3	peo3	1 - 7
	IT staff has good communication, management, planning and technical skills	peo4	peo4	1 - 7
	The project team has experience in large IT projects and good domain knowledge of ERP and Business Analytics	peo5	peo5	1 - 7
	Expectations are effectively communicated at all levels	peo6	peo6	1 - 7
	There are staff in my organisation with technical skills in advanced business analytics		peo7	1 - 7
	Some staff in my organisation with business analytics skills can easily be involved across produce, consume and enable activities		peo8	1 - 7

Dimension	Item Description	Survey 1 Code	Survey 2 Code	Scale
Operation	The ERP system was customised according to the organisation's needs	ope1	ope1	1 - 7
	Processes and procedures are regularly audited for efficiency & effectiveness	ope2	ope2	1 - 7
	There are existing standards and processes defined for use of business analytics in the organisation		ope3	1 - 7
	Real-time business analytics is available for key users to access integrated summary information from the production system		ope4	1 - 7
	Operational process intelligence is available for managers to create real-time process visibility and propose line-of-business workers appropriate actions to respond immediately on critical business situations		ope5	1 - 7
	Multichannel analytics are available for key users to create and access their desired presentation formats for decision making		ope6	1 - 7
Data Capability	The existing BA system extracts from at least one data source	dat1	dat1	1 - 7
	The existing BA system extracts data from multiple data sources	dat2	dat2	1 - 7
	Data quality tools are integrated into the existing BA platform	dat3	dat3	1 - 7
	The existing BA platform is updated in real time	dat4	dat4	1 - 7
	Unstructured data is available in the existing BA platform	dat5	dat5	1 - 7
Analytics Capability	Data is presented in static reports often raising more questions than answers	cap1	cap1	1 - 7
	Users can ask and answer their own questions about historical data sets and learn from past performance using dashboards and interactive tools	cap2	cap2	1 - 7
	Real-time data can be used to monitor actionable metrics such as KPIs	cap3	cap3	1 - 7
	Using historical data and forecasting models, users can see what might happen and take actions today that impact future events	cap4	cap4	1 - 7
	BA is leveraged to optimise future organisational performance	cap5	cap5	1 - 7

Dimension	Item Description	Survey 1 Code	Survey 2 Code	Scale
Collaboration Tools Capability	Users access specific data they need to make decisions, but the data is not open for sharing between employees	too1	too1	1 - 7
	Data is extracted from the BA system with or without the assistance of IT	too2	too2	1 - 7
	Scheduled emails push relevant data to key stakeholders on a schedule	too3	too3	1 - 7
	Decision-makers automatically receive alerts when key metrics change	too4	too4	1 - 7
	Individuals inside and outside the organisation can access data, ask questions, view shared reports and monitor progress within the BA platform	too5	too5	1 - 7
Sharing Capability	Users have access to job-related data and can track key performance metrics specific to their job only	sha1	sha1	1 - 7
	Users have access to departmental data and can track key performance metrics specific to their department only	sha2	sha2	1 - 7
	Users have access to organisational data and can track key performance metrics across multiple departments	sha3	sha3	1 - 7
	BA extends beyond organisation's boundaries to suppliers and distributors	sha4	sha4	1 - 7
	Customers are able to access self-service BA metrics and data	sha5	sha5	1 - 7

Scale: (1) Strongly Disagree; (2) Disagree; (3) Somewhat Disagree; (4) Neutral; (5) Somewhat Agree; (6) Agree; (7) Strongly Agree

APPENDIX E: MEASUREMENT INSTRUMENT TO MEASURE THE CONSTRUCT OF PERCEIVED ERP BA SUCCESS AND PERCEIVED BA CAPABILITY OF BA MATURITY IN SURVEYS 1 AND 2

Construct	Item Description	Code	Scale
Perceived ERP BA success	Level of ERP BA success in terms of data accuracy	accu	1 - 5
	Level of ERP BA success in terms of easy to learn	easy	1 - 5
	Level of ERP BA success in terms of data integration	inte	1 - 5
	Level of ERP BA success in terms of efficiency	effi	1 - 5
	Level of ERP BA success in terms of improving individual productivity	prod	1 - 5
Perceived BA success	Level of BA success in terms of data capabilities	bas1	1 - 5
	Level of BA success in terms of analytics capabilities	bas2	1 - 5
	Level of BA success in terms of collaboration capabilities	bas3	1 - 5
	Level of BA success in terms of dissemination capabilities	bas4	1 - 5

Scale for Perceived ERP BA success: 1=Unsuccessful (Basic features provided are not usable); 2=Minimally Successful (Basic features provided are just usable but some are not usable); 3=Fully Successful (Major features provided are usable); 4=Exceeds Fully Successful (Major features provided are usable with some exceed expectation); 5=Outstanding (All features provided are usable and exceed expectation)

Scale for Perceived BA capability: 1=Incapable (Unable to apply basic BA functionalities); 2=Minimally Capable (Able to apply some basic BA functionalities); 3=Fully Capable (Able to apply major BA functionalities); 4=Exceeds Fully Capable (Able to apply major BA functionalities with some exceeding expectations); 5=Outstanding (Able to apply all BA functionalities exceeding expectations)

APPENDIX F: THE FIVE DIMENSIONS OF THE ERP BA READINESS IN THE BARCMM

Dimension	Coverage in the BARCMM	Coverage by other authors	Major Literature Sources
Governance	Employees understand vision, mission, and ERP goals; Top management supports IT plans and ERP BA project; Documented data management and ownership policies; Business analytics governance team with defined roles; Enforced security policies for sensitive data.	Decision rights; strategic alignment; dynamic BA capabilities; change management; organisation; organisational management; organisational structure; dissemination; business enablement; scope; scope of BI initiatives; funding; value; strategy and program management.	Somers and Nelson (2004); Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
Culture	Staff recognise need for change; open communication culture; employee motivation for new ideas; willingness to accept new things; established funding process for BA initiatives; clearly defined BA road map; improved business processes driven by BA; strong training culture for advanced BA skills.	Evidence-based management; embeddedness; executive leadership and support; flexibility and agility; collaboration; organisational slack.	Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
Technology	Standardised IT infrastructure; stable business supported by IT legacy systems; good BA integration between ERP and other systems; good BA integration between ERP and supply chain ERP systems; mobile applications for viewing BA results; public, private, or hybrid cloud platform for BA; big data analytics infrastructure; in-memory computing platform.	Data management; systems integration; reporting and visualisation BA technology; discovery BA technology; information technology; architecture; application architecture; warehouse architecture; master data management.	Motwani et al. (2005); Ngai et al. (2008); Ifinedo et al. (2010); Rouhani and Ravasan (2013); Ram and Corkindale (2014)

Dimension	Coverage in the BARCMM	Coverage by other authors	Major Literature Sources
People	High employee morale and motivation; effective education and training strategy; strong management communication, leadership, planning, and IT skills; skilled IT staff in communication, management, planning, and technical areas; experienced project team with ERP and BA expertise; clear expectations communicated across all levels; technical proficiency in advanced business analytics among staff; involvement of BA-skilled staff in producing, consuming, and enabling activities.	Technology skills and knowledge; business skills and knowledge; management skills and knowledge; entrepreneurship and innovation; human.	Ehie and Madsen (2005); Ngai et al. (2008); Ifinedo et al. (2010); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
Operation	Customised ERP system; regular audit of processes and procedures; defined standards and processes for business analytics; real-time business analytics for key users; operational process intelligence for real-time visibility and action; multichannel analytics for decision-making formats.	Standards and processes; real-time business analytics; operational process intelligence; multichannel analytics; outcome; data quality; information quality; development; delivery.	Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)

APPENDIX G: THE FOUR DIMENSIONS OF THE BA CAPABILITY IN THE BARCMM

Dimension	Coverage in the BARCMM	Coverage by other authors	Major Literature Sources
Data Capability	Extracts from one data source, Extracts from multiple data sources, Integrated data quality tools, Real-time updates, Unstructured data availability	Flat file access, insecure and inefficient; Direct programmatic database access and improved efficiency; Large volume data access, access lifecycle management challenges; Identity management tools, controlled data access and simplified compliance; Data access lineage tracking, source identification and secure data access	Halo (2015); Hornick (2020)
Analytics Capability	Static reports, Interactive dashboards, Real-time monitoring, Historical data forecasting, Performance optimisation	Ad hoc, non-scalable tools, desktop analysis; Data management tools, open-source and commercial tools; Scalable tools for large data, big data platforms, cloud-based tools; Standardised suite of tools, collaboration, automation, multi-platform support; Regular assessment of state-of-the-art tools, improved productivity and performance	
Collaboration Tools Capability	Restricted data access, IT-assisted extraction, Scheduled data emails, Automated alerts, Internal and external access	Independent work, local data storage and silo effect; Collaboration between data keepers and users, ad hoc sharing; Recognised need for team collaboration, sharing data science work products; Standardised tools and processes for cross-enterprise collaboration	
Sharing Capability	Job-specific data access, Departmental data access, Organisational data access, Extended to suppliers and distributors, Customer self-service BA metrics	Tools for sharing, modifying, tracking, and handing off work products	

APPENDIX H: CRITICAL SUCCESS FACTORS CLASSIFICATION FRAMEWORK FOR MEASURING MATURITY OF ORGANISATIONS USING ERP SYSTEMS (SLR 1)

The first systematic literature review (SLR 1) identified a classification framework for CSFs to measure the maturity of organisations using ERP systems (Wong & Lane 2023). SLR 1 revealed gaps in understanding the dimensions of ERP maturity models (ERPMM) and CSFs for new-generation ERP systems with BA features and functionalities. These gaps are further explored in SLR 3, in Appendix J, emphasising the importance of CSFs in assessing ERP BA readiness and BA capabilities in organisations using ERP systems.

H.1. SLR 1: Introduction

New generation ERP systems are crucial for digital transformation in medium to large organisations (Elragal & Hassanien 2019; Romero & Abad 2022), driven by innovations like AI and cloud computing. Maturity models, using CSFs, measure the effectiveness of ERP system implementation (Hairech & Lyhyaoui 2020).

CSFs, defined as key areas ensuring successful competitive performance, link satisfactory results in business activities to desired outcomes (Rockart 1979). They offer a structured approach to advising management on performance improvement (Borman & Janssen 2013).

For ERP systems, CSFs are categorised into high-level factors, specific capabilities, and key process areas (KPAs) (Díaz-Reza et al. 2019). Capabilities are organisational processes and routines necessary for achieving objectives (Ray & Ramakrishnan 2006). KPAs, as described by the Capability Maturity Model (CMM), consist of practices that collectively achieve improvement goals (Paulk et al. 1993).

CSFs are more generalisable than specific capabilities, which vary between organisations. This generalisability makes CSFs useful for comparing maturity models across different contexts. This categorisation aids in selecting appropriate CSFs and developing measurement items for ERP system maturity assessments.

Organisations with higher maturity levels are expected to utilise ERP systems more effectively, leading to greater perceived success.

Paulk et al. (1993) discuss how CSFs relate to capabilities and KPAs in maturity models. CSFs include essential factors necessary for achieving organisational goals and are often used to assess and improve specific process areas. The Generic Capability Reference model by Merkus et al. (2020) categorises capabilities as generic or specific, offering a comprehensive assessment across domains. Earlier ERPMMs, often derived from the Capability Maturity Model Integration (CMMI), have varied terminologies, leading to confusion in comparison and selection of CSFs (Holland & Light 2001; Hammer 2007; Snabe et al. 2008; Becker et al. 2010; Röglinger et al. 2012). A classification framework for CSFs will facilitate precise comparison and selection of maturity models (Tarhan et al. 2016).

H.2. SLR 1: Research Gap and Research Questions

There is a lack of research on adapting CSFs used for assessing ERP implementation and post-implementation success as measurement items for evaluating the maturity levels of organisations using new-generation ERP systems. Industry 4.0 has driven the evolution of ERP systems to incorporate advanced technologies, including artificial intelligence, machine learning, cloud computing, and integration with the Internet of Things (IoT) (Gröger 2018). New generations of ERP systems offer smart functionalities, but organisations' ability to fully leverage these systems varies based on staff capabilities. The extent to which an organisation can exploit a new-generation ERP system depends on their maturity level. CSFs that contribute to ERP implementation success may also influence post-implementation success and the realisation of ERP benefits.

SLR 1 was used to identify and classify the main dimensions for evaluating CSFs to determine maturity level of organisations using ERP systems. The SLR 1 was guided by two specific research questions: (RQ1.1) “What are the main dimensions of critical success factors that can be used as measurement items to assess ERP maturity models?”, and (RQ1.2) “What are the additional dimensions of critical success factors that can be used as measurement items to assess the maturity of organisations using new generation ERP systems?”.

SLR 1 identifies and categorises dimensions of CSFs previously used to predict ERP implementation and post-implementation success as these can also be used as the basis of measurement items to assess the maturity level of organisations using new generation ERP systems.

H.3. SLR 1: Method

The main purpose of this systematic literature review was to identify and classify the key dimensions for evaluating Critical Success Factors to determine the maturity level of organisations using ERP systems. A systematic literature review (SLR) assesses and interprets all available research pertinent to a research hypothesis or question (Kitchenham 2007). The steps adapted from Kitchenham's (2007) SLR guidelines were applied to systematically search for and select the relevant papers analysed in this research. This SLR approach was utilised for the second and third systematic literature reviews (SLRs 2 and 3).

1. Define research objective and hypotheses.
2. Define the search string; identify inclusion and exclusion criteria.
3. Conduct initial search.
4. Review the title, abstract, and keywords of the initially retrieved papers.
5. Revise inclusion and exclusion criteria; select potentially relevant papers.
6. Remove duplicate papers.
7. Review the selected relevant papers.
8. Review the full content of the selected papers, identifying missing papers in the references of the selected papers.
9. Review all selected relevant papers.
10. Identify the final set of relevant papers.

Table H.1 lists the search strings for SLR 1, which reviews ERPMMs. The search, conducted across Scopus, Science Direct, and Google Scholar from 2000 to 2022, ensured comprehensive coverage of peer-reviewed articles on CSFs used for assessing ERP implementation and post-implementation strategies, including the latest ERP iterations.

Table H.1 Search Strings for Specific Terms in SLR 1

Filter	Term	Search strings
1	Enterprise Resource Planning	“enterprise resource planning” or ERP or “enterprise systems” or “extended enterprise” or “industry 4.0”
2	Critical Success Factors	“critical success factor” or CSF
3	Maturity Model	“maturity model”
4	Measure Success	(measure or assess or evaluate) and (success or performance or benefits or use or usage or application or implementation or “post-implementation”)
5	Measure Maturity Level	(measure or assess or evaluate) and (level or maturity)

The PRISMA flow diagram notation, developed by Page et al. (2021), is illustrated in Figure H.1, showing the SLR process employed to identify relevant articles published from 2000 to 2022.

SLR 1 Phase 1 involved a comprehensive search for articles on ERP systems and either CSFs or maturity models (MMs), using search filters 1 and (2 or 3): "Enterprise Resource Planning" and ("Critical Success Factors" or "Maturity Model"). The search in Google Scholar was restricted to the title field to minimise duplicate records, while Scopus and Science Direct searches covered the title, abstract, and keyword fields, filtering for English language and specific paper types like journal articles and conference proceedings. The search period was 2000 to 2022 to ensure relevance. Initially, 445 articles were identified from Scopus (n = 175), Science Direct (n = 127), and Google Scholar (n = 143). After removing 28 duplicates using Endnote, 417 articles proceeded to Phase 2 screening.

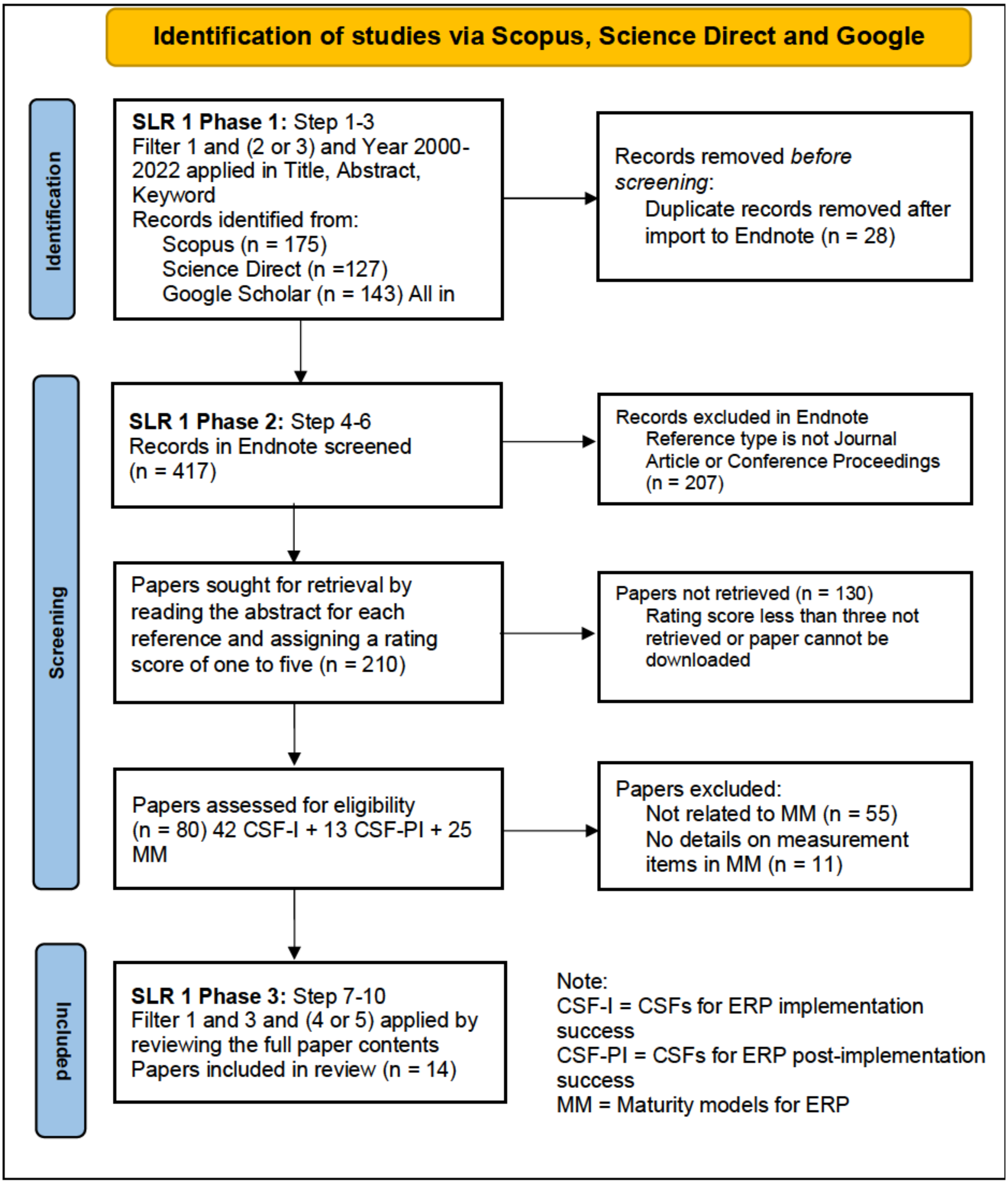

Figure H.1 PRISMA Flow Diagram of SLR 2 Procedure and Paper Filtering (ERP Maturity: CSFs Classification Framework)

In SLR 1 Phase 2, 417 records were imported into Endnote and screened. Of these, 207 were excluded for not being journal articles or conference proceedings. Two raters assessed the abstracts on a scale from one to five, resolving discrepancies by consensus. The remaining 210 papers were evaluated, with those rated 3 or above retained as relevant, and those rated 1 or 2 excluded. This review focused on papers about CSFs in ERP implementation, post-implementation, or maturity models (MMs). Consequently, 130 papers rated below three were excluded, leaving 80 for further review: 42 on CSFs in implementation (CSF-I), 13 on CSFs in post-implementation (CSF-PI), and 25 on maturity models (MMs). Of the 66 excluded papers, 55 were unrelated to MMs and 11 lacked details on measurement items.

In SLR 1 Phase 3, the full contents of the remaining papers were reviewed for relevance. The search filters applied were 1 and 3 and (4 or 5): "Enterprise Resource Planning" and "maturity model" and ("Measure Success" or "Measure Maturity Level"). Fourteen papers were included for review, and papers lacking sufficient detail on measurement items were excluded. The contents of the 14 included papers were examined for additional relevant papers, but no further significant papers were identified.

H.4. Results of SLR 1: Dimensions for Classification of CSFs for ERP Implementation and Post-implementation Success

The CSFs identified in SLR 1 Phase 2 are categorised into seven dimensions: Governance, Culture, Technology, Operation, People, Project, and Performance. Table H.2 summarises these dimensions, sub-dimensions, and related CSFs for ERP implementation and post-implementation success.

Table H.2 CSF Dimensions and Specific Indicators for ERP Implementation and Post-Implementation Success (with Sources)

High Level Dimensions	Sub-dimensions	Specific CSF Indicators	Major Literature Sources
Governance	Change management	Change agents & leadership; Management readiness for change; Scope for change; Management of change	Somers and Nelson (2004); Motwani et al. (2005); Ngai et al. (2008); Ram and Corkindale (2014)
	Strategic planning	Business plan/ vision/ goals/ justification; Clear goal/ objectives/ strategy; Acquisition strategy; Strategic IT plans & governance	Somers and Nelson (2004); Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	Top management support	Top management engagement/ involvement/ commitment/ awareness/ incentives; Dedicated resources; Funds support; Leaders support	Somers and Nelson (2004); Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
Culture	Organisational culture	Learning & development; Participative decision making; Power sharing; Support & collaboration; Conflicts & risk tolerance culture	Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	Employee morale	Employees' morale and motivation	Ram and Corkindale (2014)
Technology	Customisation	Customisation of ERP; Organisational fit of ERP; Minimal customisation; ERP adaptation	Ngai et al. (2008); Ram and Corkindale (2014)
	Compatibility	ERP compatibility; Legacy systems; Data conversion; Fitness factors	Ngai et al. (2008); Ram and Corkindale (2014)
	Quality	Implementation quality; Information, system & service quality; Data accuracy; Data migration; Vendor quality & support	Motwani et al. (2005); Ngai et al. (2008); Ifinedo et al. (2010); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	IT infrastructure	Technological complexity; IS resources; IS capabilities; System integration; System use	Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)

Table H.2 CSF Dimensions and Specific Indicators for ERP Implementation and Post-Implementation Success (with Sources)

High Level Dimensions	Sub-dimensions	Specific CSF Indicators	Major Literature Sources
Operation	Business process management	Business process improvement; Business process re-engineering (BPR); Process formalisation	Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	Cooperation	Cross-functional/Inter-departmental cooperation; Network relationships; Connectedness with user departments	Ifinedo et al. (2010); Ram and Corkindale (2014)
People	User satisfaction	Key user satisfaction; Employee satisfaction; Ease of use; User expectations	Ifinedo et al. (2010); Ram and Corkindale (2014)
	Perceived usefulness	Shared belief in system benefits; Shared understanding of implemented technology; Behavioural intention; Individual impact	Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	Skills	Communication/ analytical/ leadership/ personal/ management/ technical skills; ERP experience/ expertise; Learning skills; User learning capacity; Users' absorptive capacity	Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	Social factors	Users attitude towards ERP system; Facilitating conditions; Near-term/ Long-term consequences; Affect; Competitive pressure	Ram and Corkindale (2014)
	Human resource management	Recruit, appraise, develop and preserve qualified employees	Ehie and Madsen (2005); Rouhani and Ravasan (2013)
	Training and education	Training of personnel; Train IT staff in new skills; Training plan; Well-established education and training strategy; Effective training	Ifinedo et al. (2010); Rouhani and Ravasan (2013); Ram and Corkindale (2014)

Table H.2 CSF Dimensions and Specific Indicators for ERP Implementation and Post-Implementation Success (with Sources)

High Level Dimensions	**Sub-dimensions**	**Specific CSF Indicators**	**Major Literature Sources**
Project	Project management	Project justification; Full-time project manager; Project champion; Proven implementation plan; Project planning; Cost benefit analysis; Leadership; Steering committee	Motwani et al. (2005); Ngai et al. (2008); Ram and Corkindale (2014)
	Project team competence	Project team empowerment; Teamwork participation/ composition; Team with multiple skills; Knowledge management competence; Group cohesion	Motwani et al. (2005); Ngai et al. (2008); Rouhani and Ravasan (2013); Ram and Corkindale (2014)
	ERP selection	Feasibility of ERP project/ consulting services/ costing issues; ERP package selection; Use of consultants	Somers and Nelson (2004); Ram and Corkindale (2014)
Performance	Organisational performance	Measurement of internal efficiency, competitiveness, profitability; Organisational objective consensus/ readiness/ impact; Performance evaluation & management/ auditing & control	Ngai et al. (2008); Ifinedo et al. (2010)
	Overall efficiency	Coordination improvement; Task efficiency	Chou and Chang (2008); Tsai et al. (2009)
	Usage performance	Utilisation performance/ metrics	Ram and Corkindale (2014); Abu Ghazaleh et al. (2019)

H.5. Results of SLR 1: Use of CSFs in Maturity Models for ERP Systems

In SLR 1 Phase 3, fourteen papers on ERP maturity models were identified and summarised in Table H.3 by year, application area, measurement item, and maturity level.

Table H.3 ERPMMs by Author, Application, Measurement, and Maturity Levels (2001-2021)

Authors (Year of publication)	**Application area of maturity model**	**Measurement item**	**Maturity levels**
Holland and Light (2001)	ERP maturity	CSFs for Specific Capabilities	3 stages Self-defined
Hammer (2007)	Process and enterprise maturity	CSFs for Specific Capabilities	4 levels Self-defined
Parthasarathy and Ramachandran (2008)	ERP maturity	CSFs for Specific KPAs	3 levels Self-defined
Hwang and Grant (2014)	ERP integration maturity	High level CSFs	5 levels Self-defined
Rockwell Automation (2014)	Industry 4.0 IT capability of enterprise	CSFs for Specific Capabilities	5 stages Self-defined
Lichtblau et al. (2015)	Industry 4.0 readiness maturity	CSFs for Specific Capabilities	6 levels Self-defined
Castor et al. (2016)	Manufacturing Operations Management (MOM) maturity	CSFs for Specific Capabilities	6 levels Self-defined
Geissbauer et al. (2016)	Industry 4.0 maturity	CSFs for Specific Capabilities	4 stages Self-defined
Schumacher et al. (2016)	Industry 4.0 maturity	High level CSFs	5 levels CMM
Deloitte (2017)	Extended ERP maturity	CSFs for Specific Capabilities	5 levels CMM
Pulkkinen et al. (2019)	Industry 4.0 Digital extended enterprise maturity	CSFs for Specific KPAs	5 levels Self-defined
Gërvalla (2020)	ERP maturity	High level CSFs	5 levels CMM
Rafael et al. (2020)	Industry 4.0 maturity	CSFs for Specific Capabilities	6 levels Self-defined
Wagire et al. (2021)	Industry 4.0 maturity	CSFs for Specific Capabilities	4 levels Self-defined

H.6. Results of SLR 1: Selection of CSFs as Measurement Items for ERP Maturity Models

In Table H.3, nine out of the fourteen MMs use CSFs for specific capabilities as measurement items, three models use high level CSFs as measurement items, and two models use CSFs for specific KPAs as the measurement items.

H.7. Results of SLR 1: Adding CSF Dimensions for Industry 4.0 ERP Maturity Models

Table H.4 shows the additional dimensions of CSFs that can be used as measurement items in ERP Maturity Models that accommodate Industry 4.0.

Table H.4 Additional CSF Dimensions and measurement items, Industry 4.0, used in ERP Maturity Models

High Level Dimensions	Sub-dimensions	Specific CSF Indicators	ERP Industry 4.0 References
Technology	Innovation	Operations technology, Innovation management, Technological innovations	Rockwell Automation (2014), Lichtblau et al. (2015), Rafael et al. (2020), Wagire et al. (2021)
	Compliance & Security	Enterprise networks security policies, Data security & data privacy	Rockwell Automation (2014), Geissbauer et al. (2016), Wagire et al. (2021)
Products & Services	Disruptive business models	Business model innovation, Digital business models	Geissbauer et al. (2016), Pulkkinen et al. (2019), Rafael et al. (2020)
	Smart products/services	Smart manufacturing, Smart product/factory, Individualisation of products, Digitalisation of products, Product integration into other systems	Rockwell Automation (2014), Lichtblau et al. (2015), Geissbauer et al. (2016), Schumacher et al. (2016), Rafael et al. (2020), Wagire et al. (2021)

APPENDIX I: METHODOLOGICAL APPROACHES FOR DESIGNING, ASSESSING AND VALIDATING BUSINESS ANALYTICS MATURITY MODELS (SLR 2)

The second systematic literature review (SLR 2) identified a research gap (RG2.3) in the documentation and explanation of BAMMs. This review guides the selection of suitable methodological approaches for designing, assessing, and validating the proposed BARCMM in Chapters 4 to 6. It also establishes a robust framework informed by existing research and practices (Wong et al. 2021).

I.1. SLR 2: Introduction

Prior studies of BAMMs focus on technological and operational aspects. Maturity models (MMs) are widely used for documenting and guiding organisational development based on best practices (Paulk et al. 1993). However, research on the methodological approach to designing, assessing, and validating BAMMs is limited. With the growing diversity of MM research, systematic categorisation and analysis are necessary to develop a methodologically rigorous approach (Wendler 2012).

I.2. SLR 2: Research Gap and Research Questions

In this research, a systematic literature review was conducted in relation to MMs, BIMMs, and more specifically, BAMMs. SLR 2 is intended to address Research Gap RG2.3: "Limited Documentation and Explanation of BAMMs and Their Empirical Processes". This gap is addressed by RQ2.3: "What is the state of research on BAMMs, and how can they be empirically designed, assessed, and validated?". The objective of RQ2.3 was to report on the state of research on BAMMs and identify how they can be empirically (1) designed, (2) assessed, and (3) validated.

I.3. SLR 2: Method

SLR 2 followed the same steps as SLR 1, adapted from Kitchenham's (2007) SLR guidelines, to systematically search for and select relevant papers. Science Direct provides articles from around 1,500 journals across various disciplines, while Google Scholar allows broad searches across multiple disciplines and sources. The search strings used in SLR 2 are listed in Table I.1. Figure I.1 illustrates the refinement steps and resulting number of papers from January 2000 to December 2020.

Table I.1 Search Strings for Specific Terms in SLR 2

Filter	**Term**	**Search strings**
1	Business Intelligence	“business intelligence”
2	Business Analytics	“business analytics”
3	Maturity Model	“maturity model”
4	Design	“design” or “develop” or “create”
5	Assess	“assess” or “measure” or “evaluate”
6	Validate	“validate” or “validation”

In SLR 2 Phase 1, a filtering process applied combinations (1 and 3) or (2 and 3) to title, abstract, keyword, and publication year (2000-2021) of academic papers. Science Direct yielded 300 records (240 for (1 and 3), 60 for (2 and 3)), and Google Scholar yielded 88 records (76 for (1 and 3), 12 for (2 and 3). In total, 388 records were identified from both sources during SLR 2 Phase 1.

In SLR 2 Phase 2, during Steps 4-6, a screening process in Endnote identified 85 relevant records by excluding 288 deemed irrelevant to the study's focus on BIMMs and BAMMs. Additionally, 15 duplicate records were removed. Of the screened records, 36 papers were assessed for eligibility.

In SLR 2 Phase 3, Steps 7-10 involved filtering papers based on criteria (1 or 2) and 3, and (4, 5, or 6). Eight papers on BIMMs and BAMMs were included, while 28 papers were excluded for lacking details on the design, assessment, or validation of maturity models. The eight selected papers, sorted by ascending year of publication, are summarised in Table I.2. This table indicates that prior research evaluated BI/BA maturity models in terms of characteristics of different types, methodological approaches for design, assessment, and validation, and key results.

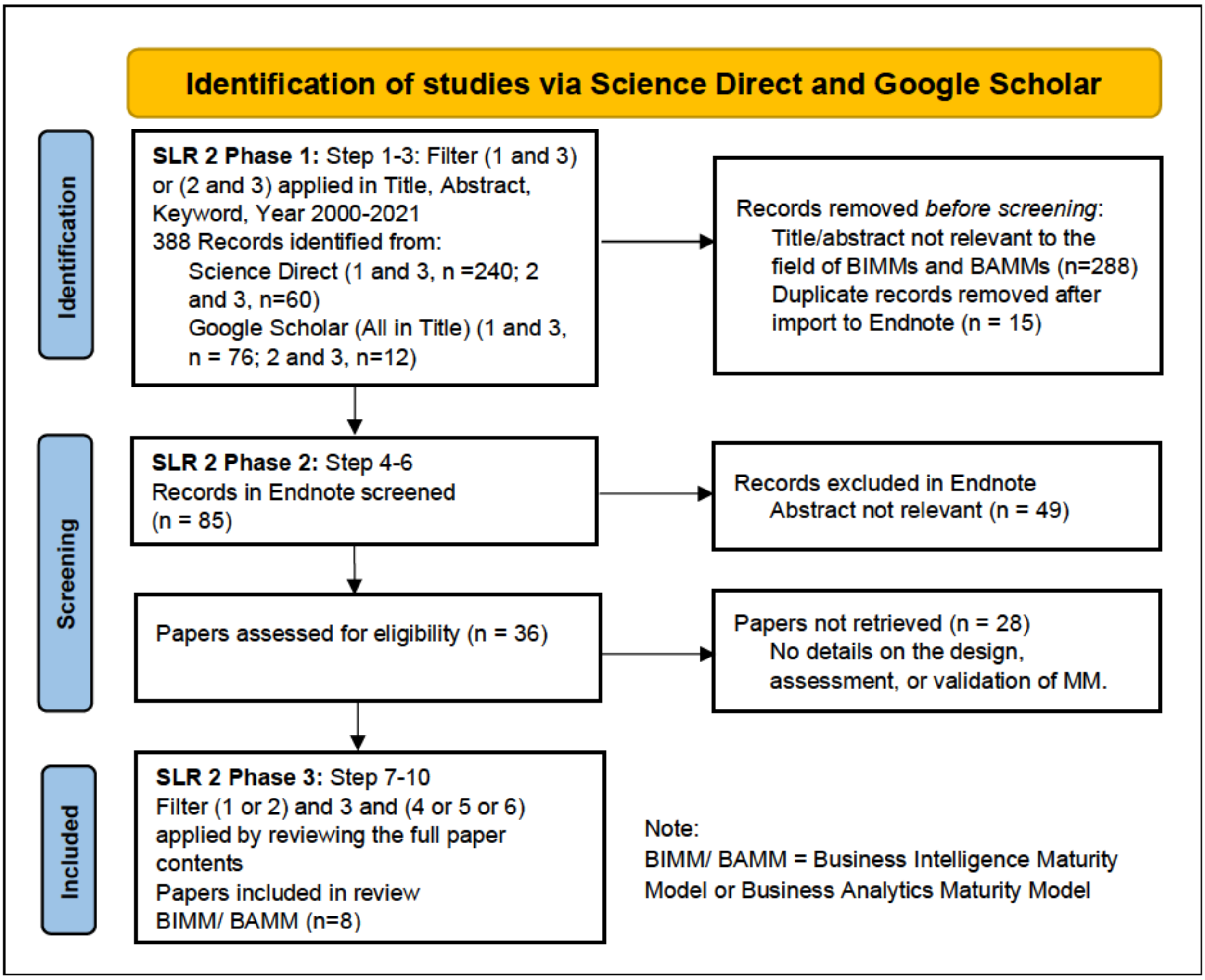

Figure I.1 PRISMA Flow Diagram of SLR 2 Procedure and Paper Filtering (BAMM Methodologies)

I.4. Results of SLR 2: BIMMs/BAMMs

Table I.2 reveals that systematic literature reviews of the eight BIMMs/BAMMs offer general descriptions of their characteristics and classification but lack technical details on the application of their methodological approaches. Table I.3 summarises the properties, characteristics, and references of maturity models.

Table I.2 Design, Assessment, and Validation of BIMMs/BAMMs

Author(s) (Year)	Focus	Maturity Model	Design	Assessment	Validation	Summary
Lahrmann et al. (2011)	Inductive design of MMs: applying Rasch analysis	BI	Yes	Yes	No	Positive impacts on organisational performance, financially and functionally, from actionable BI system outcomes.
Lukman et al. (2011)	BI maturity in Slovenia	BI	Yes	Yes	No	BI maturity considers three aspects: technology, business, and information quality.
Cosic et al. (2012); Cosic (2020)	BA Capability Maturity Model (BACMM)	BA	Yes	Yes	Yes	Holistic view of sixteen BA capabilities grouped into four areas: governance, culture, technology, and people.
Raber et al. (2013b, 2013a)	Situational BI Maturity Models: Exploratory Analysis	BI	Yes	Yes	Yes	Explored contextual factors influencing BI maturity. Assessed BI maturity using Rasch Analysis and Hierarchical Clustering to determine item difficulty and maturity levels, then assigned items to maturity levels.
Halper and Stodder (2014)	TDWI Analytics Maturity Model (AMM) Guide	BA	No	Yes	No	Five stages: nascent, pre-adoption, early adoption, corporate adoption, mature/visionary. Online assessment measures maturity across five essential dimensions.
The Institute for Operations Research and the Management Sciences (2017)	INFORMS Analytics Maturity Model (AMM) User Guide	BA	No	Yes	No	Online platform for organisations to self-assess three critical themes. Calculates overall, category, and factor scores for 12 questions, determining if scores are Beginning, Developing, or Advanced.
Lasrado et al. (2017)	The influence of different quantitative methods on the design and assessment of maturity models	BA of social media	Yes	Yes	Yes	Compared scale sensitivity and maturity stages using Additive Logic, Variance Techniques, Cluster, Minimum Constraints, and Rasch Analysis. Validated social media maturity and business value relationship with PLS-SEM.
International Institute for Analytics (n.d.)	Analytics Maturity Assessment (AMA)	BA	No	Yes	No	Software-driven MM based on Five Stages of Analytics Maturity (Davenport & Harris 2007) and DELTA Model (Davenport et al. 2010).

Table I.3 Characteristics of Maturity Models (Adapted from Lasrado (2018); Menukhin et al. (2019))

Property	Characteristics	References
Maturity levels	Archetypal maturity states. Each level has distinct, empirically testable characteristics.	Raber et al. (2013b)
Number of stages or levels	3 to 6, depending on model and its purpose.	Raber et al. (2013b); Van Steenbergen et al. (2013)
Stage fixed or Continuous	Continuous models score characteristics at different levels. Staged models require all elements of a level to be achieved.	Raber et al. (2013b); Van Steenbergen et al. (2013)
Maturity score	Uses numeric values for benchmarking. Commonly visualised with a spider cobweb design.	Raber et al. (2013b); Van Steenbergen et al. (2013)
Dimensions	Also termed benchmark variables, process areas, capabilities, and CSFs. Each dimension is characterised by measures like practices, objects, or activities at each maturity level.	Lasrado (2018); Menukhin et al. (2019)
Sub-categories	Second level variables on which key dimensions depend.	Van Steenbergen et al. (2013)
Assessment Approach	Qualitative assessments use descriptions. Quantitative use numeric measures.	Lasrado (2018); Menukhin et al. (2019)
Assessment method	Self-assessment via surveys is most common. Third-party assessments or certifications by experts are also used.	Wendler (2012)

I.5. Results of SLR 2: Business Intelligence Maturity Models

Table I.4 summarises three of the eight identified BIMMs/BAMMs listed in Table I.2 that are BIMMs, focusing on their design, assessment, and validation.

Table I.4 Comparison of BIMMs with Sources

Maturity Model	Focus	Design	Assessment	Validation	Source
BI	Dimensions: Strategy, Organisation/ Process, IT support	Quantitative bottom-up approach (Rasch analysis with cluster analysis for maturity levels)	Questionnaire results: 51 companies; cross-industry	Not specified.	Lahrmann et al. (2011) [Academia]
BI	BI in Slovenia	Quantitative bottom-up approach (K-Means algorithm)	Questionnaire results: 131 companies; cross-industry	Not specified.	Lukman et al. (2011) [Academia]
BI	Dimensions: Strategy, Social System, Technical System, Quality, Use/Impact	Quantitative bottom-up approach (Rasch analysis with cluster analysis for maturity levels)	Questionnaire results: 51 companies; cross-industry	Discussion of final model with three industry experts on comprehensiveness, self-assessment, potential BI roadmap	Raber et al. (2013b, 2013a) [Academia]

I.6. Results of SLR 2: Business Analytics Maturity Models

Table I.5 summarises five of the eight identified BIMMs/BAMMs (BAMMs) listed in Table I.2, detailing their focus, design, assessment, validation methods, and sources.

Table I.6 shows a comparison of the Business Analytics Capability Maturity Model (BACMM) with three other practitioners' BAMMs.

Table I.5 Comparison of BAMMs with Sources

Maturity Model	Focus	Design	Assessment	Validation	Source
Business Analytics Capability Maturity Model (BACMM)	Assess BA initiatives within large-scale Australian organisations	The model development process is based on approach of Becker et al. (2009)	16 key capabilities aggregated to measure maturity for each of the four high-level BA capabilities and overall BA capability.	A Delphi study with an expert panel used to validate and refine BA Capability Framework constructs	Cosic et al. (2012); Cosic (2020) [Academia] based on Becker et al. (2009)
TDWI Analytics Maturity Model	Predictive analytics, social media/ text analytics, cloud computing, and big data analytics approaches	Not specified.	Assess enterprises' analytics capabilities	Not specified.	Halper and Stodder (2014) [Practitioner]
INFORMS Analytics Maturity Model	Benchmarking capabilities and identifying actions to improve analytical maturity	Not specified.	Each dimension has a potential high score of 10 points.	Not specified.	The Institute for Operations Research and the Management Sciences (2017) [Practitioner]
BA of social media maturity model	The influence of different quantitative methods on the design and assessment of maturity models	Not specified.	Analysis of dataset and maturity scores using five methods: Additive Logic, Variance Techniques, Cluster, Minimum Constraints, Rasch Analysis.	Compared sensitivity of measurement scale and maturity stages. Relationship between social media maturity and business value were validated using PLS-SEM.	Lasrado et al. (2017) [Academia]
International Institute for Analytics (IIA) Analytics Maturity Model	Optimising performance by improving analytics capabilities	Not specified.	Assesses analytics maturity against 33 competencies within five DELTA model categories.	Not specified.	International Institute for Analytics (n.d.) [Practitioner]

Table I.6 Comparison of BAMMs: Academia and Practitioners

<table>
<tr><td>Maturity Model</td><td>Business Analytics Capability Maturity Model (BACMM)</td><td>TDWI Analytics Maturity Model</td><td>INFORMS Analytics Maturity Model</td><td>International Institute for Analytics (IIA) Analytics Maturity Model</td></tr>
<tr><td>Purpose</td><td>Descriptive</td><td>Prescriptive</td><td>Prescriptive</td><td>Prescriptive</td></tr>
<tr><td>Origin</td><td>Cosic et al. (2012); Cosic (2020)
[Academia]</td><td>Halper and Stodder (2014)
[Practitioner]</td><td>The Institute for Operations Research and the Management Sciences (2017)
[Practitioner]</td><td>International Institute for Analytics (n.d.)
[Practitioner]</td></tr>
<tr><td>Stages/ Levels</td><td>5 levels: Non-existent, Initial, Intermediate, Advanced, Optimised</td><td>5 stages: Nascent, Pre-adoption, Early Adoption, Corporate Adoption, Mature/ Visionary</td><td>3 levels:
Beginning, Developing, Advanced</td><td>5 stages: Analytically impaired, Localised analytics, Analytical aspirations, Analytical companies, Analytical competitors</td></tr>
<tr><td>Dimensions</td><td>4 dimensions: Technology, People, Culture and Governance</td><td>5 dimensions: Organisation, Infrastructure, Data Management, Analytics, Governance</td><td>3 dimensions: Organisational, Analytics Capability, Data & Infrastructure</td><td>5 dimensions: Data, Enterprise, Leadership, Targets, Analysts</td></tr>
<tr><td>Assessment</td><td>• BACMM combines BA capabilities framework with five-level maturity scale (Paulk et al. 1993).
• Maturity scale applied to each of the 16 BA capabilities.
• Aggregated maturity levels assess four high-level and overall BA capability.</td><td>Each dimension potential high score of 20 points.
<table>
<tr><td>Score per Dimension</td><td>Stage</td></tr>
<tr><td>4–7.1</td><td>Nascent</td></tr>
<tr><td>7.2–10.1</td><td>Pre-Adoption</td></tr>
<tr><td>10.2–13.3</td><td>Early Adoption</td></tr>
<tr><td>13.4–16.6</td><td>Corporate Adoption</td></tr>
<tr><td>16.7–20</td><td>Mature/ Visionary</td></tr>
</table></td><td>Each dimension potential high score of 10 points.
<table>
<tr><td>Score per Dimension</td><td>Stage</td></tr>
<tr><td>1 – 3</td><td>Beginning</td></tr>
<tr><td>4 – 7</td><td>Developing</td></tr>
<tr><td>9 – 10</td><td>Advanced</td></tr>
</table></td><td>• Evaluated against 33 competencies within five DELTA categories.
• DELTA scores on a 1.00-5.99 scale, with maturity stages for each score range (1-1.99, 2-2.99, etc.).</td></tr>
</table>

I.7. Results of SLR 2: Methodological Approaches used in Design, Assessment and Validation of Maturity Models

Table I.7 presents a comprehensive comparison of three methods: Set Theoretic Approach (STA), Rasch Analysis, and Hierarchical Clustering, for developing and validating maturity models.

Table I.7 Comparison of Methods for Developing and Validating Maturity Models

Aspect	Set Theoretic Approach (STA)	Rasch Analysis	Hierarchical Clustering
Method Type	Qualitative	Statistical	Statistical
Purpose	Analysing complex relationships	Measuring latent variables	Grouping similar cases
Fundamental Concept	Sets and relationships between sets	Probability and item difficulty	Distance matrix and similarity
Key Features	Equifinality Multiple conjunctural causation Case diversity	Measures ability/maturity Develops and validates models Tests unidimensionality	Groups similar cases Identifies characteristics of different groups
Analysing Conditions for Outcomes	Identifies necessary and sufficient conditions	Validation of maturity models	Grouping based on similarity
Ability to Analyse Cases	Wide range of cases, positive and negative outcomes	Sample-based analysis	Sample-based analysis
Suitability for Research Goals	Exploratory research	Confirmatory research	Confirmatory research
Causal Relationship Understanding	Able to identify necessary and sufficient conditions for outcomes	Measures the construct in a unidimensional and invariant way	Identifies characteristics of different groups
Best Use Case	Explore relationships between variables	Validate pre-existing model of maturity	Develop and validate maturity models

Lasrado et al. (2017) examined how various quantitative methods impact the design and assessment of maturity models. Table I.8 summarises these methods by their design, assumptions, and applications.

Figure I.2 shows the Methodological Framework for the Multi-Method Comparative Study of Maturity Models, adapted from Lasrado et al. (2017).

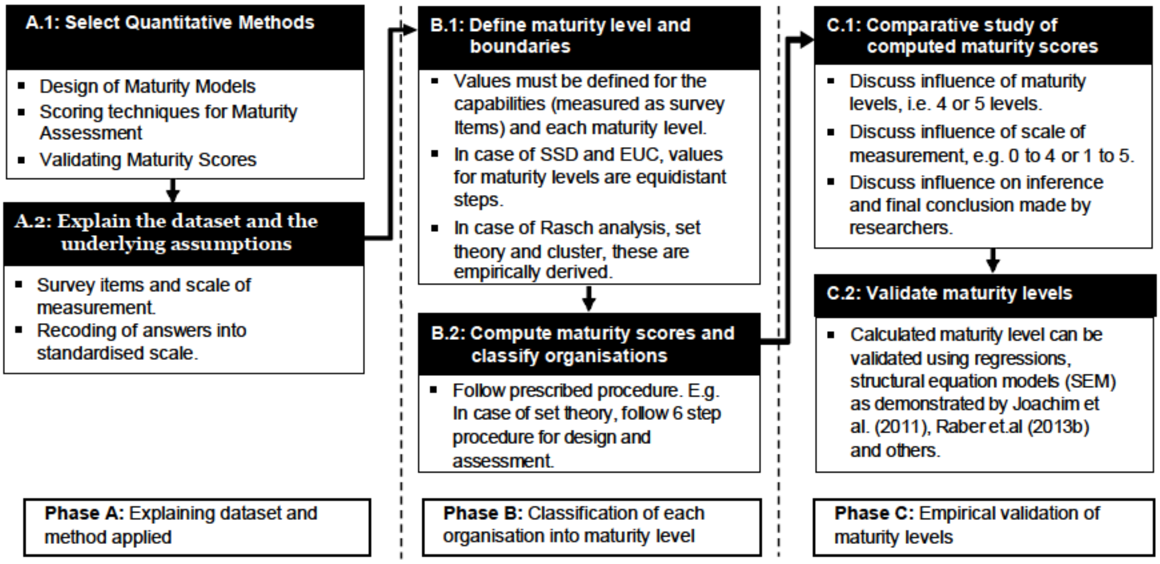

Figure I.2 Methodological Framework for the Multi-Method Comparative Study of Maturity Models (Lasrado et al. 2017)

Table I.8 Quantitative Methods in Maturity Models Research with Sources (Lasrado et al. 2017)

Phase	Method	Assumption	Application Summary	Source
(1) Design	Rasch Analysis	Organisations with higher maturity have high probability of successfully implementing capabilities.	Rasch and cluster analysis used to describe software development process evolution with CMM questionnaire	Dekleva and Drehmer (1997)
			Initial MM derived in design phase from Rasch and cluster analysis results	Lahrmann et al. (2011); Berghaus and Back (2016); Raber et al. (2013a)
	Set Theory: QCA and NCA applied together	Equifinality assumes multiple paths to maturation	QCA and NCA used to design social media maturity model with six-step procedure	Lasrado et al. (2017)
(2) Assessment	Cluster: Two Step Clustering, Fuzzy Clustering	Groups of organisations are homogeneous in specific maturity capabilities	Cluster analysis categorised companies by organisational maturity and information system skill needs	Benbasat et al. (1980)
			Clustering used to assess corporate collaboration maturity with mixed-scaled data	Jansz (2016)
	Additive Logic: Summation or average of capabilities, with or without weights	A single linear path to higher maturity; higher maturity implies more capabilities implemented	Summation, simple average, and weighted average (with arbitrary or non-empirical weights) are common in maturity assessments	Luftman (2001); Van Steenbergen et al. (2013); Chung et al. (2017)
			Empirical weight calculation using methods like PLS-SEM is rare	Winkler et al. (2015)
	Minimum Constraints: (c) Statistical Squared Distance (SSD)	Single linear path to higher maturity based on the theory of constraints; overall maturity determined by lowest capability level	SSD for each maturity level is calculated using 21 items' characteristic values; organisation is categorised by lowest SSD, weighted by standard deviation at capability level	Joachim et al. (2011)
	(d) Euclidian Distance (EUC)		EUC is computed for a maturity dimension based on responses to specific items	Raber et al. (2013a)
(3) Validation	Variance Techniques: Regression, correlation coefficients, and significance tests	High maturity organisations achieve greater business benefits, performance, and value than lower maturity organisations	Validating maturity using regression and statistical significance tests	Sledgianowski et al. (2007); Chen (2010); Joachim et al. (2011)
			Validating maturity with correlation coefficients against self-reported maturity, benefits, or performance	Marrone and Kolbe (2011)
			Maturity level validated using PLS-SEM	Raber et al. (2013a); Lasrado et al. (2017)

I.8. Results of SLR 2: Methodological Approaches used in Design, Assessment and Validation of BIMMs/BAMMs

Figure I.3 illustrates the methodological approach used by Raber et al. (2013a, 2013b) for designing, assessing, and validating BIMMs/BAMMs.

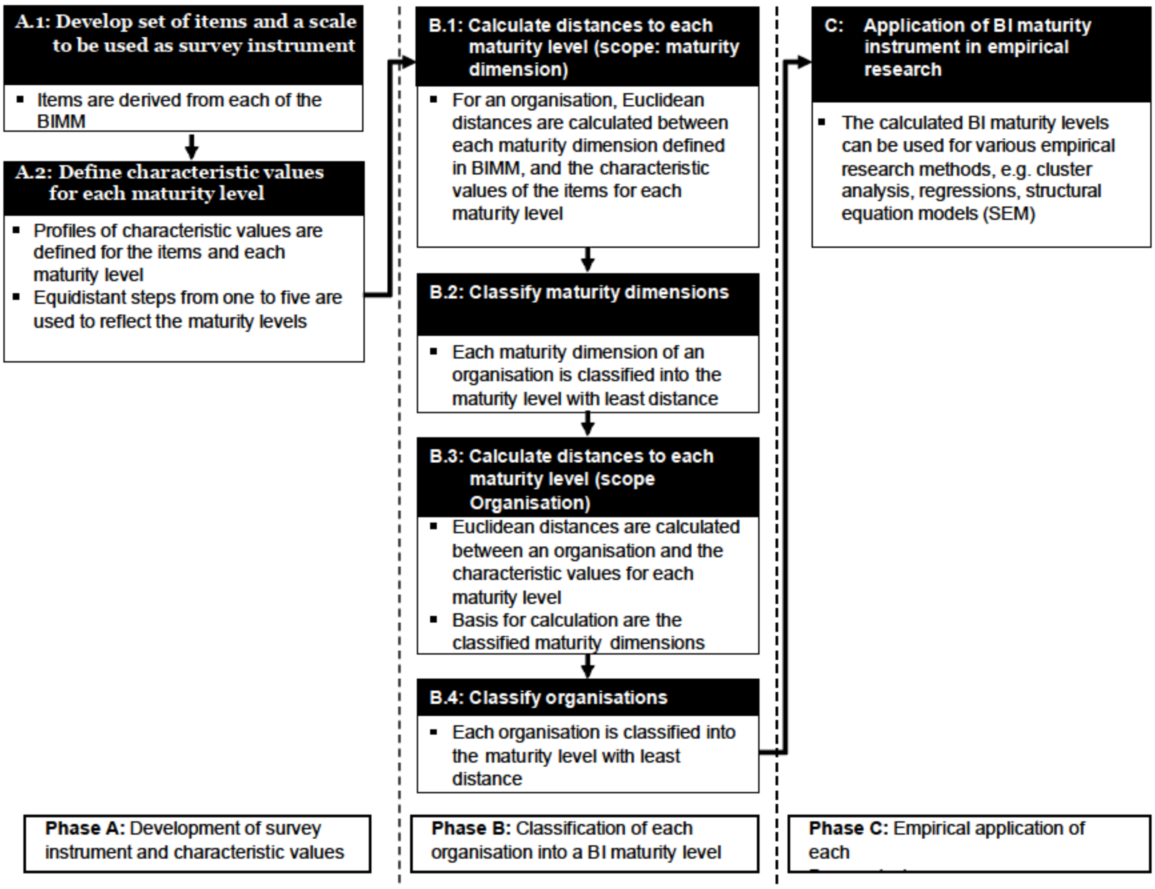

Figure I.3 Methodological Approach used in Design, Assessment and Validation of BIMMs/BAMMs (Raber et al. 2013b)

APPENDIX J: MEASURING BUSINESS ANALYTICS MATURITY IN ERP SYSTEMS (SLR 3)

The third systematic literature review (SLR 3) was conducted on measuring BA maturity for organisations using ERP systems. Two research gaps were identified in SLR 3. RG2.1 is the limited documentation of methodological approaches in designing, assessing, and validating BAMMs. RG2.2 is the lack of research on adapting BAMMs underpinned by CSFs for new-generation ERP systems. The key findings of SLR 3 will guide and inform the development of the BARCMM for this research in Chapter 4.

J.1. SLR 3: Introduction

Two research gaps were identified in SLR 3. RG2.1 is the limited documentation of methodological approaches in designing, assessing, and validating BAMMs. RG2.2 is the lack of research on adapting BAMMs underpinned by CSFs for new-generation ERP systems.

RG2.1 refers to the limited documentation of methodological approaches in designing, assessing, and validating BAMMs. This gap highlights that, while maturity models are widely accepted for assessing the maturity of key capabilities in organisations, there is insufficient documentation of the processes involved in their development. Many researchers and practitioners conceptualise their own models without adequately explaining their decisions, which raises questions about the validity of these models (de Bruin et al. 2005; Becker et al. 2009; Ariyarathna & Peter 2019).

RG2.2 highlights the lack of research on adapting BAMMs based on CSFs for new-generation ERP systems. ERP vendors are enhancing BA capabilities within their ERP applications, including real-time dashboards (Drobik & Rayner 2015). These systems play a critical role in improving business decision-making and performance. New-generation ERP systems increasingly use artificial intelligence and serve as the information backbone of Industry 4.0, featuring in-memory technology, a service-oriented architecture, cloud computing, and integration with shop floor systems (Zeba et al. 2019). Existing BAMMs do not accommodate the sophisticated BA capabilities of these advanced ERP systems, which incorporate technologies such as artificial intelligence, blockchain, and IoT sensor networks.

J.2. SLR 3: Research Gap and Research Questions

An extensive literature review shows most BAMMs are generic and not industry-specific. SLR 3 focuses on BA maturity in organisations using ERP systems, as advanced BA features are increasingly embedded in new ERP systems. However, BA maturity can vary even with the same ERP system and BA tools. Achieving a specified set of CSFs indicating higher ERP capability maturity suggests higher BA capability maturity and BA success. This research addresses the gap by examining existing ERP and BA MMs to assess BA maturity in organisations using new ERP systems, focusing on their design, development, and validation. It answers two research questions (RQs 2.1 and 2.2) through a systematic literature review.

Research Gap RG2.1: "Limited Documentation of Methodological Approaches in Designing, Assessing, and Validating BAMMs", is addressed by RQ2.1: "What are the main methodological approaches used to design, assess, and validate BA maturity models?". Research Gap RG2.2: "Lack of Research on Adapting BAMMs Underpinned by CSFs for New-Generation ERP Systems", is addressed by RQ2.2: "How can the BA maturity level of organisations using a new generation of ERP system be determined by adapting existing BA maturity models?".

J.3. SLR 3: Method

SLR 3 applied the same steps used in SLRs 1 and 2, adapted from Kitchenham's (2007) SLR guidelines, to systematically search for and select relevant papers. The search strings for specific terms used in SLR 3 are listed in Table J.1.

Table J.1 Search Strings for Specific Terms in SLR 3

Filter	Term	Search strings
1	Business Intelligence	"business intelligence"
2	Business Analytics	"business analytics"
3	Enterprise Resource Planning	"enterprise resource planning" or "ERP" or "enterprise systems" or "extended enterprise"
4	Industry 4.0	"the fourth industrial revolution" or "industry 4.0" or "smart manufacturing"
5	Maturity Model	"maturity model"
6	Design	"design" or "develop" or "create"
7	Assess	"assess" or "measure" or "evaluate"
8	Validate	"validate" or "validation"

The literature search used Science Direct for academic papers and Google Scholar for a broader range of publications, including journal articles, open access works, and practitioner white papers. Figure J.1 shows the PRISMA flow diagram, outlining the systematic review process and article selection from 2000 to 2023. The search range was chosen because maturity models for ERP systems date back to 2000, while newer ERP systems with BA functionalities have emerged more recently.

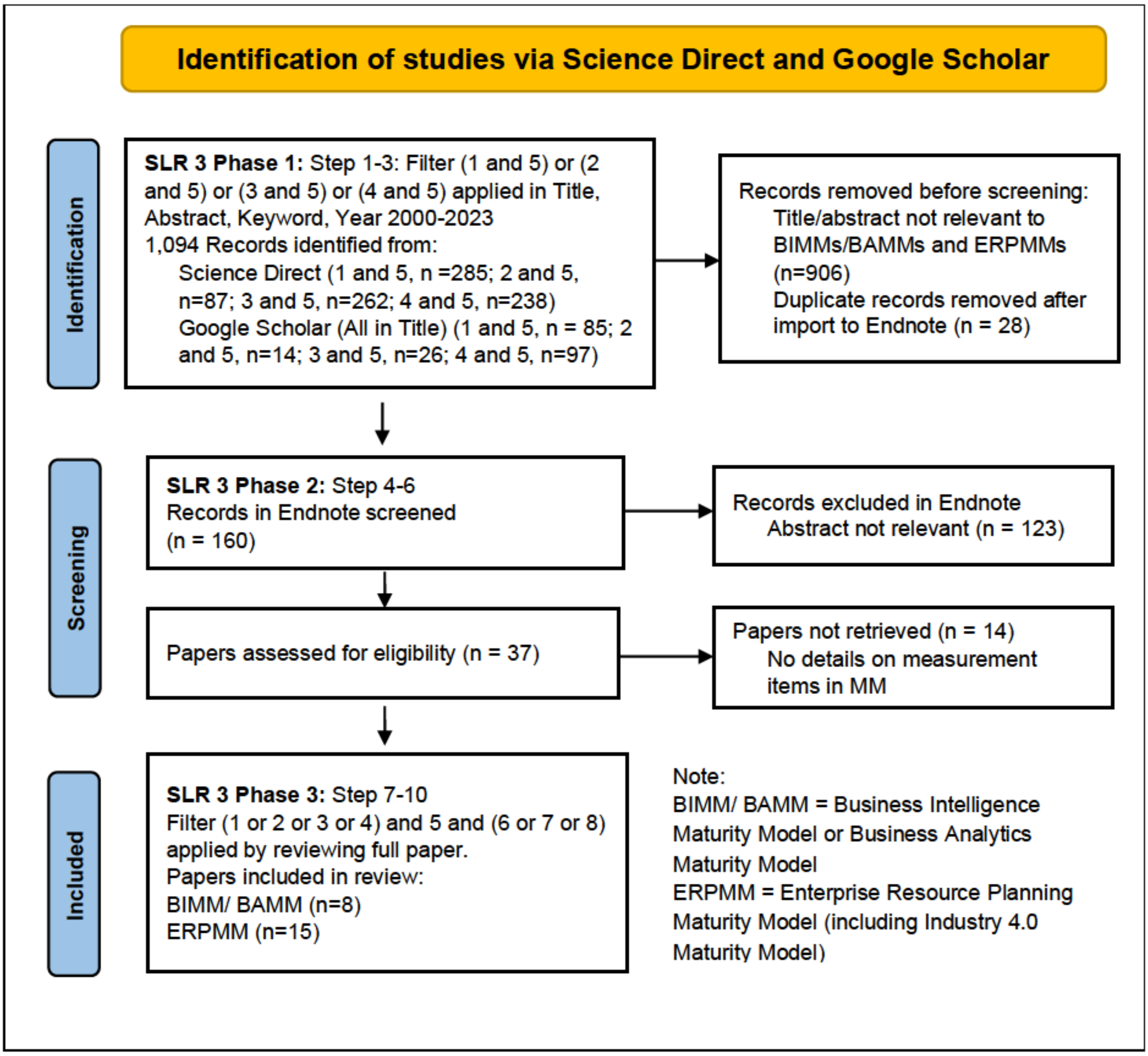

Figure J.1 PRISMA Flow Diagram of SLR 2 Procedure and Paper Filtering (Business Analytics Maturity in ERP Systems)

In SLR 3 Phase 1, Steps 1-3 involved applying filters (1 and 5), (2 and 5), (3 and 5), or (4 and 5) to Title, Abstract, Keyword, and the year range 2000-2023. A total of 1,094 records were identified from Science Direct and Google Scholar using specific filter combinations, with corresponding counts provided for each combination.

In SLR 3 Phase 2, Steps 4-6, a total of 160 records were screened in Endnote. Before screening, 906 records were excluded because their titles or abstracts were not relevant to the field of BIMMs, BAMMs, ERPMMs and Industry 4.0 MMs. Additionally, 28 duplicate records were removed after importing into Endnote.

In SLR 3 Phase 3, Steps 7-10, a further filter (6: "Design," 7: "Assess," or 8: "Validate") was applied, and each paper was read in full to ensure relevance. Papers relevant to the design, assessment, and validation of BIMMs/BAMMs, ERPMMs, and Industry 4.0 MMs were downloaded. Fifteen papers on ERPMMs (including Industry 4.0 MMs) and eight on BIMMs/BAMMs were retained and analysed. Fourteen papers lacking detailed information on measurement items in maturity models were excluded.

J.4. Results of SLR 3: ERP Maturity Models

Table J.2 summarises literature on ERP Maturity Models, covering focus, maturity levels, measurement items, design, assessment, and validation.

Table J.3 provides a detailed comparison of the fifteen ERP maturity models, examining focus, research methodology, and assessment method.

J.5. Results of SLR 3: Business Intelligence and Business Analytics Maturity Models

Table J.4 summarises eight papers, sorted by ascending publication year, on how previous research assessed BIMMs/BAMMs regarding focus, design, assessment, and validation.

Table J.5 compares the three BIMMs and five BAMMs in terms of focus, research methodology, and assessment methods, offering general observations on various BIMMs/BAMMs.

Table J.2 Comparison of ERPMMs: Maturity Model, Focus, Levels, Measurement Type, Design, Assessment, and Validation

Maturity Model and Focus	Number of Maturity Levels and Type of Measurement Item	Design of ERPMM	Assessment of ERPMM	Validation of ERPMM	Source
ERPMM ERP usage maturity framework	3 stages Self-defined Capabilities	Not specified	Additive logic	Not specified	Holland and Light (2001) [Academia]
Process and enterprise maturity framework	4 levels Self-defined Capabilities	Not specified	Cluster using conditional assessment logic	Not specified	Hammer (2007) [Practitioner]
ERPMM Measure usage of ERP maturity in enterprises	3 levels Self-defined Key Process Areas (KPAs)	Not specified	Additive logic	Validated by Requirements Engineering method	Parthasarathy and Ramachandran (2008) [Academia]
ERPMM Assess ERP integration for global or local strategy	5 levels Self-defined CSFs	Empirical studies using 37 measurement items	Partial least squares	Validation and model testing by Partial Least Square	Hwang and Grant (2014) [Academia]
The Connected Enterprise Maturity Model Assess ERP Integration	5 stages Self-defined Capabilities	A study of manufacturers by IndustryWeek and Rockwell Automation	Not specified	Not specified	Rockwell Automation (2014) [Practitioner]
Industry 4.0 readiness maturity model	6 levels Self-defined Capabilities	Questionnaire based on Industry 4.0 Readiness Model	Additive logic	Not specified	Lichtblau et al. (2015) [Practitioner]
Manufacturing Operations Management Capability Maturity	6 levels Self-defined Capabilities	Not specified	Cluster using conditional assessment logic	Not specified	Castor et al. (2016) [Practitioner]
Industrial capabilities of Industry 4.0	4 stages Self-defined Capabilities	Not specified	Additive logic	Not specified	Geissbauer et al. (2016) [Practitioner]

Table J.2 Comparison of ERPMMs: Maturity Model, Focus, Levels, Measurement Type, Design, Assessment, and Validation

Maturity Model and Focus	Number of Maturity Levels and Type of Measurement Item	Design of ERPMM	Assessment of ERPMM	Validation of ERPMM	Source
An empirical model to assess the maturity of Industry 4.0	5 levels CMM CSFs	Based on the development of maturity models by Becker et al. (2009)	Additive logic	Qualitative and quantitative methods for empirical validation	Schumacher et al. (2016) [Academia]
Extended Enterprise maturity model (EEMM)	5 levels CMM Capabilities	Not specified	Cluster using conditional assessment logic	Not specified	Deloitte (2017) [Practitioner]
Digital Extended Enterprise (DEXTER)	5 levels Self-defined KPAs	Not specified	Additive logic	Validated with case descriptions and quantified by participants.	Pulkkinen et al. (2019) [Academia]
Implementation and application of ERP Usage	5 levels CMM CSFs	Based on Holland and Light (2001), Parthasarathy and Ramachandran (2008)	Additive logic	Validation and model testing by Partial Least Square	Gërvalla (2020) [Academia]
Industry 4.0 Maturity Model	6 levels Self-defined Capabilities	Based on IMPULS model by Lichtblau et al. (2015)	Additive logic	Not specified	Rafael et al. (2020) [Academia]
Industry 4.0 Maturity Model	4 levels Self-defined Capabilities	Based on the development of maturity models by Becker et al. (2009)	Additive logic	Validated with case descriptions and quantified by participants	Wagire et al. (2021) [Academia]
Industry 4.0 Maturity Model	6 levels Self-defined Capabilities	Based on the technology-organisation-environment framework	Additive logic	Validated with a focus group before empirical testing	Senna et al. (2023) [Academia]

Table J.3 Focus, Research Methodology and Assessment Method in ERP Maturity Models

Author(s), Year	**Focus**	**Research Methodology**	**Assessment Method**
Holland and Light (2001) [Academia]	ERP Usage: ERP usage maturity framework	Qualitative and quantitative using stage theory	Additive Logic - Calculate scores for comparative maturity analysis.
Hammer (2007) [Practitioner]	Business Processes: Process and enterprise maturity framework	Self-assessment of Process and Enterprise maturity Excel tool provided by Hammer & Company	Cluster using conditional assessment logic - Assess process and enterprise maturity levels based on statements selection.
Parthasarathy and Ramachandran (2008) [Academia]	ERP Usage: Measure usage of ERP maturity in enterprises	Requirements Engineering method	Additive Logic - Assign scores to measurement items for ERP maturity assessment.
Hwang and Grant (2014) [Academia]	ERP Integration: Assess ERP integration levels for implementation	Quantitative (using questionnaire)	Partial least squares (PLS) - Evaluate CSFs for ERP integration levels.
Rockwell Automation (2014) [Practitioner]	ERP Integration: The Connected Enterprise Maturity Model	Study conducted by IndustryWeek and Rockwell Automation	Not specified
Lichtblau et al. (2015) [Practitioner]	Industry 4.0: Industry 4.0 readiness maturity	Online self-assessment questionnaire by IMPULS Foundation	Additive Logic - Answer questions and calculate weighted scores for readiness dimensions.
Castor et al. (2016) [Practitioner]	Manufacturing operations: Manufacturing Operations Management Capability Maturity	Self-assessment questionnaire tool provided by the National Institute of Standards and Technology (NIST)	Cluster using conditional assessment logic - Assess manufacturing operations capability maturity based on question responses.

Table J.3 Focus, Research Methodology and Assessment Method in ERP Maturity Models

Author(s), Year	Focus	Research Methodology	Assessment Method
Geissbauer et al. (2016) [Practitioner]	Industry 4.0: Industrial capabilities of Industry 4.0	Online self-assessment questionnaire provided by Pricewaterhouse Coopers (PwC)	Additive Logic - Rate assessment items for current and target state in six dimensions.
Schumacher et al. (2016) [Academia]	Industry 4.0: An empirical model to assess the maturity of Industry 4.0	Quantitative using questionnaire	Additive Logic - Calculate weighted average of maturity items to determine overall maturity level.
Deloitte (2017) [Practitioner]	Extended Enterprise: Extended Enterprise maturity model (EEMM)	Online self-assessment questionnaire by Deloitte	Cluster using conditional assessment logic - Determine maturity level based on capabilities achieved in dimensions.
Pulkkinen et al. (2019) [Academia]	Extended Enterprise: Digital Extended Enterprise (DEXTER)	Qualitative and quantitative methods	Additive Logic - Convert interview responses to maturity levels and calculate average maturity scores.
Gërvalla (2020) [Academia]	ERP Usage: Implementation and application of ERP	Quantitative (using questionnaire) then qualitative (using interview)	Additive Logic - Aggregate scores to define maturity levels and display in a Maturity Matrix.
Rafael et al. (2020) [Academia]	Industry 4.0: Industry 4.0 Maturity Model	Quantitative (using questionnaire)	Additive Logic - Assign scores to questions and weight dimensions for radar representation.
Wagire et al. (2021) [Academia]	Industry 4.0: Industry 4.0 Maturity Model	Expert interview with questionnaire in Excel	Additive Logic - Calculate weighted average scores for dimension maturity levels.
Senna et al. (2023) [Academia]	Industry 4.0: Industry 4.0 Maturity Model	Expert interview to assess each measurement item	Additive Logic - Calculate weighted average scores for dimension maturity levels.

Table J.4 Comparison of BIMMs/BAMMs: Maturity Model, Focus, Measurement Type, Design, Assessment, Validation

Maturity Model and Focus	Number of Maturity Levels and Type of Measurement Item	Design of BIMM/BAMM	Assessment of BIMM/BAMM	Validation of BIMM/BAMM	Source
BIMM design and assessment	5 levels Self-defined Capabilities	Quantitative bottom-up approach (Rasch and cluster analysis)	Rasch analysis with clustering	Not specified	Lahrmann et al. (2011) [Academia]
BIMM design, assessment and validation	4 levels Self-defined Capabilities	Quantitative bottom-up approach (K-Means algorithm)	K-means clustering	Qualitative experts verified results for consistency and integrity	Lukman et al. (2011) [Academia]
BAMM design, assessment and validation (BACMM)	5 levels Self-defined Capabilities	Model development based on approach of Becker et al. (2009)	Additive logic	A Delphi study with an expert panel used to validate and refine BA Capability Framework constructs	Cosic et al. (2012); Cosic (2020) [Academia]
BIMM design, assessment and validation	5 levels Self-defined Capabilities	Quantitative bottom-up approach (Rasch and cluster analysis)	Rasch analysis with clustering	Discuss final model with three industry experts on self-assessment, and BI roadmap.	Raber et al. (2013b) [Academia]
BAMM assessment (TDWI Analytics Maturity Model)	5 stages Self-defined Capabilities	Not specified	Additive logic	Not specified	Halper and Stodder (2014) [Practitioner]
BAMM assessment (INFORMS Analytics Maturity Model)	3 stages Self-defined Capabilities	Not specified	Additive logic	Not specified	The Institute for Operations Research and the Management Sciences (2017) [Practitioner]
BAMM comparison (Social media analytics)	5 levels Self-defined Capabilities	Set theory	5 methods: Additive Logic, Variance Techniques, Cluster, Minimum Constraints, Rasch Analysis	Relationship between social media maturity and business value validated using PLS-SEM technique.	Lasrado et al. (2017); Lasrado (2018) [Academia]
BAMM assessment (Analytics Maturity Model)	5 stages Self-defined Capabilities	Not specified	Additive logic	Not specified	International Institute for Analytics (n.d.) [Practitioner]

Table J.5 Focus, Research Methodology and Assessment Method in BIMMs/BAMMs

Author(s), Year,	Focus	Research Methodology	Assessment Method
Lahrmann et al. (2011) [Academia]	BIMM design and assessment: BI dimensions derived from existing literature, Dimensions: Strategy, Organisation/ Process, IT support	Paper-based questionnaire using 5-point Likert scale	Rasch analysis with clustering: Calculates distances to maturity levels within maturity dimensions. Classifies maturity dimensions. Calculates distances to maturity levels for organisations. Classifies organisations into the maturity level with least distance.
Lukman et al. (2011) [Academia]	BIMM design, assessment and validation: Development and validation of a BIMM for organisations in Slovenia	Structured questionnaire with 7-point Likert scale	K-means clustering: Uses the algorithm to minimise sum of squared errors (SSE). Determines optimal cluster number by plotting SSE values. Classifies organisations into maturity levels by clustering.
Cosic et al. (2012); Cosic (2020) [Academia]	BAMM design, assessment and validation: Assess BA initiatives within large-scale Australian organisations	Qualitative and quantitative using Delphi study	Additive Logic: Applies maturity scale to 16 BA capabilities. Aggregates levels to measure maturity across four high-level capabilities and overall BA capability.
Raber et al. (2013b) [Academia]	BIMM design, assessment and validation: Dimensions: Strategy, Social System, Technical System, Quality, Use/Impact	Paper questionnaire distributed at a BI practitioner event and an online questionnaire.	Rasch analysis with clustering: Calculates distances to maturity levels within maturity dimensions. Classifies maturity dimensions. Calculates distances to maturity levels for organisations. Classifies organisations into the maturity level with least distance.
Halper and Stodder (2014) [Practitioner]	BAMM assessment: Predictive analytics, social media/ text analytics, cloud computing, and big data analytics approaches	Online self-assessment provided by TDWI	Additive Logic: Questions are presented individually or in matrices, possibly weighted by importance. Each dimension can score up to 20 points, with sections scored separately and averaged across dimensions.
The Institute for Operations Research and the Management Sciences (2017) [Practitioner]	BAMM assessment: Benchmarking capabilities and identifying actions to improve the analytical maturity	Online self-assessment provided by INFORMS	Additive Logic: Assesses 12 questions on a 1-10 scale, allowing goal setting with target dates. Offers detailed maturity level summaries per factor with visualised charts.
Lasrado et al. (2017); Lasrado (2018) [Academia]	BAMM comparison: Influence of quantitative methods on maturity models using social media analytics dataset	Used a social media dataset of 231 organisations from a cross-sectional survey.	Additive Logic, Variance Techniques, Cluster, Minimum Constraints, and Rasch Analysis.
International Institute for Analytics (n.d.) [Practitioner]	BAMM assessment: Optimising performance by improving analytics capabilities	Online self-assessment provided by IIA	Additive Logic: Maturity Assessment includes 33 competencies across five DELTA model categories. Scores range from 1.00 to 5.99, aligning with five descriptive maturity stages.

APPENDIX K: BEST CONFERENCE PAPER AWARDED AT THE 2021 INTERNATIONAL CONFERENCE ON INFORMATION RESOURCES MANAGEMENT

Conf-IRM

2021 International Conference on Information Resources Management

recognizes

Wai Yip Freddy Wong, Michael Lane and Sophie Cockcroft

For

Best Conference Paper

entitled

Systematic Review of Methodological Approaches for Designing, Assessing and Validating Business Analytics Maturity Models

Online, Johannes Kepler University Linz, Austria

May 19-21, 2021

AFFILIATED CONFERENCE

Conf-IRM Executive Committee