UNIVERSITY OF SOUTHERN QUEENSLAND

THE INFLUENCE OF CONSUMERS' TRUST AND COGNITIVE ABSORPTION ON BEHAVIOURAL INTENTIONS TO REUSE RECOMMENDER SYSTEMS

A Thesis Submitted by

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ABSTRACT

There has been a dramatic increase in the quantity and variety of product information available online. This has intensified consumers' perceptions of information overload, making it harder for online shoppers to pick between numerous online products and services. Consequently, e-vendors are progressively outfitting their e-commerce sites with different product recommender systems to assist customers in dealing with this difficulty. Recommender systems (RSs) have gained popularity to assist online shoppers in their purchasing decisions. Recommender systems can provide highly tailored product recommendations, and assist in discovering, comparing, and assessing product information. However, many online shoppers may not be making their online purchasing decisions using a recommender system because they do not yet have trust in them, as evidenced by the current Amazon sales percentage based on recommender systems usage. Regardless of how useful recommender systems are, understanding whether consumers accept and reuse them is crucial. This is a critical yet under-researched topic in existing studies on recommender systems. Using a three-study quantitative research method that employs an online survey, this research explores post-adoption factors influencing the reuse intentions of consumers in relation to recommender systems. In particular, the main research question of this research is "How do flow experience, trusting beliefs, and perceived usefulness of recommender systems influence consumers' behavioural intentions to reuse recommender systems?"

This research proposes three unique research models. The research draws on the ResQue model, the technology acceptance model, trust literature, flow theory and cognitive absorption theory

to describe the causal linkages between the determinants of consumers' behavioural intentions to reuse recommender systems. Six important post-adoption factors, trusting beliefs, perceived usefulness, cognitive absorption, focused immersion, temporal dissociation and curiosity were linked to consumers' behavioural intentions to reuse recommender systems.

The primary data for this study was gathered using a questionnaire that represents the research constructs. The online survey was administered by an established research firm employing an Australian consumer panel. A sample of 452 Amazon users who had used recommender systems for at least six months was used to evaluate the predicted correlations between the constructs. Since this is a three-study quantitative research with a deductive approach, it applies Partial Least Squares-Structural Equation Modelling (PLS-SEM) to validate and corroborate the research models by evaluating the hypothesised relationships.

The findings of this research have revealed that trusting beliefs, perceived usefulness, cognitive absorption, focused immersion, and curiosity were linked to consumers' behavioural intentions to reuse recommender systems. The results also confirmed that trusting beliefs and cognitive absorptions mediate consumers' behavioural intentions to reuse recommender systems. Interestingly, in contrast to earlier findings, the relationship between the constructs was statistically insignificant in search and experience products. The findings of this research also confirm that gender serves as a moderator on consumers' behavioural intentions to reuse RSs.

Theoretically, the research findings contribute to and expand upon the body of knowledge built by previous research on the user-centric evaluation of recommender systems. This research advances

our understanding of the factors influencing customers' behavioural intentions to reuse recommender systems. This research is one of the very few to examine the role of cognitive absorption in the context of recommender systems. This research is the first to examine unique antecedents of consumer behavioural intentions to reuse recommender systems such as focused immersion, curiosity and heightened enjoyment. For practitioners, the findings emphasise the necessity of tailoring the design of recommender systems such that they are useful, convenient, trustworthy, and improve the holistic consumer experience.

Keywords: Recommender systems, Trusting beliefs, Flow theory, Cognitive absorption

CERTIFICATION OF THESIS

I Nirmal Acharya declare that the PhD Thesis entitled "Consumers' trust and cognitive absorption on behavioural intentions to reuse recommender systems" is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This Thesis is the work of Nirmal Acharya except where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

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STATEMENT OF CONTRIBUTION

Journal Papers Currently Under Review

Paper 1:

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Student contributed 80% to this paper. Collectively Dr. Anne-Marie Sassenberg and Professor Jeffrey Soar contributed the remainder.

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Student contributed 80% to this paper. Collectively Dr. Anne-Marie Sassenberg and Professor Jeffrey Soar contributed the remainder.

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Finally, this completion is another start point for the future, so I want to say to myself, please take good care, eat well, sleep well, keep healthy, and be happy. Though tomorrow may bring fresh difficulties, my faith in myself remains firm.

कर्मण्येवाधिकारस्ते मा फलेषु कदाचन |

मा कर्मफलहेतुर्भूर्मा ते सङ्गोऽस्त्वकर्मणि ||

— Shri Krishna, The Bhagavad Gita

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
CA	Cognitive absorption
CFA	Confirmatory factor analysis
CUI	Continuous use Intention
IPMA	Important-performance map analysis
IS	Information systems
IT	Information technology
MICOM	Measurement invariance of composite models
PLS-MGA	Partial least squares multi-group analysis
PLS-SEM	Partial least squares structural equation modelling
PU	Perceived usefulness
RSs	Recommender systems
ROI	Return on investments
TAM	Technology acceptance model
TB	Trusting beliefs

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CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The purpose of the current chapter is to provide an introduction of this thesis**.** The chapter is organised as follows: Section 1.2 provides the background to the research to gain basic understanding of it. Section 1.3 presents the objectives of the research and articulates the research questions gleaned from the identified gaps in the literature. Section 1.4 provides the overview of research methodology. Section 1.5 highlights the contribution and significance of the research in theory and practice. Section 1.6 provides ethical consideration relating to this research. Next, Section 1.7 depicts the structure of this thesis. Finally, Section 1.8 draws a conclusion to this chapter.

1.2 RESEARCH BACKGROUND

1.2.1 E-COMMERCE

Online shopping has increased drastically (Shobeiri et al., 2015); both retailers and customers are pushing the growth of online shopping services (Pu et al., 2011). E-commerce is one of the most important areas for a business to concentrate on because it encompasses a wide range of operations from marketing to producing to selling to delivering to servicing (Turban et al., 2002; Wigand, 1997). E-commerce is becoming an integral aspect of business operations because of the multitude of factors such as universal accessibility, the ease of use, the broad range of products available, and the manageability of their compassion, as well as trusted payment methods (Ratnasingham, 1998). It serves as a foundation for a new type of global commerce and is one of the fastest growing industries (Qin & Liu, 2022). Global internet sales in 2020 increased from US$ 1336 billion in 2014 to US$ 4280 billion

(Argilés-Bosch et al., 2022). Worldwide e-commerce is expected to expand by 16.8 percent in 2021 to $4.921 trillion (Abrams, 2021). In just four years, the global e-commerce market will be worth around $7 trillion. Online retail revenue in Australia is predicted to rise by an annualised 6.8% over the next five years, reaching $61.2 billion by 2025-26 (Cloutman, 2021). E-commerce and online shopping have transformed the retail industry, which increasingly relies on customising information systems and business processes in order to provide superior online customer service experiences. Increases in internet users, online shopping, and the amount of digital information available have created a possible information overload dilemma (Konstan & Riedl, 2012), that makes it difficult to get quick access to items of interest on the Internet. As a result, there has never been a greater need for recommender systems.

1.2.2 Recommender systems

Many human-facing applications have advanced as artificial intelligence (AI) technology has grown. Artificial intelligence (AI) can be described as the ability of a machine to mimic intelligent human behaviour or the ability of an agent to achieve goals in a variety of contexts (Aghion et al., 2019). One of the most well-known applications of artificial intelligence to the real world is recommender systems (RSs). Recommender systems are information filtering systems that deal with the problem of information overload (Konstan & Riedl, 2012; Shambour, 2021) by selecting critical information fragments out of a vast volume of dynamically generated information according to user preferences, interest or observed behaviour about the item (Pan & Li, 2010). Providing recommendations assists customers in decision making (Benlian et al., 2012), reduces the cognitive load (Gemmis et al., 2015; Pu et al., 2012) while also increasing the likelihood that they will purchase and be satisfied in general (Ricci et al., 2015).

Recommender systems are applied not just in e-commerce (Pal & Pal, 2018); they have also been used in marketing (JothiLakshmi & Thangaraj, 2018), healthcare (Galeano & Paccanaro, 2018), e-learning (Tarus et al., 2018), the Internet of Things (IoT) (Park, 2019), news (Shin & Park, 2019), social networks (Liu et al., 2018), music (Katarya & Verma, 2018), food and nutritional information systems (Toledo et al., 2019). Personalization in the e-commerce context is automated with RSs by using both classic and current methodologies (Li et al., 2019), such as machine learning techniques (Shoja & Tabrizi, 2019). RSs resulted in several advantages for its providers and users. Providers gain from utilising RSs as it increases cross-selling by providing relevant product recommendations, while users gain from using them as it reduces their search effort exertion (Choi et al., 2011; Pu et al., 2011). RSs can reduce the transaction costs of finding and selecting items as a result online purchasing has become more affordable for consumers (Hu & Pu, 2009). There is evidence to support the use of RSs in helping people improve decision making process and make better decisions (Benlian et al., 2012; Pathak et al., 2010). Because they are a more efficient way to sell more products in an e-commerce scenario, recommender systems can boost revenues (Pu et al., 2011). RSs employ multiple sources of information such as the consumers' demographic information, buying history, search and browsing behaviour, product ratings and product characteristics to predict their preferences (Resnick & Varian, 1997).

Due to the advancements in technology and the internet's global reach, these e-commerce application features have elevated the quality of consumers' lives (Guo et al., 2017). People accept the decision precision of RSs in exchange for less effort required by them to find a product (Li & Karahanna, 2015), but there is a risk that if a customer makes a poor choice based on the advice of RSs, they may develop a negative attitude towards the retailer.

A number of new approaches to constructing recommendation systems have been developed. These approaches include collaborative filtering, content-based filtering, or hybrid filtering (Logesh et al., 2020; Nilashi et al., 2018). In terms of maturity and implementation frequency, the most often used filtering method is collaborative filtering (Isinkaye et al., 2015). When using collaborative filtering, products are recommended based on the opinions of other users with similar preferences. There have been numerous implementations of collaborative recommender systems in digital platforms such as Amazon, Spotify, Netflix, and Alibaba (Schrage, 2021). E-commerce platforms such as Amazon use a range of recommendation algorithms that vary across many dimensions. The recommendation systems have been constantly evolving. For example, Amazon shows various associated products under the following categories when visitors are looking for a certain product on Amazon Marketplace: (a) "Frequently bought together", (b) (b.1) “Customers who bought this item also bought” and (b.2) “Customers who viewed this item also viewed”, (c) “Sponsored products related to this item”, and (d) “Compare to similar items” (Li et al., 2020). Amazon also utilises topic diversity algorithms to increase the quality of its recommendations (Ziegler et al., 2005). The system makes use of a collaborative filtering mechanism to generate an offline database of related items using an item-to-item matrix in order to overcome the scalability issue. After that, the system recommends other items that are similar based on the user's online shopping history. These recommendations offered by RSs alleviate the cognitive stress placed on customers as a result of information overload (Pu et al., 2012; Shambour, 2021).

Although the deployment of RSs addresses the key issue of protecting customers from being overloaded with irrelevant and uninteresting information in e-commerce, a critical but often ignored question is whether consumers continue to use RSs after their initial adoption (Sheng et al., 2014). Several scholars have claimed that the success and long-term viability of a technology are dependent on its ability to be reused or to be used continuously (Ashraf et al., 2020; Benlian et al., 2012; Bhattacherjee, 2001; Yan et al., 2021). Correspondingly, customers must trust RSs and communicate their attitudes, preferences and wants on a continuous basis in order to use and reuse RSs effectively.

1.2.3 RSs adoption process

Pre-use, initial usage, and reuse are the three stages in which consumers acquire services, with activity and decisions taking place at each stage (Montazemi & Saremi, 2014; Rogers, 2010). In the same vein, RSs adoption process includes three stages i.e., pre-use, initial use and reuse. The pre-use stage of the adoption process, before consumer utilise RSs, is awareness. This awareness can lead to their mental evaluation of the offering, which can then lead to their initial usage of RSs. Initial use is usually a trial, and it may result in consumers deciding to use RSs repeatedly i.e., reuse. In the reuse stage, the consumer evaluates the overall quality of the service based on the future effects and may commit to the adoption decision they made previously. The consumer can decide to terminate using RSs at any of these stages. Consumers may have varying perceptions of the service during the course of its adoption process, which may be influenced by various characteristics of RSs.

Prior research on user-centric evaluation of recommender system has focused on antecedents of behavioural intentions and categorised them into two main groups: (1) Social-psychological factors: refer to the factors that causes an individual to behave in a certain way in the presence of others (Allport & Lindzey, 1954), and (2) technological factors: focus on the attitude, perception, and interaction between humans and technology (Yan et al., 2021). Several past studies have asserted that social-psychological factors can influence technological factors (Ashraf et al., 2020; Wang & Benbasat, 2005). Technological factors can also influence social-psychological factors (Pu et al., 2011). Social-psychological factors and technological factors can influence behavioural intentions in online buying decision process (Abumalloh et al., 2020; Ashraf et al., 2019; Benlian et al., 2012; Ghasemaghaei, 2020; Xiao & Benbasat, 2007; Xu et al., 2014).

The majority of the prior studies have experimentally tested the first two stages of RSs adoption i.e., pre-use and initial use but controlled and highly structured laboratory experiments were unable to study how decision makers actually get and use information in the decision-making process because of their lack of attention to the real-world phenomena (i.e., customer environment). There is scarcity of user-centric evaluation research based on third stage of RSs adoption i.e., RSs reuse based on the real consumer environment. This stage can be referred to as post-adoption stage. Bhattacherjee (2001) developed the expectation confirmation model to reveal post-adoption behaviours of information technologies. In the discipline of post-adoption research, researchers examine attitudes, beliefs, and behaviours of information system users to determine whether they intend to reuse/ continue using the system (Fleischmann et al., 2016). Based on the content analysis six post-adoption factors are considered, social-psychological factors: trusting beliefs, cognitive absorption focused immersion, temporal dissociation and curiosity, and technological factor: perceived usefulness. As a result, this study examines consumers' behavioural intentions to reuse RSs and uncovers the post-adoption factors that influence it from the perspective of Amazon customers. Figure 1.1 depicts the research problems being investigated in this thesis and serve as the thesis framework.

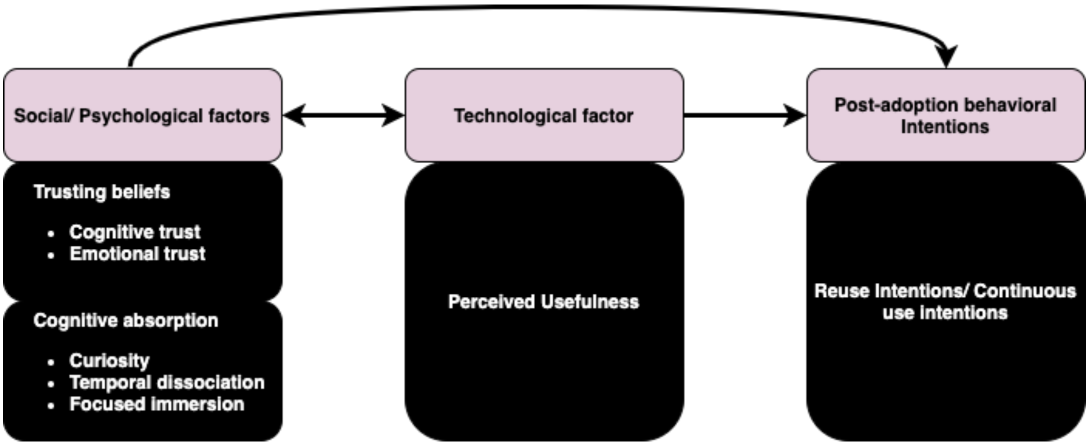


FIGURE 1.1 THESIS FRAMEWORK

1.2.4 TRUST

Trust can be defined as "a willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993). Trust is a crucial aspect in the success of e-commerce (Gefen et al., 2003; Gefen & Straub, 2000). In the adoption of new technology, trust is a stewardship factor, especially in complex systems (Lee & Katrina, 2004; Shin, 2010). There is a critical role played by trust in the evaluation, intention, and diffusion processes (Zhang et al., 2014). Consistently providing customers with unsatisfactory recommendations might erode consumer trust over time. When it comes to personalised systems, the decline in trust is more pronounced than when it comes to generic systems (Harman et al., 2014). Customers' lack-of-trust of RSs is partly explained by the principal-agent relationship paradigm (van Ackere, 1993). A principal-agent conflict arises when information is insufficient or asymmetric, the goals of the two parties are not aligned, and it is difficult to monitor and measure an agent's performance (Eisenhardt, 1989). On top of that, the RSs' faceless and interpersonal nature makes it challenging for businesses to establish trust and relationships online. consumers' lack of trust and unwillingness to interact with RSs frequently lead to consumer confusion and unnecessary expenditure of e-vendors (Zhang et al., 2014). Hence, trust in RSs is crucial for a positive customer-firm relationship.

1.2.4.1 Trusting beliefs

This research is based on Mayer et al. (1995) early formulation of trusting beliefs, which was used by McKnight et al. (2002a) in their work on e-commerce before being used by Wang and Benbasat (2005) in their work on recommender systems. trusting beliefs is multi-dimensional, consisting of cognitive trust and emotional trust (Ashraf et al., 2019). Cognitive trust has at least three separate constituent beliefs about the trusted: benevolence is the trustee's motives such as goodwill and altruism, competence is the trustee's ability to fulfill the trustor's needs and integrity is the trustee's honesty and reliability (e.g., (Blau, 1964; Butler Jr, 1991; Giffin, 1967; Komiak & Benbasat, 2006; Ridings et al., 2002). Whereas, emotional trust refers to the sense of security and comfort a trustor gets from relying on the trustee (Komiak & Benbasat, 2004).

1.2.4.2 Trust propensity

Trust-related behaviours (e.g., reuse of RSs) highly depend on trust propensity also known as dispositional trust and trusting beliefs (McKnight et al., 2002a; Wang & Benbasat, 2007). Trust propensity can be defined as a person's proclivity to believe in others (Gefen et al., 2003). One's general willingness to rely on others, based on life experience and extensive socialisation, can be measured by their trust propensity (Ridings et al., 2002). The trust propensity has been enhanced and is now a strong indicator of trusting beliefs (Colquitt et al., 2007; Lu et al., 2010; Mayer et al., 1995; Yakovleva et al., 2010). Trust propensity can increase as a result of the platform being used for various contexts like e-commerce (Yaobin & Tao, 2007), virtual communities (Kuo & Thompson, 2014), and recommender systems (Fang et al., 2015).

Despite the fact that trust-related issues have been extensively researched in the sectors of e-commerce and human-computer interaction, several limitations remain. Most conceptions of trust have been focused on the space where consumers first encounter particular websites to build a certain degree of trust (Wang et al., 2018). This trust may differ from that of existing customers, who have built trust with the e-vendor over time. Trust-based research have mainly ignored enhancing the design of RSs, instead focusing on the privacy policy, security, statistic efficiency, and reputation of RSs (Zhang & Curley, 2018). There is also a lack of empirical studies detailing how multiple dimensions of trusting beliefs as a comprehensive framework of trusting beliefs contribute to consumers behavioural intention to reuse RSs. This research used a comprehensive framework of trusting beliefs to estimate customers behavioural intention to reuse RSs with the aim to contribute to the design of a trusted recommender system for ongoing relationships.

In addition to trust-related issues, given the growing relevance of technologies such as RSs in online shopping, it is also crucial for e-vendors to ensure that consumers have a satisfactory experience and thus prefer to purchase at their online shops rather than those of their competitors.

1.2.5 Customer experience

Customer experience refers to the assessment, perception, psychological state, or subjective response generated from the customer's engagement with the online object, comprising affective, functional, and social features and responses, as well as a sense of flow (Becker & Jaakkola, 2020; Novak et al., 2000; Rose et al., 2012). Customer experience have received attention in the academic and corporate world during the last few decades (Gao et al., 2021). Poor online customer experiences are claimed to have cost businesses around the world millions of dollars each year (Bilgihan et al., 2014). Customer experience is critical to the success of businesses both online and offline (Barari et al., 2020; Bleier et al., 2018; Bustamante & Rubio, 2017; Rose et al., 2012; Verhulst et al., 2020), since it helps generate positive customer relationships and creates a sustainable competitive advantage (Andreini et al., 2018; Klaus, 2013; Lemon & Verhoef, 2016). With the rise of the e-commerce, recommender systems can play a critical role in enhancing the consumer experience at every stage, from finding through engaging with a product (Barragáns-Martínez et al., 2010; Schafer et al., 2007). Customers may value the experience more than the monetary value of a purchase (Barta et al., 2021; Bilgihan et al., 2014). Customers that use recommender systems report a more enjoyable purchasing experience because they feel understood and recognised, which helps to foster customer loyalty and establish trust (Dadoun et al., 2021; Qazi et al., 2020). Online shopping interactions between customer and recommender systems provide chances to be a part of more positive online experiences and achieve a flow state (Mahfouz et al., 2020). The flow experience, state of flow, or optimal experience is described as the sensation people have when they are in a state of optimal mental focus and are completely absorbed in a single task over which they have complete control (Csikszentmihalyi & Csikzentmihaly, 1990). It's possible that these flow states have an impact on the consumer experience, which encompasses emotional, cognitive, sensory, behavioural, and social aspects (Schmitt, 1999; Verhoef et al., 2009).

The concept of flow has its roots in psychology (Csikszentmihalyi & Csikzentmihaly, 1990). Flow was first applied to computer-mediated environments by Hoffman and Novak (1996), who described it as "the state occurring during network navigation which is: (1) characterized by a seam-less sequence of responses facilitated by machine interactivity, (2) intrinsically enjoyable, (3) accompanied by a loss of self-consciousness, and (4) self-reinforcing" (p. 57). This description of flow was extended by Agarwal and Karahanna (2000) to a similar construct, cognitive absorption, which encompasses the following flow dimensions: curiosity, temporal dissociation, focused immersion, heightened enjoyment, and control. The state of cognitive absorption occurs when people feel satisfied and enjoy technology activities, and their conflicts are reduced whenever they are in a pleasurable and enjoyable state (Hyun et al., 2021).

Although these studies have enriched our knowledge of customer experience, it remains to be seen if the customer experience of recommender systems enhances its reuse. This research followed the concept of cognitive absorption to determine the holistic experience of RSs.

1.3 Research questions

This thesis aims to contribute to the growing conversations and research on RSs reuse intentions and contributes to the literature on user centric evaluation of RSs as it advances an original understanding on post-adoption factor influencing consumers' RSs reuse intentions. In particular, the overarching research question is:

How do flow experience, trusting beliefs and perceived usefulness of RSs influence consumers' behavioural intentions to reuse RSs?

This thesis addresses this overarching research question and meets the research aims through three studies. Study 1, discussed in detail in Chapter 3, addresses the following research questions (RQs):

- *RQ1a: Does consumers' trust propensity influence their trusting beliefs in an ongoing relationship with RSs?*
- *RQ1b: Does perceived usefulness act as an antecedent of trusting beliefs of RSs?*
- *RQ1c: Does a comprehensive framework of trusting beliefs have a direct effect on the consumers' behavioural intentions to reuse RSs?*
- *RQ1d: Is the relation between perceived usefulness and behavioural intentions to reuse RSs mediated by trusting beliefs of RSs?*
- *RQ1e: Does product type serve as a moderator on consumers' behavioural intentions to reuse RSs?*

Study 2, discussed in detail in Chapter 4, addresses the following research questions:

- *RQ2a: Does cognitive absorption have a direct effect on consumers' behavioural intentions to reuse RSs?*
- *RQ2b: Does cognitive absorption have a direct effect on consumers' perceived usefulness of RSs?*
- *RQ2c: Is the relation between cognitive absorption and behavioural intentions to reuse RSs mediated by the perceived usefulness of RSs?*

- *RQ2d: Does gender serve as a moderator on consumers' behavioural intentions to reuse RSs?*

Study 3, discussed in detail in Chapter 5, addresses the following research question:

- *RQ3: Do focused immersion, temporal dissociation and curiosity have a significant direct effect on RSs continuous use intention?*

1.4 Overview of research methodology

1.4.1 Research paradigm

"Research Onion" is a framework that analyses several philosophical paradigms (Saunders et al., 2012). The four paradigms in social sciences are realism, interpretivism, positivism, and pragmatism (Bryman, 2012; Creswell & Creswell, 2017; Creswell & Plano Clark, 2011). In social science, ontology and epistemology are two core philosophical assumptions (Zou & Sunindijo, 2015).

This research adheres to the positivist paradigm, which is the primary approach in consumer behaviour research (Hunt, 1991; Shankar & Patterson, 2001). Figure 1.2 provides a graphical representation of the philosophical assumptions of this research. The positivist epistemological stance advocates a natural science approach to social studies (Park et al., 2019). Positivism corresponds to the hypothetico-deductive model of science, which is a circular process that begins with literature review, moves to the formulation of testable hypotheses, and finishes with the identification of variables, empirical analysis, and refinement or reinforcement of theory (Park et al., 2019). The positivists argue that rationality is superior to subjectivity, and that there is a single, objective truth (Hudson & Ozanne, 1988). Positivists control variables in experiments to collect data on variables or to see if a hypothesis is valid, while also measuring if there is a linear relationship between cause and effect (Tekin & Kotaman, 2013).

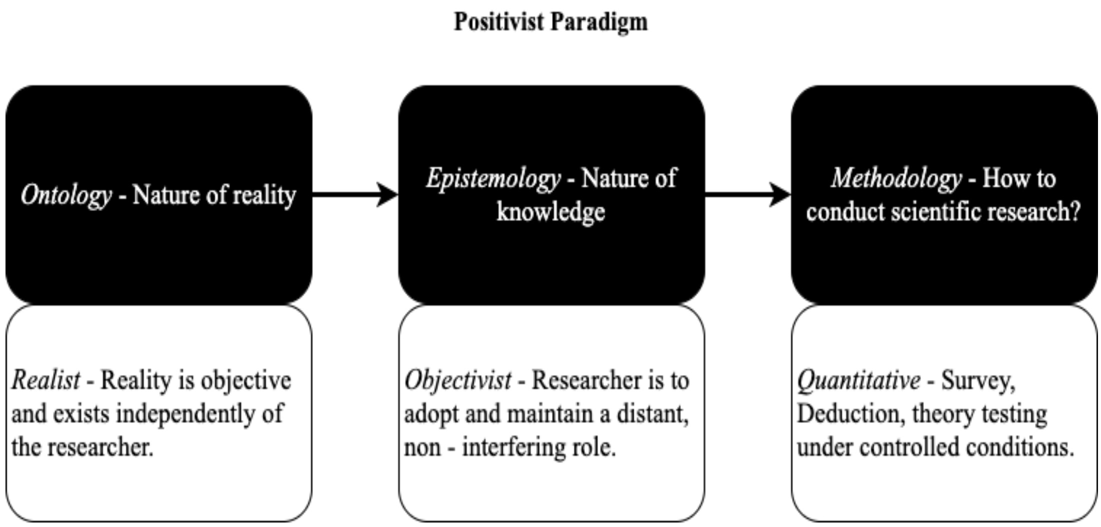


FIGURE 1.2 PHILOSOPHICAL ASSUMPTIONS OF THIS RESEARCH

ONTOLOGY: NATURE OF REALITY

The positivist ontology holds that the universe exists independently of the researcher (Cohen et al., 2017; Grix, 2002). Positivist analysis can be used to examine the nature of occurrences, how they are connected, and what are the effects of those variables (Tuli, 2010). Social reality, according to the positivists, is built on already-existing patterns and is largely stable (Saunders et al., 2012).

EPISTEMOLOGY: NATURE OF KNOWLEDGE

Positivism asserts that knowledge can and must be developed objectively, independent of the researchers' or participants' values (Scotland, 2012). A positivist approach derives a theoretical framework and formulates hypotheses to explain this phenomenon (Park et al., 2019). The hypotheses are then subjected to testing and retesting to ensure the most effective solution (Grant & Giddings, 2002).

METHODOLOGY: HOW TO CONDUCT SCIENTIFIC RESEARCH?

The emphasis of positivist methodology is on conducting research in controlled and manipulable environments (Cook et al., 2002). The emphasis of positivist methodology is on conducting research in controlled and manipulable environments (Park et al., 2019). Positivists conduct surveys to collect data, which provide a significant amount of evidence that appears persuasive enough to allow them to generalise the whole population based on their findings (Johnson & Duberley, 2000).

1.4.2 RESEARCH DESIGN

The philosophical paradigm discussed in aforementioned section guided the research design in order to answer the research questions posed in Section 1.4.1. A literature analysis was conducted before deciding on the research approach, and the research problem and questions were identified as a first step. It was found that limited attention has been paid towards investigating the post adoption usage of RSs (i.e., RSs reuse intentions). A quantitative research design was then adopted to investigate the relationship between RSs reuse intentions and their antecedents as well as possible cause and effect between variables.

Study 1, 2 and 3 presented in Chapters 3, 4 and 5 respectively used a self-administrated cross-sectional, quantitative survey methodology to collect data. The questions employed in the cross-sectional survey were of a closed-ended. Respondents find it easy to answer the closed-ended questions, the survey can be performed with a wide range of participants, and the responses can be promptly coded and analysed (Kelley et al., 2003). The ability to test and validate hypothesis through the quantitative approach is a key aspect of its relevance (Babbie, 2015; Scotland, 2012). A quantitative approach makes it easier to facilitate the comparison of responses, draw conclusions and produce generalization (Bryman, 2012). For the following reasons, the research selects survey approach. Surveys are one of the most commonly used tools for gathering data in a wide range of fields, including marketing, social science, economics, information systems, hospitality, business, and psychology (Babbie, 2015; Kuechler, 1998; Pinsonneault & Kraemer, 1993; Roztocki, 2001). Research on casual interactions between constructs is best done with cross-sectional studies. It is both valid and prevalent to collect data via an organised, self-reported survey in consumer behaviour research. It is acknowledged to be the optimal way to gather data to help social scientists understand an extremely vast or distributed population (Babbie, 2015; Spector, 2019). Pinsonneault and Kraemer (1993) in their study on the application of survey research methodology in the management information systems' studies, claim that survey research is particularly well suited for research that specifies independent and dependent variables, presents expected correlations, and tests them against the observation of the phenomena. This research includes constructs and assesses them with relative measures adopted from prior studies, which makes surveys the ideal approach for this study.

The next sections provide greater details on the research methods used, and each individual study is well-outlined (Chapters 3-5).

1.4.3 Research method

This section discusses the methods utilised to do the research for this thesis. A substantial portion of this thesis is comprised of published research publications. As a result, repetition is inescapable as readers from various journals are introduced to or reintroduced to the research. This section contributes to a more comprehensive understanding of the thesis research process.

The research for this thesis commenced with a thorough examination of the existing literature. This examination of the literature began with a body of theory relating to psychology, consumer behaviour, and information systems. This assessment of the literature had a critical role in the framing, questioning, and thinking that guided the remainder of my research. The review of the literature persisted throughout the research process. As new concepts developed from the study data, they had to be investigated in the literature. This constant absorption in the literature was required to develop the research method as new notions arose from the research data. It's evident throughout this thesis that the existing data is periodically re-examined for new concepts and themes, which then serve as the basis for further study in later chapters. For example, in Chapter 5:, dimensions of second-order factor that was analysed in Chapter 4: was found to be directly related to the dependent variable.

This thesis then adopted a three-study quantitative research method to answer the research questions that arose after the initial literature review. Figure 1.3 shows the outline of the applied quantitative research strategy.

Individual quantitative studies and their research methods are outlined below.

Chapter 3

Study 1: Consumers' behavioural intentions to reuse recommender systems: assessing the effects of trust propensity, trusting beliefs and perceived usefulness.

Research aim: To determine the causal relationships between trust propensity, trusting beliefs and perceived usefulness and consumers' behavioural intentions to reuse RSs.
Research questions: RQ1a, RQ1b, RQ1c, RQ1d, RQ1e
Theoretical underpinning: Technology Acceptance Model (TAM) and Trust Literature
Study design: Quantitative
Data collection: Online cross-sectional survey, n = 452
Data analysis: Confirmatory factor analysis, PLS-SEM, MICOM, PLS-MGA, PLSpredict

Chapter 4

Study 2: The impact of cognitive absorption on perceived usefulness of recommender systems and shoppers' behavioural intentions to reuse recommender systems.

Research aim: To determine the effect of cognitive absorption on shoppers' intentions to reuse RSs.
Research questions: RQ2a, RQ2b, RQ2c, RQ2d
Theoretical underpinning: Technology Acceptance Model (TAM) and Flow Theory
Study design: Quantitative
Data collection: Online cross-sectional survey, n = 452
Data analysis: Confirmatory factor analysis, PLS-SEM, MICOM, PLS-MGA, PLS-IPMA

Chapter 5

Study 3: The impact of cognitive absorption on perceived usefulness of recommender systems and shoppers' behavioural intentions to reuse recommender systems.

Research aim: To determine the effect of the cognitive absorption dimensions independently on RSs continuous use intention
Research questions: RQ3
Theoretical underpinning: Cognitive absorption
Study design: Quantitative
Data collection: Online cross-sectional survey, n = 452
Data analysis: Confirmatory factor analysis, PLS-SEM

Chapter 6

Outcome: The results of the findings of the three studies included in this research have been synthesised and interpreted in the general discussion section as the overall conclusion of this research.

FIGURE 1.3 OUTLINE OF THE APPLIED QUANTITATIVE RESEARCH STRATEGY

1.4.3.1 CHAPTER 3

In Chapter 3: of this thesis, an empirical paper is presented. It is the Study 1 of three quantitative studies planned for this research project.

1.4.3.1.1 AIM AND THEORETICAL UNDERPINNING

The study aimed to examine the influence of trusting beliefs on behavioural intentions to reuse RSs, emphasising the effects of trust propensity, perceived usefulness.

In order to investigate the causal relationships between trust propensity, trusting beliefs and perceived usefulness and consumers' behavioural intentions to reuse RSs, Study 1, the study proposed a research model consisting social/psychological factors, instrumental factor of RSs evaluation and RSs reuse intentions was derived from ResQue Model (Pu et al., 2011) and trust literature (a comprehensive framework of trusting beliefs (Ashraf et al., 2019) and trust propensity (Murphy, 2003)). The adopted constructs are mapped into the proposed research model, portraying the direct, mediating and moderating effect between the construct, for this study is depicted in Figure 3.2.

1.4.3.1.2 DATA COLLECTION

This research was conducted using a non-probability sampling method, which is an approach often applied in the field of information systems research (Loehlin & Beaujean, 2016). Zoho Survey Platform (survey.zoho.com.au) was used to send an online survey to a sample of Australian Amazon customers. The online survey was carried out by Zoho, and a total of 1361 responses were collected. The concept of recommender systems was explained to all the participants. The research design was also informed by knowledge of Amazon's recommender systems, for example that Amazon often provides recommendations under the labels

"Frequently bought together" or “Compare to similar items” or "Customers who bought... also bought". In order to determine if the respondents were current Amazon customers and had purchased at least one of the products listed in Table 3.2 from amazon.com.au using RSs in the six months before to responding to the survey, they were subjected to two screening questions. (1) Have you used RS for buying product(s) online over last six months? (2) Please specify the product(s) that you have purchased from Amazon.com.au over last six months. Based on the survey questionnaire’s screening criteria, 452 responses were considered usable and valid.

1.4.3.1.3 Data analysis

The data analysis was conducted following the data collection. This study followed Ashraf et al. (2019)'s pretested classification of product type and categorised the respondents into search product and experience product groups based on their purchased product responses. The collected data was subject to acquiescence response bias, univariant outlier and multivariant outlier assessment (Ho, 2013; Podsakoff et al., 2003). 86 responses were deleted out of 452 usable and valid responses. Accordingly, only 366 of the responses were used for subsequent analysis. Then statistical analysis evaluated the causal relationships in the proposed model. Confirmatory factor analysis (CFA) and partial least square structural equation modelling was performed using SmartPLS v3.3.3 statistical software. The scales’ reliability, convergent validity and discriminant validity were tested as part of the measurement model evaluation using Cronbach's alpha (ɑ), composite reliability (CR), Dijkstra–Henseler’s rho (ρ_A) and the average variance extracted (AVE) (Hair et al., 2021). The result of the analysis is presented in Table 3.4. Heterotrait Monotrait (HTMT) Ratio and HTMT inference criterion was used to assess the discriminant validity of the constructs. The result of the analysis is presented in Table 3.5 and

Table 3.6 respectively. Then, multi-collinearity test was performed prior to structural model assessment. The explanatory power and predictive relevance of the proposed structural model was assessed using the R^2 values and the Stone–Geisser's Q^2 values (Hair et al., 2021). Then, a bootstrapping routine of 5000 subsamples was used to explore the significance of the path coefficients. Mediation analysis was performed using bootstrapping method by comparing the total, direct and indirect effects between the constructs. The result of the analysis is presented in Table 3.8. Subsequently, MICOM was estimated to check measurement invariance and PLS-MGA (Multi-group analysis) using the Welch-Satterthwait test was performed to estimate the moderating effect of product type. PLSpredict analysis was then used to examine the holdout sample-based point predicting power of the model (Shmueli et al., 2016). This analysis allowed to understand that the inclusion of emotional trust to the model is more efficient in explaining consumers' behavioural intentions to reuse RSs

1.4.3.2 Chapter 4

An empirical paper is presented in Chapter 4: of this thesis. It is the Study 2 of three quantitative studies planned for this research project.

1.4.3.2.1 Aim and theoretical underpinning

The study aimed to determine the effect of cognitive absorption (CA) on shoppers' intentions to reuse RSs. An extension of technology acceptance model (TAM) is proposed to empirically estimate shoppers' behavioural intentions.

To determine the effect of cognitive absorption on shoppers' intentions to reuse RSs, TAM (Davis, 1989), IS continuance model (Bhattacherjee, 2001) and flow theory (Csikszentmihalyi & Csikzentmihaly, 1990) were used to derive the proposed model consisting consumers' flow experience, instrumental factor of RSs evaluation and RSs reuse intentions. The adopted constructs are mapped into the proposed research model for this study is depicted in Figure 4.2.

1.4.3.2.2 Data Collection

Data was obtained in accordance with the process outlined in the Section 1.4.3.1.2.

1.4.3.2.3 Data analysis

Following the completion of data collection, normality and common method bias test was performed using Kolmogorov–Smirnov (KS) normality tests and Lindell and Whitney (2001) marker variable method respectively. Further, full collinearity test based on variance inflation factor (VIF) was also carried out. Next, the data was analysed in SmartPLS v3.3.3 statistical software. Confirmatory factor analysis (CFA) and partial least square structural equation modelling was performed. Construct validity and reliability were assessed using the average variance extracted (AVE), Cronbach's alpha and composite reliability (CR). The result of the analysis is presented in Table 4.3. Discriminant validity was assessed using the Heterotrait–monotrait (HTMT) ratios method and cross-loadings. The result of the analysis is presented in Table 4.4 and Table 4.5 respectively. Then, a bootstrapping routine of 5000 sub-samples was performed to estimate the degree of significance of the path coefficient. Mediation analysis was then performed using bootstrapping method and VAF method to determine the indirect effect of cognitive absorption on RSs reuse intentions. The predictive accuracy and predictive relevance of the proposed structural model was assessed using the R^2 values and the Stone–Geisser's Q^2 values (Hair et al., 2021).

Subsequently, MICOM was estimated to check measurement invariance and PLS-MGA (Multi-group analysis) using the Welch-Satterthwait test was performed to determine the moderating effect of gender. An Importance-Performance Map Analysis (IPMA) was also conducted to recognize the elements that are most significant in the construct and thus have a high overall impact on the construct but low yield. This analysis allowed to understand that cognitive absorption should be given more priority to further increase the performance of behavioural intentions to reuse RSs.

1.4.3.3 Chapter 5

Chapter 5: presents a quantitative paper. It is the Study 3 of three quantitative studies planned for this research project.

1.4.3.3.1 Aim and theoretical underpinning

This study aimed to determine the effect of the cognitive absorption dimensions namely focused immersion, temporal dissociation and curiosity independently on RSs continuous use intention.

To determine the effect of the cognitive absorption dimensions independently on RSs continuous use intention, the concept of cognitive absorption (Agarwal & Karahanna, 2000) was used to derive the research model consisting of focused immersion, temporal dissociation, curiosity and RSs continuous use intention. The adopted constructs are mapped into the proposed research model for this study is depicted in Figure 5.2.

1.4.3.3.2 Data Collection

Data was obtained in accordance with the process outlined in the Section 1.4.3.1.2.

1.4.3.3.3 Data analysis

Following the completion of data collection, non-response bias using paired t-test. Then, common method bias test was performed using Lindell and Whitney (2001) marker variable technique and a full collinearity test. The analysis of the research model was conducted using PLS-SEM (SmartPLS v3.3.3) in two stages: (a) measurement model analysis and (b) structural model analysis. In the measurement model analysis stage Cronbach's alpha value, composite reliability (CR) and rho_A was assessed to check the internal consistency among the components in each construct. Factor loadings and average variance extracted (AVE) were assessed to examine the convergent validity of the model. The discriminant validity was then assessed using Fornell-Larcker criterion and Heterotrait–monotrait (HTMT) ratios method. The model was deemed suitable for structural model analysis after meeting the thresholds set for each of these analyses. In the structural model analysis stage collinearity assessment was performed using VIF values. Bootstrapping procedure with a 5000-resampling was then performed to determine the statistical significance of the path coefficients. The predictive accuracy and predictive relevance of the proposed structural model was assessed using the R^2 values and the Stone–Geisser's Q^2 values (Hair et al., 2021).

1.5 Contribution of this thesis

Addressing the proposed research gaps is both necessary and beneficial from a conceptual standpoint. This research aimed to contribute to the body of knowledge of consumer behaviour and user-centric evaluations of recommender systems. User-centric evaluation is the study of recommender systems from the perspective of user in order to ensure that they are not only useful and accurate, but also enjoyable to use (Knijnenburg & Willemsen, 2015). This research aimed to extend the existing lines of research that attempt to provide fine-grained knowledge about the different mechanisms affecting consumers' behavioural intentions to reuse RSs. In order to evaluate the success of RSs (Bhattacherjee, 2001; Sheng et al., 2014; Yan et al., 2021), it is necessary to identify the determinants that influence the behavioural intentions to reuse RSs which has been ignored in the past related literatures (Muhammad Ashraf et al., 2020; Benlian et al., 2012; He et al., 2021). The purpose of this research is to identify these determinants. Three theoretical frameworks are presented in this research, all of which centre on the perspective of the users on the evaluation of RSs.

Most importantly, this thesis contributes to the body of knowledge on trust theory. The study investigates the issue of trust, which is critical in an e-commerce environment when competitors are only a click away (B. Zhang et al., 2014). In contrast to the majority of prior research, which have focused primarily on the influence of overall trust, this research investigates the role of emotional trust as well as dimensions of cognitive trust on consumers' behavioural intentions to reuse RSs. Amazon customers will be used in this research to evaluate the performance and success of RSs, with the ultimate aim of determining the factors that influence customers' behavioural intentions to reuse RSs. The findings of this study will be used to inform future research.

In addition to that, this study is significant for several reasons as follows:

RSs are widely available to consumers as a value-added service technology (Sheng et al., 2014), they must be administered properly in order to meet the needs of online customers and e-vendors alike (Xiao & Benbasat, 2007). Sheng et al. (2014) argued that, regardless of how beneficial RSs are, a key concern is whether customers accept recommendations from RSs and continue to utilise them beyond initial acceptance. Consequently, the purpose of this research is to determine the factors that influence customers' behavioural intentions to reuse RSs.

Several prior investigations reported that RSs consisted of a condensed collection of recommended items that were tailored to the preferences of the consumers, hence reducing information overload and search effort in the process of selecting products that met their requirements (Alamdari et al., 2020). Consumers' claims of the benefits supplied by RSs in terms of enhanced buying decision quality and reduced choice effort serve as a motivating factor for them to continue to use similar types of suggestions for their future purchases (Sheng et al., 2014; Xiao & Benbasat, 2007). Consumers can decide whether or not to keep using them. When taking into consideration the real-world consumer environment, it is critical to explore the elements that influence the performance of RSs, which in turn influences the consumers' behavioural intentions to reuse RSs in the future (Sheng et al., 2014).

Since the users of RSs are online customers who are critical to the profitability of businesses, the primary goal of e-retailers in providing RSs is to keep existing customers while expanding their market share (Abumalloh et al., 2020). It is also critical for e-vendors to be prepared when it comes to designing or implementing a recommender system that assures customers receive timely service and so improves their online shopping decision-making (Ghasemaghaei, 2020). As a result, it is critical for e-vendors to investigate the elements that improve the effectiveness of RSs from the perspective of their consumers in order to create effective RSs by highlighting the RSs throughout the customers' purchase funnel (Riesenbeck & Perrey, 2009). RSs divides the customer-product interaction process into four successive parts, which are: awareness of the product, contemplation of the product, purchase intention, and loyalty (Benlian et al., 2012).

Limited research focused on identifying the factors that influence RSs evaluation, it may be beneficial to understand more about the factors that influence evaluation and their link with RSs performance. In literature, little is known about the impact of cognitive absorption perceptions on consumers’ behavioural intentions to reuse RSs. However, while the initial adoption and usage of RSs have been extensively documented in the RSs literature, little study has been conducted to examine the crucial role of RSs evaluation factors in the context of RSs reuse or continuous use (Sheng et al., 2014). The purpose of this research is to understand and explain the factors that influence consumers' perception of the performance of RSs, as well as to conduct an empirical evaluation of the factors that influence customers' behavioural intention to continue using a similar type of RSs in the future. Consequently, the findings may contribute to the existing RS literature by filling in the gaps.

This research attempts to develop three research models which are applicable to different kinds of innovation that also has consumer appeal. The findings are expected to provide empirical validation for the utility of the research models and help us better understand the consumers’ behavioural response towards the reuse of RSs.

On a more practical level, this research also aims to provide practitioners with insights on how to address customers' behavioural intentions to reuse RSs, which is of particular importance. It may be insufficient to focus solely on optimising machine-learning models for precise recommendations. This is important: the best algorithms for precision are not necessarily the most successful in practise in an offline process with historical data (Garcin et al., 2014; Gomez-Uribe & Hunt, 2015). The insight from this research may serve as a guideline to employing RSs mechanisms more appropriately.

In terms of methodology, this study is one of the first to employ the most recent and robust statistical analysis methods, such as MICOM and PLS-MGA (Hair et al., 2021), to investigate the moderating effect of product type and gender on consumers' behavioural intentions to reuse RSs, which pushes the boundaries of traditional methods. The research also employed PLSpredict technique to determine the appropriate causal-predictive model. Partial Least Square Importance-Performance Map Analysis (PLS-IPMA) was also used to provide additional evidence that cognitive absorption is an important determinant of consumer behavioural intention to reuse RSs

The study aimed to contribute to management by presenting practical implications for e-retailers in terms of developing recommendation-based product marketing strategies and constructing sales-efficient e-commerce websites that improve the overall shopping experience of online customers.

1.6 Ethical considerations

The ethical issues around marketing and information system research have been on the rise (Fraedrich et al., 1994; Mark, 1969; Tsalikis & Fritzsche, 2013). In the wake of these developments, researchers are being required to discuss the research's data collection methods and potential ethical considerations stemming from the research itself (Saunders et al., 2012). "Ethics" is described as "norms or standards of behaviour that guide moral choices regarding our behaviour and our relationships with others" (Blomberg et al., 2008, p. 34). Two factors in particular, privacy of participants and voluntary involvement, are essential for the research to be conducted. The key ethical issues with regard to participant privacy in this study were withdrawal at any time and having the right to be informed. A further necessity for conducting the research was the protection of the personal information given by participants (Zikmund et al., 2013).

The University of Southern Queensland's Ethics Committee approved this research (approval number H20REA201). To be cleared by the Human Research Ethics Committee, all research done at the university that involves human intervention must be reported. Information sheets were used throughout the research to ensure that the rights of respondents to information, privacy, confidentiality, and voluntariness were protected, as well as the researchers' responsibility to maintain ethical standards and offer contact information.

1.7 Structure of the thesis

This thesis is comprised of six chapters which provides important implications to theory and management with a better understanding of subjective factors influencing the user centric evaluation of recommender systems. Throughout the course of the candidacy, many of the topics addressed in this thesis were developed, refined, and eventually submitted for publication. As a result, many chapters have inevitable repetition as readers from different journals are exposed to or reintroduced to important themes.

Chapter 2: discusses the current literature on recommender systems adoption, trust, and customer satisfaction. Drawing on existing knowledge and literature, gaps in the existing literature and knowledge have been identified. The literature review provided in Chapter 2: is not aimed to provide an exhaustive summary of the thesis themes because several chapters throughout this thesis feature detailed literature reviews unique to the particular chapter. But it provides adequate information for the reader to allow the reader to position these themes in the existing literature so that they can follow the development of this thesis.

Chapter 3: presents an empirical paper that at the time of submitting this thesis is under review by a Q1 journal. This chapter focuses on the technological factor: perceived usefulness, the social-psychological factor: trusting beliefs, and behavioural intentions to reuse recommender system. The paper equipped a trust-centred lens and presented a research model based on the ResQue Model. The proposed model investigates the effect of perceived usefulness and trusting beliefs on behavioural intentions to reuse recommender systems, the influence of perceived usefulness on trusting beliefs, and the mediating role of trusting beliefs. The findings of the paper demonstrates that trust propensity has a positive and significant direct effect on consumers' trusting beliefs in an ongoing relationship. The findings also imply that consumers' trusting beliefs and perceived usefulness of RSs influence their intention to reuse recommender systems in a positive and significant way. The findings indicated that perceived usefulness has a positive and significant direct effect on trusting beliefs. The findings confirmed that trusting beliefs acts as a mediator between perceived usefulness and behavioural intentions to reuse recommender systems. The findings also revealed that the effect of different product types on Australian customers' behavioural intention to reuse recommender systems was insignificant. The findings of the paper provide design recommendations to improve customer trust. The paper contributes to the ResQue Model of user-centric evaluation of recommender systems.

Chapter 4: presents an empirical paper that at the time of submitting this thesis is under review by a Q1 journal. This chapter focuses on the social-psychological factor: cognitive absorption, technological factor: perceived usefulness and intentions to reuse recommender systems. This paper investigates the effect of cognitive absorption and perceived usefulness on shoppers' intentions to reuse recommender systems, and the mediating role of perceived usefulness. An extended technology acceptance model is proposed to empirically estimate shoppers' behavioural intentions. The findings highlight the direct and indirect effect of cognitive absorption perception on shoppers' behavioural intentions to reuse recommender systems. The finding also suggests that shoppers' behavioural intentions to reuse RSs is moderated by gender. The paper provides significant areas of improvement for e-vendors. This paper contributes to advancing knowledge on cognitive absorption and behavioural intentions and provides e-vendors with insights into online shoppers' decision-making.

Chapter 5: presents an empirical paper, a response to a call for paper on application of AI and e-commerce, that at the time of submitting this thesis is published by Foresight, a Q2 journal. This chapter focuses on the social-psychological factor: cognitive absorption and recommender systems continuous use intention. The paper was written in response to a call for paper on "AI and e-commerce". The influence of cognitive absorption dimensions: curiosity, focused immersion, and temporal dissociation on RSs continuous use intention is investigated in this paper. This paper argues that curiosity, focused immersion, and temporal dissociation are often treated as the dimensions of cognitive absorption, but exploring them separately can provide valuable insights into their dynamics. The findings of the paper indicated that curiosity and concentrated immersion were found to have a direct effect on RSs continuous use intention, whereas temporal dissociation had no effect on RSs continuous use intention. The findings of the paper may be of interest to executives working both in public and private industries to better harness the potential of recommendations driven by AI to maximise RSs reuse and to enhance customer loyalty. The paper contributes to the body of knowledge on cognitive absorption.

Chapter 6: consolidates the findings of the preceding chapters. The chapter also provides a summary of the contributions made by this thesis to the body of knowledge of user centric evaluation of recommender systems. It explicitly outlines the implications that these contributions have for theory and management to improve the reuse of recommender systems. This chapter also addresses the limitation of this study. Finally, future research directions are also presented.

1.8 Chapter summary

In summary, this chapter highlighted the context of the research, an overview of research methodology, and the contribution of the thesis. Research gaps were identified and questions were posed to address them. Three conceptual models were developed in order to properly answer to the research questions. The methodological approach was presented and the quantitative research method was discussed to validate the relationships indicated in the research models. Finally, a summary of each chapter was provided to show how this research has proceeded. The following chapter, Chapter 2:, analyses the relevant literature that shapes the theoretical framework of this particular research and will detail the research gaps.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

This chapter provides a review of relevant literature. The literature review in this chapter is not intended to offer a thorough summary of the thesis themes because various chapters throughout this thesis have detailed literature studies that are specific to the chapter. It provides enough information for the reader to identify these themes in the existing literature and track the evolution of this theory. The chapter begins with a discussion about the recommender systems (Section 2.2). This discussion is followed by a detailed review of past research in Section 2.3 that provides detail on the adoption process of recommender systems and in particular highlights the gap in recommender systems adoption literature. Section 2.4 reflects on the influential factors of information systems reuse or continuous use, and discussion on the correlation between the factors. Section 2.5 addresses trust in recommender systems and in particular discusses the significance of cognitive trust, emotional trust and trust propensity in recommender systems adoption. Next, customer satisfaction is reviewed in the domain of information systems, especially the state of flow and cognitive absorption in Section 2.6. Section 2.7 reviews theoretical foundation of the thesis. A detailed discussion on research gaps identified from the relevant literature is provided in section 2.8. Section 2.9 provides a brief summary of the chapter.

2.2 RECOMMENDER SYSTEMS

Recommender systems (RSs) provide product-related information to help online customers decide whether or not to purchase a product (Xiao & Benbasat, 2007). An RS is internet-based software that performs or executes a set of operations on behalf of customers, such as providing shopping advice based on their previous purchasing behaviour, specified preferences, or the preferences of other customers in their affinity group (Benlian et al., 2012; Xiao & Benbasat, 2007; Xu et al., 2014). Amazon, for example, is a pioneer in the use of recommendations on a large scale (Linden et al., 2003), and offers recommendations in a wide range of item categories, typically under the labels "Frequently bought together" or "Customers who bought... also bought" (Lin, 2014; Nilashi et al., 2016).

A variety of filtering algorithms have been used to develop different sorts of recommendation systems in an effort to improve the efficiency of internet sales. There are several types of recommender systems based on how they filter information: content-based, collaborative, context-aware, hybrid, and random (Logesh et al., 2020; Panniello et al., 2016). This research is based on Amazon’s recommender systems that use collaborative filtering algorithms (Smith & Linden, 2017).

In collaborative filtering, products are evaluated and filtered in light of other people's opinions (Schafer et al., 2007). In addition to Amazon, many organisations, including YouTube, Netflix, and Spotify, employ collaborative or social filtering to recommend products or services to its customers. When a collaborative filtering system detects other database users whose tastes correlate with those of a specific user, it suggests other products that the matched database users have appreciated or liked to the user (Mooney & Roy, 2000). It is assumed that the interests and preferences of each user in the system are roughly the same, and that product rating information is readily available (Mooney & Roy, 2000; Schafer et al., 2007). Collaborative filtering has the advantage of not requiring information about the product or service (e.g., descriptive restaurant or product reviews). As a result, it can be valuable in situations when the product's descriptive text is slight or difficult to obtain (e.g., movies and music). In some cases, users may evaluate an item or product based on a feature that the system cannot automatically extract and analyse (e.g., images, audio, or video on a website). Since other users have rated the item/product, rather than the system's capacity to extract and analyse features, collaborative filtering is employed instead of content-based filtering (Schafer et al., 2007). In general, researchers believe that user-based collaborative filtering produces more unexpected and distinct outcomes that are equally worthwhile (Herlocker et al., 2004). There are some downsides to user-based collaborative filtering systems. They cannot properly propose products or services if they do not have enough user ratings for them since they do not have enough data (Mooney & Roy, 2000; Ricci et al., 2011).

E-vendors must have the ability to engage and retain customers for long-term survival or, more importantly, to become successful. Offering recommendations for products or services to customers might be one approach to keep them engaged and assist them in their purchase decisions (Chinchanachokchai et al., 2021). RSs are an important supporting tool in modern e-commerce technologies that assist customers in their decision-making process (Benlian et al., 2012), while e-vendors get a competitive edge by increasing the likelihood of customers' loyalty, satisfaction and intention to purchase (Abumalloh et al., 2020; Nilashi et al., 2016; Pu et al., 2011). In fact, using recommender systems has increased Amazon's revenue by 35% and boosted sales by 29% (Nguyen et al., 2019). These data reinforce the idea that recommender systems can assists customers in their decision-making process. Even more importantly, the rise of e-commerce and online marketing is making it easier for businesses to implement modern technologies like recommender systems. In view of the opportunities, it is important to examine the characteristics that improve the possibility of a customer to reuse RSs.

2.3 RSs ADOPTION PROCESS

User-centric evaluation of recommender systems refers to the study of recommender systems from the point of view of the consumer in order to ensure that they are not only useful and accurate, but also enjoyable to interact with (Knijnenburg & Willemsen, 2015). The three stages of product/service adoption process were used in this research in order to accurately understand how consumers become aware, seek knowledge, evaluate, try, and reuse recommender systems.

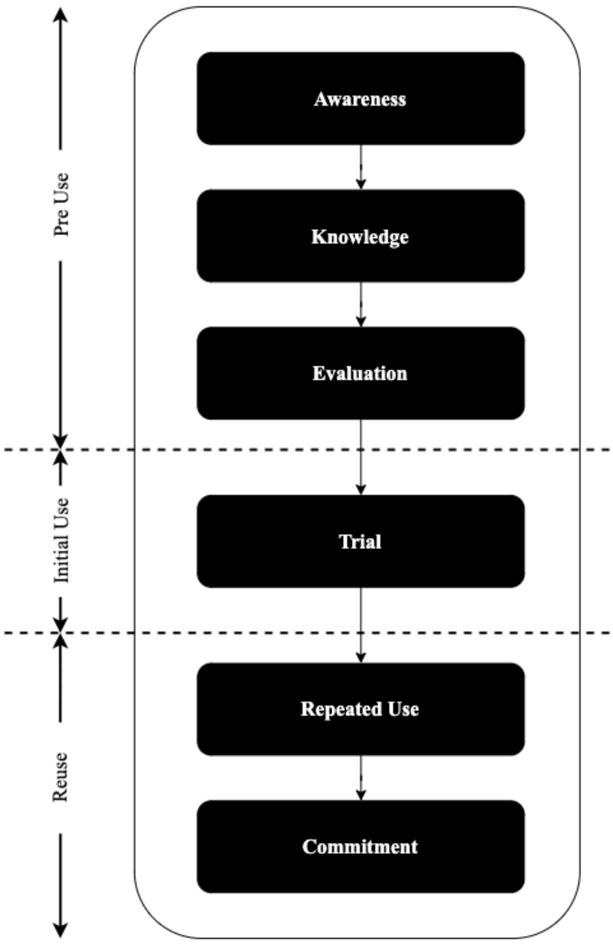


FIGURE 2.1 THREE STAGE OF ADOPTION PROCESS

Adopted from (Montazemi & Saremi, 2014; Rogers, 2010)

2.3.1 Three stages of products/ services adoption process

Consumers' adoption of services occurs in a time order sequence of three stages: pre-use, initial use, and reuse with action and decisions occurring at each stage (Montazemi & Saremi, 2014; Rogers, 2010). The consumer can decide to terminate using the service at any of these stages (Rogers, 2010). Consumers may have varying perceptions of the service during the course of its adoption process, which may be influenced by various characteristics of the service (Montazemi & Saremi, 2014; Xia & Lee, 2000). The three-stage adoption process is illustrated in Figure 2.1.

2.3.1.1 The pre-use stage

The pre-use stage of the adoption process, before a consumer utilise a service, is awareness, which can lead to their mental evaluation of the offering, which can in turn lead to initial use (Looney et al., 2008). Consumers are made aware of the presence of the invention in the first step, *awareness*. Awareness can occur either actively or passively (Rogers, 2010). Active awareness comprises individuals actively searching out an innovation to meet a specific need. For example, a person looking for a better strategy to invest their money can come across the online service channel while doing research. Passive awareness, on the other hand, occurs when a consumer becomes aware of an innovation by chance. A television commercial, for example, could alert a person to the presence of an internet service channel. When consumers become aware of an invention, they move on to the *knowledge* stage, where they learn how the innovation works (Rogers, 2010). Consumers become more intrigued by the innovation and want to learn more about it. Individuals are particularly interested in learning how to use an innovation correctly, as well as the underlying concepts that allow the innovation to function. Consumers are particularly interested in learning how to correctly use an innovation and the underlying concepts that enable the innovation to operate (Looney et al., 2008). Consumers establish an opinion about the invention during the evaluation stage, armed with knowledge. Consumers examine how the innovation might assist an anticipated future state and/or test the innovation vicariously. Consumers may examine whether they can successfully use the online service channel, weigh the future repercussions of using it, and create an opinion about whether they prefer the online or offline strategy while evaluating it. The innovation-decision process in the first three stages of adoption have thus far been solely a cerebral exercise of thinking and deciding therefore they can be referred to as early stages of adoption (Rogers, 2010). Consumers may conduct a virtual trial of the innovation, but the processes that are evoked are mental rather than behavioural. Individuals have yet to engage in any adoption-related behaviours.

2.3.1.2 The initial-use stage

Initial use is usually a *trial*, and it may result in a person using the services repeatedly i.e., reuse or rejecting the innovation (Looney et al., 2008). The trial period is the initial step of adoption (Meuter et al., 2005). Consumers move from thinking about the innovation to acting on it by trying it out (Qahri-Saremi, 2014). After the user has put the innovation into action, they assess its simplicity to use and usefulness and decide whether to continue using it (Looney et al., 2008). These activities and decisions are made when attempting to use the online service channel. After the trial period, if consumer decide to adopt the innovation, they enter the reuse stage.

2.3.1.3 The reuse stage

The first phase in the reuse stage is *repeated use* of services (Montazemi & Saremi, 2014). Consumers can assess their overall happiness with the innovation at this point. When consumers are pleased with an innovation, it is more probable that they will continue to use it rather than discontinue it (Massey et al., 2007; Stafford et al., 2004). Consumers compare their satisfaction levels with the online service channel and choose between the two options. Either their satisfaction justifies repeated use of the channel, or they are sufficiently unsatisfied that they are willing to incur the substantial switching costs associated with transferring to a new service channel (Looney et al., 2008). In addition to satisfaction, people consider the long-term ramifications of repeated use or switching, as well as the associated benefits and drawbacks of each action. The final phase of the adoption process is *commitment* (Montazemi & Saremi, 2014). Consumers require encouragement for committing to the previously made adoption commitment (Qahri-Saremi, 2014). Consumers that utilise online service channels require assistance in order to continue using the channel. Consumers may choose to use a different service channel if they find inadequate or no reinforcement (Looney et al., 2008). Consumers weigh the future repercussions, as well as the benefits and drawbacks of committing to or moving from the service channel being used, just as they did during the repeated use stage (Qahri-Saremi, 2014).

2.3.2 Application of services adoption process in IS

Prior studies in have documented the three-stage adoption phenomenon in IS. Davis (1989) reported that after a single hour of using technology, ease of use had a substantial effect on use, but after weeks of use, it was no longer significant. Agarwal and Prasad (1997) studied consumer perception of information technology (IT) and found that same IT innovation characteristics have a different effect on customers' perceptions in different stages of the adoption process. Karahanna et al. (1999) revealed that user attitudes regarding IT usage differed significantly between the pre-adoption and post-adoption stages. The researchers requested a longitudinal study to be conducted, which follows the same users throughout the IT adoption process. Subsequent research has also reported that customers' adoption of services is differently influenced by external factors in different stages of the adoption process. For example, Visinescu et al. (2015) reported that the same antecedent factors have different impact on consumer’s intention to buy online in different stages of 2D and 3D website usage. Venkatesh and Davis (2000) found that customers' service usage is impacted by same antecedent factors differently in different step of the adoption process. Similarly, Qahri-Saremi (2014) also revealed that the consumers' adoption of online recommendation was differently affected by factor such as perceived usefulness, ease of use and trust. The current research applies three stages of the adoption process to accurately capture the RSs adoption process in the studies.

THE PRE-USE STAGE

As illustrated in the Figure 2.1 the pre-use stage includes awareness, knowledge and evaluation. Consumers are made aware of the existence of the service during the *awareness* phase (Ng, 2020). Amazon shoppers, for instance, can be introduced to a product via RSs. After they have been recommended the products they should try, consumers move on to the *knowledge* phase and the *evaluation* phase, where they can gather knowledge about the service provided by RSs and assess the service respectively. Looney et al. (2008) reported that customers assess how the service would meet their needs and expectations. As online customers cannot touch and experience the products before they are purchased (Wang et al., 2015), they confront challenges and insecurities in evaluating their product qualities and anticipated performance throughout the pre-use phase (Benlian et al., 2012). RSs include elements that can help customers understand and assess the items better, which can minimize this uncertainty (Benlian et al., 2012). They advance to the initial use stage of the adoption process upon favourable evaluation of the recommended product (Looney et al., 2008; Montazemi & Saremi, 2014).

THE INITIAL-USE STAGE

As customers utilise the service for the first time, they transition from the mental processing stage to actual use in the initial use stage (Montazemi & Saremi, 2014). *Trial* represents the initial use stage, and in this stage an individual tries the RSs for the first time. After first adoption or use, the service's experience, usefulness, and trustworthiness can be assessed, and then the decision to continue or terminate its service can be drawn (Bhattacherjee, 2001; Montazemi & Saremi, 2014). If the consumer is eager to adopt the service, they would then advance to the next step where they would be committed to use the service (Looney et al., 2008; Ng, 2020).

THE REUSE STAGE

The two-step reuse process for service adoption consists of *repeated use* followed by *commitment*. Customer evaluates the overall quality of the service based on the future effects of continued or discontinued use after repeated use. If customers are satisfied with the service, they are more likely to continue using it, but if they are dissatisfied, they may discontinue its use (Looney et al., 2008; Ng, 2020). It is during this reuse stage that the sustainability of an IS and its ultimate success are determined (Bhattacherjee, 2001; Yan et al., 2021). Further, as the sustainability and success of RSs depends upon the reuse stage (Muhammad Ashraf et al., 2020), this research focused on user-centric evaluation of post-adoption factors pertaining to the RS reuse stage.

A literature content analysis was performed drawing upon the PRISMA guidelines (Haddaway & McGuinness, 2021; McInnes et al., 2018), to recognise thematic patterns, seminal studies and emerging trends. The data collection was made from Scopus, Web of Science, EBESCO Host. These publication databases were searched from March 2019 to find articles that was based on recommender system and consumer behaviour. Initial set of papers were identified using the following search query:

("recommender system" **OR** "recommendation agent*" **OR** "recommendation system*" **OR** "personali?ation agent" **OR** "personali?ed product recommendation*" **OR** "online product recommendations") **AND** ("consumer behavio*" **OR** "consumer choice*" **OR** "consumer preference*" **OR** "consumer attitude") **AND** (ecommerce **OR** "e-commerce" **OR** "online shopping" **OR** "online purchase" **OR** "online buying" **OR** "online choices" **OR** "electronic market*)*

The search was restricted to indexed journals and conference papers. Studies published between 2005 and 2020 were considered. The search returned 2659 publication entries that was reviewed for quality. Endnote (X9) was used as a working database for sorting included and excluded studies. For relevance and inclusion, the abstracts of selected papers were reviewed. Excluded studies included those with primary focus on algorithm development than consumer behaviour. Studies with primary focus on pre-use, adoption/ initial-use and reuse were included. The title and abstract of 2659 articles were screened and 85 full articles were reviewed, out of which 14 met the inclusion criteria.

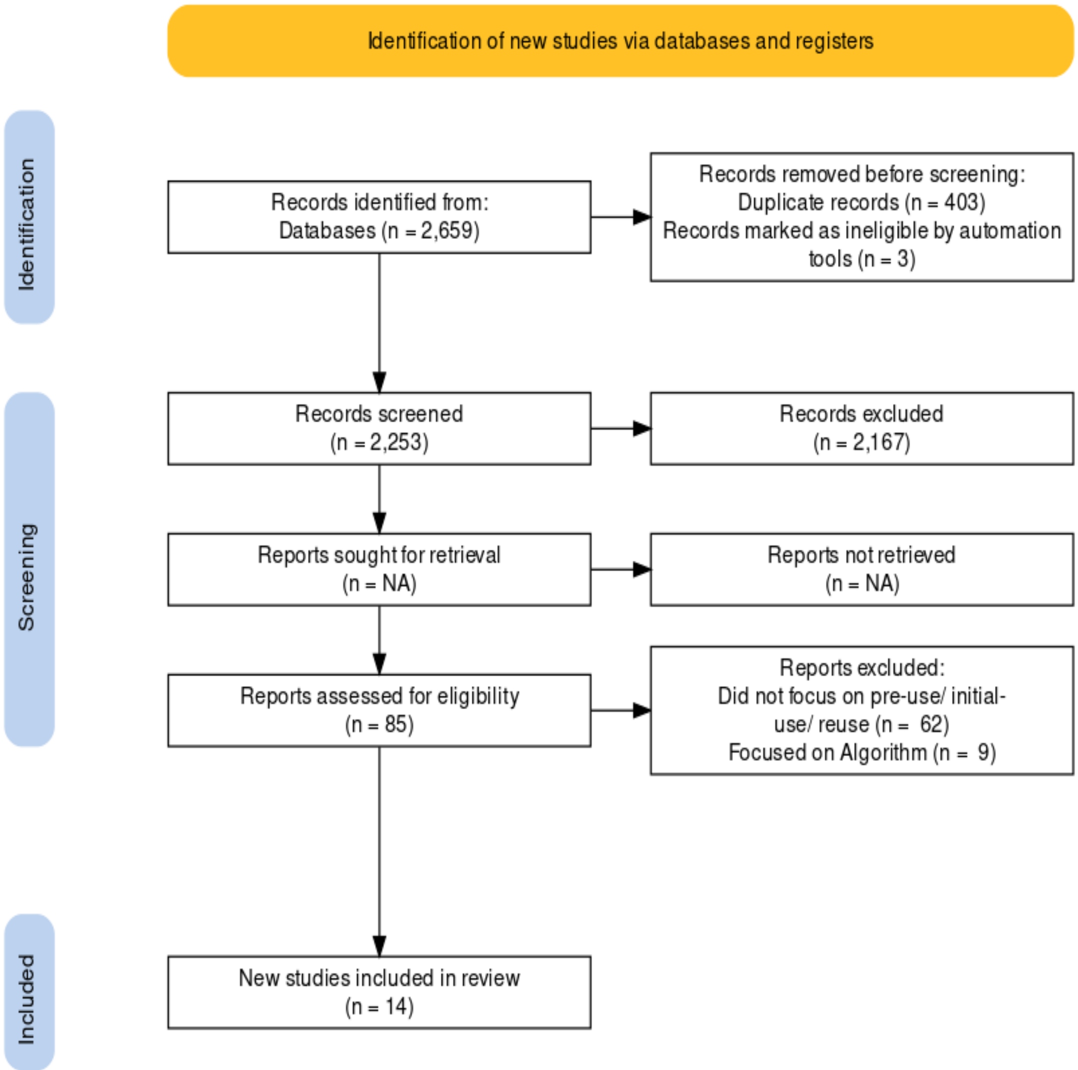


FIGURE 2.2 PRISMA FLOW DIAGRAM

(Adopted from Haddaway & McGuinness (2021))

The studies were structured into three categories: on pre-use, initial-use and reuse (See Table 2.1). Most of the studies focused on the initial-use stage. One recent study focused on the reuse stage. The study identified that perceived usefulness, perceived confirmation, continuous trust, and satisfaction as important post-adoption factors influencing RSs continuous use intention. Even though the three stages of the adoption process are of paramount importance, recommender systems have been in use for more than two decades (Smith & Linden, 2017) and the literature content analysis revealed that there are limited studies examining the post-adoption factors influencing the reuse stage (See Table 2.1).

TABLE 2.1 SUMMARY OF PRIOR RECOMMENDER SYSTEM STUDIES FOCUSING ON DIFFERENT ADOPTION STAGES

Author(s) (Year)	Pre-use stage	Initial-use stage	Reuse stage
(Benlian et al., 2012)		✓	
(Ghasemaghaei, 2020)		✓	
(Ashraf et al., 2020)			✓
(Bigras et al., 2019)		✓	
(Martínez-López et al., 2015)		✓	
(Xu et al., 2014)		✓	
(Wang & Benbasat, 2005)		✓	
(Pu et al., 2012)		✓	
(Wang et al., 2015)		✓	
(Wang & Benbasat, 2009)		✓	
(Choi et al., 2011)		✓	
(Komiak & Benbasat, 2006)		✓	
(Su et al., 2008)		✓	
(Knijnenburg et al., 2012)		✓	

The following section presents important factors relevant to IS reuse or continuous use.

2.4 Post-adoption factors in IS reuse or continuous use

Numerous factors can motivate consumers to reuse different type of IS. These factors can be categorised mainly in terms of social-psychological and technological/ instrumental (Allport & Lindzey, 1954; Ashraf et al., 2020; Yan et al., 2021). Social-psychological factors refer to the factors that causes an individual to behave in a certain way in the presence of others (Allport & Lindzey, 1954), and technological factors focus on the attitude, perception, and interaction between humans and technology (Yan et al., 2021). In particular, psychological factor such as satisfaction (Mouakket, 2018; Yang, 2021), perceived enjoyment (Chiu et al., 2019), trust (Sun et al., 2014), and attitude (Wu & Chen, 2017) as well as technological factor such as perceived usefulness (Benlian et al., 2012; Susanto et al., 2016) have been found to significantly influence consumers' intention to reuse an IS. Several past studies IS have asserted that social-psychological factors can influence technological factors (Ashraf et al., 2020; Wang & Benbasat, 2005). Technological factors can also influence social-psychological factors (Harrigan et al., 2021; Pu et al., 2011). Social-psychological factors and technological factors can influence behavioural intentions in online buying decision process (Mouakket, 2018; Shang & Wu, 2017; Sun et al., 2014; Yang, 2021). Figure 2.3 depicts the influential diagram of the factors investigated in this research and serves as the framework of this thesis.

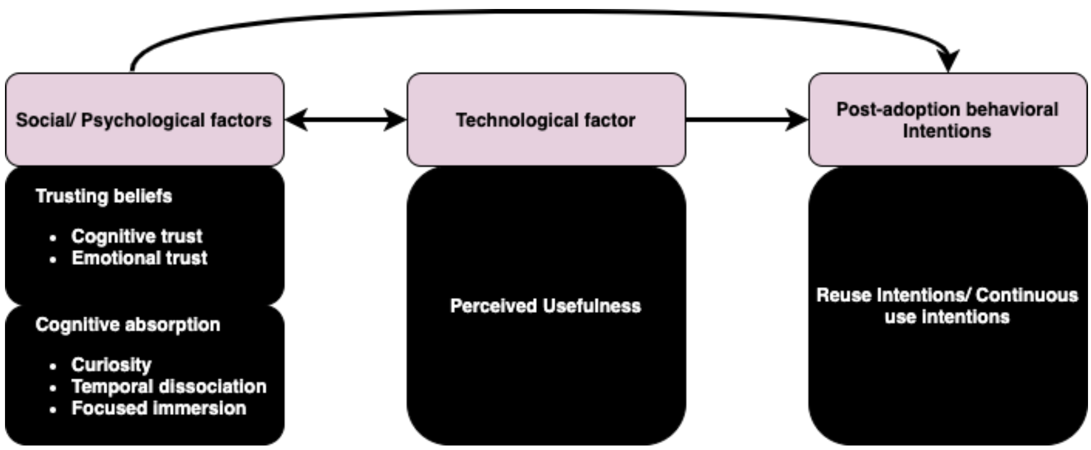


FIGURE 2.3 THESIS FRAMEWORK

Yang (2021) reported that satisfaction and trust in RSs positively and significantly affect RSs reuse intentions. Similarly, Mouakket (2018) indicated that satisfaction was the strongest predictor of intention to continue using Facebook, compared to other antecedents like perceived usefulness. Chiu et al. (2019) found that consumers' continuance intention towards Mobile Travel Service System is predicted by perceived enjoyment and e-engagement, which in turn is jointly determined by personal innovativeness and e-interaction quality. According to Sun et al. (2014), consumers' continuous use intention for online social networks was found to be dependent on their perceptions of enjoyment, effort expectancy, usefulness, social influence, satisfaction, social norms, tie strength, and trust. Consumers' perceived usefulness, perceived ease of use, perceived affective quality and trust significantly affect RSs reuse intentions (Benlian et al., 2012). Similarly, Shang and Wu (2017) also found that attitude and perceived usefulness are critical to the continuance intention. They also reported perceived usefulness as a significant mediator for continuance intention.

Furthermore, the significance of perceived ease of use on continuous use intention is conflicting in the extant literature. Shang and Wu (2017) indicated that perceived ease of use directly affects continuous use intention. Consistent with TAM (Davis, 1989) many studies indicated the effect of perceived ease of use as insignificant on continuous use intentions (Bhattacherjee, 2001; Cheng et al., 2019; Karahanna et al., 1999).

Finally, several earlier researchers have also included a number of other predictors of continuous use intention, including: compatibility (Hubert et al., 2019), perceived playfulness (Ifinedo, 2017), perceived risk (Martins et al., 2014), perceived reputation (Zhang et al., 2015), hedonic gratification (Osatuyi & Qin, 2018), hedonic value (Gan & Li, 2018), effective commitment (Jin et al., 2010), perceived quality (Zhou et al., 2014) and habit (Mouakket, 2018). Yan et al. (2021) argued that besides concentrating on consumers' perceptions of a technology like enjoyment, satisfaction, and trust, a closer examination of mental processes engaged while using a technology (e.g., flow (Csikszentmihalyi & Csikzentmihaly, 1990)) should be conducted.

Based on the discussion above it is evident that a variety of factors can contribute to the adoption and success of IS and these factors can also be similar in the context of e-commerce RSs. The studies presented thus far provide evidence that trust is an important influential factor and a closer examination of flow experience is lacking in extant literature.

2.5 Trust

Trust in social construction stems from interpersonal relationships (Sztompka, 1999) and acts a social glue in groups, society and relationships (Van Lange, 2015). Socially, trust is a personal trait. According to Mayer et al. (1995, p. 712), trust is defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party". Studies have shown that the formation of trust in technological artefacts is just as important as it is in interpersonal relationships (e.g., Jian et al., 2000; Komiak & Benbasat, 2006; Reeves & Nass, 1997; Sztompka, 1999). People treat computers as social actors and apply social rules to them (Reeves & Nass, 1997). Technology-savvy people treat technological artefacts like humans (Reeves & Nass, 1997). Trust in humans and technology is not fundamentally different because people design and operate all human-made technologies (Sztompka, 1999). People assign personalities (e.g., helpfulness, friendliness) to technological artefacts. They are applied to both sophisticated conversational computer agents (Cassell & Bickmore, 2000) and text-based computer systems (Sztompka, 1999). Previous research shows no significant difference between human and technological trust components. In an empirical study, Jian et al. (2000) found that components of trust are similar across the three types of trust investigated: human-human trust, trust in human-machine relationships, and trust in general.

2.5.1 Trusting beliefs

The theory of reasoned action categorises three general types of trust: (1) trusting beliefs (the trustor's perception that the trustee is beneficial to them), (2) trusting intention (the trustor's willingness to rely on a trustee in a given situation), and (3) trust propensity (the degree to which an individual trusts the technology in various situations and information technology artefacts) (Kim et al., 2008, 2009). The majority of IS studies (e.g., Gefen et al.,2003; Komiak & Benbasat, 2006; Komiak & Benbasat, 2004; Wang, 2005; Wang & Benbasat,2007, 2008) define trust as trusting beliefs. A person's trusting beliefs are based on perceptions of the technology's competence, benevolence, and integrity (Bock et al., 2012). It emphasises the trustors' rational expectations of the traits of trustees that they can rely on, a belief that is consistent with cognitive trust (Komiak & Benbasat, 2004; Zhang et al., 2014).

Developing trust involves both cognitive and emotional elements of trust (Komiak & Benbasat, 2006; Punyatoya, 2019; Sun, 2010). A small amount of research has focused on emotional trust (Ashraf et al., 2019). According to Komiak and Benbasat (2004), emotional trust also known as affective trust is the user's emotional reactions of feeling secure and assured towards relying on the trustee. The emotional aspect of trusting beliefs is vital in its impact mechanisms and to examine how a customer actually decides whether or not to trust online recommendations, cognitive trust is insufficient (Komiak & Benbasat, 2004; Komiak & Benbasat, 2006).

An emotional trust is built on strong social-emotional relationships that extend much beyond a typical business relationship (Kim, 2005). Customers form emotional attachments and ties with one another, which is the foundation of this strategy. Rather than good rational reasoning, a strong favourable feeling towards a trustworthy object may motivate trust (Punyatoya, 2019).

A review of the RSs literature revealed that most previous research focuses on cognitive rather than emotional trust. A few studies examined trusting beliefs from both cognitive and emotional aspects of trust (Ashraf et al., 2019; Komiak & Benbasat, 2006). For example, Ashraf et al. (2019) defined customer trusting beliefs as a combination of cognitive and emotional trust, assuming that trust decisions are based on both reasoning and feelings. A lack of physical contact with the product (Jiang & Benbasat, 2004), as well as the absence of face-to-face personal interaction with e-vendors (Komiak & Benbasat, 2006), contributes to the importance of customers' affective reactions in various consumption situations. This is especially true when purchasing products online. Customers' product selection becomes more affective in an uncertain environment (Komiak & Benbasat, 2006).

The cognitive and emotional trust focused lens aligns with the cognition-affect-intention framework (Robertson & Kassarjian, 1991; Thompson & Fine, 1999) and the theory of rational action (Fishbein & Ajzen, 1975). The relevance of trusting beliefs in online environments has been studied before and proven to be a crucial factor in IS adoption (Ashraf et al., 2019; Benlian et al., 2012; Gefen et al., 2003; McKnight et al., 2002b; Pavlou, 2003). Trusting beliefs in e-commerce vendors and RSs has both a direct and indirect effect via (for example, perceived risk, perceived usefulness, or satisfaction) on RSs adoption (Ashraf et al., 2019; Benlian et al., 2012; Komiak & Benbasat, 2006; Wang & Benbasat, 2007, 2008). Customers' initial trusting beliefs in RSs are based on their cognitive and emotional evaluation of the truthfulness of RSs (Komiak & Benbasat, 2006). Customers assess the credibility of RSs by examining their explanations. Explanatory information about how and why, and that attribute trade-offs that are cognitively justified and reveals the underlying reasoning process improves customers' trust in RSs (Benlian et al., 2012). The RSs needs to be trusted in order to be effective (Urban, Sultan, & Qualls, 2000).

The development of trust is influenced by a variety of factors (Lee & See, 2004). Partner factors (referring to the technology), human factors, and environment factors were identified as three main factors influencing trust development (Schaefer et al., 2016). The environmental factor consists of aspects of the task, teamwork and the context. Human factors include cognitive and emotional factors, such as attitudes, understanding and expectancy, and states such as stress and fatigue. Human characteristics such as age and gender can influence the development of trust [e.g., (Ho et al., 2005)]. Among different traits, trust propensity is frequently mentioned in the literature, and has also been applied to human-technology contexts (Jessup et al., 2019).

2.5.2 Trust propensity

Trust propensity measures the degree to which an individual trusts the technology in various situations and using information technology artefacts (Tussyadiah et al., 2020). Prior research supports the positive association of trust propensity to trusting beliefs (Murphy, 2003; Tussyadiah et al., 2020). Trust propensity influences an individual's trust in online shopping (Amin et al., 2015; Chang & Fang, 2013; Salam et al., 2005). Trust propensity also affects how people perceive and interact with the environment, especially when dealing with new people, new things, or in uncertain situations (Colquitt et al., 2007; Rotter, 1971). A significant degree of uncertainty in an e-commerce environment may assuage individuals' suspicions depending on their trust propensity which in turn may alter their trusting beliefs in RSs in an ongoing relationship. The relevance of trust propensity in an ongoing relationship has been studied in the trust literature and proven to a critical antecedent of trusting beliefs (Alarcon et al., 2018; Colquitt et al., 2007). Trust propensity has a significant impact on the trustworthiness dimension in both initial and subsequent evaluations (Colquitt et al., 2007). Trust propensity is a significant factor in in predicting trust actions, beliefs and intentions throughout the trust process.

Together, these studies highlight that emotional trust refers to the consumer's emotional sense of security and comfort in depending on RSs recommendations, while cognitive trust refers to the consumer's rational expectations of the capacity of RSs to deliver accurate and reliable product recommendations. Trust propensity of an individual would affect the consumers' trusting beliefs in RSs.

2.6 CUSTOMER EXPERIENCE

Creating a great customer experience is vital for all businesses, as it can influence the customer's future behaviour towards the company and its products (Homburg et al., 2017). When it comes to winning the hearts and minds of customers in today's fiercely competitive market, companies must focus on providing positive experiences (Pine & Gilmore, 2011). Consumers in today's society are more concerned with the experience than the actual value of a product (Barta et al., 2021; Bilgihan et al., 2014). As a result, experience has become an important component of the overall product or service being purchased (Gopalani & Shick, 2011; Rust & Lemon, 2001).

2.6.1 FLOW

The notion of flow can help to better understand and improve consumer experiences (Hoffman & Novak, 1996). Flow is a state in which people can become so immersed in an activity that they may lose track of time, space, and even themselves (Csikszentmihalyi, 2000; Csikszentmihalyi & Csikzentmihaly, 1990). An individual's decision-making and actions are in complete control during this flow experience, which is also known as a state of flow or optimal experience. When engaged, the level of task difficulty and the level of each person's ability are equal (Mahfouz et al., 2020). Numerous studies in a variety of fields, including information technologies, sports, art, dance, online shopping, interactive interfaces, retail, and video games, have used this concept extensively to understand optimal or holistic experiences (Csikszentmihalyi et al., 2014; Mahfouz et al., 2020).

2.6.2 COGNITIVE ABSORPTION

Holistic experience in the context of information technology can be described using the concept of cognitive absorption, which is defined as a deep involvement with software (Agarwal & Prasad, 1997). Research in individual psychology, in particular, studies related to the concept of cognitive engagement (Webster & Ho, 1997), the state of flow (Csikszentmihalyi & Csikzentmihaly, 1990) and a trait dimension called absorption (Tellegen & Atkinson, 1974), provides the theoretical foundation for cognitive absorption. Cognitive absorption is generally conceptualized in information technology literature the same way that "flow" is conceptualised in other fields (Hoffman & Novak, 2009; Mpinganjira, 2019; Ozkara et al., 2017). It is clear from the reviews on flow and cognitive absorption by Ozkara et al. (2017), Hoffman and Novak (2009), Nah et al. (2012), and Rissler et al. (2017) that similar dimensions are used to measure flow experience and cognitive absorption in information technology studies. Cognitive absorption is the operational term for flow in the context of information technology (Tan et al., 2015). Cognitive absorption exhibits five dimensions associated with five elements of flow experience (Agarwal & Karahanna, 2000). These dimensions are referred to as temporal dissociation, focused immersion, heightened enjoyment, control, and curiosity (Agarwal & Karahanna, 2000). They can be classified as cognitive and emotional components. The cognitive component only includes heightened enjoyment, whereas the affective components include temporal dissociation, focused immersion, curiosity and control. Zhu and Morosan (2014) argued that the conceptualisation of cognitive absorption should only include curiosity, focused immersion, and temporal dissociation. The significance of heightened enjoyment in cognitive absorption is debatable, with some considering it to be either an antecedent (Ghani & Deshpande, 1994), or a core dimension of flow (Trevino & Webster, 1992). Likewise, the role of control over the interaction with technology within the literature is contradictory, being recognised as either an antecedent (Ghani & Deshpande, 1994; Webster & Ho, 1997) or dimension of flow (Trevino & Webster, 1992). Webster and Ho (1997) defined flow as a multidimensional construct and used the term cognitive engagement to refer to the combination of curiosity, attention focus, and interest, but excluding the control component. Prior studies have also argued that heightened enjoyment and control should be excluded due to their unambiguous role within the cognitive absorption construct (Mpinganjira, 2019; Zhu & Morosan, 2014). In the view of these arguments this research used curiosity, focused immersion, and temporal dissociation as the core dimension of cognitive absorption and did not include heightened enjoyment and control.

An individuals’ willingness to adopt new technology can be influenced by cognitive absorption (Agarwal & Karahanna, 2000; Agarwal & Prasad, 1997). Recent studies have encouraged the investigation of users' perceptions of cognitive absorption in order to build strong technological adoption (Ghasemaghaei, 2020). Previous research has shown that flow on the web is likely to occur during information-seeking activities when shopping (Mahnke et al., 2015). Interactions with technology such as recommender systems when shopping online in an e-commerce environment provide the chance for customers to achieve the flow state. Extending upon the current discussion, this research focuses on the notion of cognitive absorption to capture the holistic experience of RSs with regards to behavioural intentions to reuse RSs in an e-commerce environment.

The following section presents the theoretical foundation of the thesis.

2.7 Theoretical foundation of the thesis

2.7.1 ResQue model

The ResQue model (Recommender Systems' Quality of User Experience) is a user centric evaluation framework that assesses users' attitudes towards and acceptance of an RS (Pu et al., 2011). The ResQue model not only measures how closely the recommendations match the preferences of the users, but also how easy the system is to use, how satisfied users are with the system, and how much the users trust the suggestions (Iovine et al., 2020). (a) perceived system qualities: refers to the user's opinion on the objective characteristics of RSs, (b) user beliefs: refers to the user's perception of RSs interaction, (c) user attitudes: refers to the user's overall feeling about the RSs, and (d) behavioural intentions: refers to the user's acceptance of the RSs and agreement to use it in the future (Pu et al., 2012). The perceived quality layer has positive effects on user beliefs, which in turn positively affects users' attitudes, and as the chain reaction continues, will have a positive impact on users' behavioural intentions (Pu et al., 2011).

The ResQue model was heavily influenced by the well-known models such as Software Usability Measurement Inventory and Technology Acceptance Model, both of which have been widely used to assess software usability and acceptance (Karga & Satratzemi, 2019; Pu et al., 2012). For instance, the ResQue model has incorporated the original constructs of the Technology Acceptance Model as follows: (a) construct of the system's perceived usefulness and perceived ease of use have been embedded into ResQue's beliefs layer, and (b) construct of users' intention to use the system has been embedded into ResQue's behavioural intentions layer. ResQue's beliefs layer also incorporates some notions from the Software Usability Measurement Inventory model, e.g., learnability.

The ResQue model is extensively applied for the evaluation of RSs from a user-centric perspective in different context such as digital assistants (Iovine et al., 2020), geoinformation (Vandecasteele & Devillers, 2015), e-learning (Karga & Satratzemi, 2019), music (Millecamp et al., 2018), e-commerce (Chen et al., 2019). As the ResQue model has been widely used for the evaluation of RSs from a user-centric perspective in various contexts, it seems reasonable to use the ResQue model as a theoretical underpinning of the current study.

The next sections present the Technology Acceptance Model.

2.7.2 Technology acceptance model

The Technology Acceptance Model (TAM) was created by Davis (Davis, 1989) to investigate the factors that influence people's willingness to accept new technologies (Kamal et al., 2020; Zhu & Morosan, 2014). According to prior research, TAM is the best-known model for predicting technological acceptance (Kamal et al., 2020). Prior to widespread usage, one of TAM's most significant objectives is to forecast user adoption patterns for new technologies and identify information system design concerns that may arise (Yi et al., 2006). Though derived from Fishbein and Ajzen's Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1977), TAM proved to be more effective in describing behavioural intention than TRA and TPB (Theory of Planned Behaviour) (Leong et al., 2013; Taylor & Todd, 1995). TAM relies on two core constructs: perceived ease of use, as well as perceived usefulness, both of which are linked to the attitudes and intentions of users towards a specific technology (Davis, 1989). In light of its straightforward theoretical underpinning (Chang et al., 2016), it's well recognised and regularly used as a model for assessing the likelihood that people would adopt new technologies. This strength, on the other hand, acts as its primary flaw. For example, the present technical environment such as Internet of Things (IoT), artificial intelligence (AI), and recommender systems (RSs) is different from the one in which TAM was established (Yan et al., 2021). This raises the question of how much a technology's characteristics influence continuance intentions and how the antecedents of continuance intention alter depending on the digital technology used. Incorporating the TAM with other theories would broaden its use while also providing new insights (Chooprayoon et al., 2007; Li & Karahanna, 2015). A review of the extant literature pertaining to information system reuse also highlights the use of TAM (Bhattacherjee, 2001; Mpinganjira, 2019; Wu & Chen, 2017). It is also used in the RSs studies, in particular, to understand the consumer’s adoption intention (Wang & Benbasat, 2005) and intention to reuse RSs (Alharbi & Sandhu, 2018; Benlian et al., 2012). Alharbi and Sandhu (2018) used an extended TAM to predict the reuse intention of e-learning RSs. Benlian et al. (2012)

also used an extended TAM to investigate consumer's behavioural intention to reuse RSs and consumer reviews. "Perceived ease of use" explores the extent to which a system is perceived to be free from mental efforts, while "Perceived usefulness" refers to the benefits arising from the use of an IS. Several previous studies have used perceived usefulness and perceived ease of use as instrumental beliefs and found them to be directly linked with behavioural intention (Ayanso et al., 2015; Lee, 2010; Recker, 2010; Sun et al., 2014). TAM posits that individuals' behavioural intentions towards an information system are directly and indirectly impacted by perceived usefulness (Brömmelstroet, 2017; Cheng et al., 2015).

The relevance of perceived ease of use is only noticeable if the nature of the task carried out if an information system is complex and needs special skills or knowledge. Using RSs to purchase a product is a task that does not require special skills or knowledge (Gefen & Straub, 2000). Evidence from a number of empirical studies pertaining to reuse intention has reported an inconsistent role of "perceived ease of use" (Joo et al., 2016; Karahanna et al., 1999). Joo et al. (2016) ascertained that there was no significance of "perceived ease of use" in the reuse of a mobile learning management system. For the reuse of Windows technology, Karahanna et al. (1999) argued that "perceived ease of use" is not essential at the post adoption stage. This research focused only on people who are currently active Amazon shoppers. The respondents could be considered to be already well-informed and know how to use RSs to purchase a product. Some prior studies based on TAM and information system reuse intention have also ignored "perceived ease of use" in their research model (Bhattacherjee, 2001; Mpinganjira, 2019). Based on the above arguments and empirical evidence, "Perceived ease of use" was not integrated into the model for this research to aid the understanding of the consumer’s behavioural intention to reuse RSs.

2.8 Research gaps identified from relevant literature

Recommendations are inarguable necessities in both retail and corporate environments (Behera et al., 2020). With the rise of e-commerce (e.g., Amazon), users have the ability to receive and interact with recommendations made by RSs, other individuals, and experts. While human agents' advice has been studied, little research has focused on the advice provided by RSs (Srivastava et al., 2020). RS is becoming important in online purchase decision-making process (Benlian et al., 2012). Rather than taking over the decision-making process, RSs reduces consumers’ cognitive efforts by providing them with a collection of “best match” products that obviates the need for shoppers to make decisions on their own (Aljukhadar & Senecal, 2021; Todd & Benbasat, 2000).

Contrary to statements that praise the significance of RSs to retail and corporates, most websites employing RSs have reported very low ROI (Wang et al., 2015). A prime example is Amazon, which generates up to 35% of sales being attributed to RSs (Jannach & Jugovac, 2019). Perhaps this means that buyers have not yet established trust in RS' performance (Sheng et al., 2014). Past studies have revealed that customers doubt RSs’ performance and trustworthiness because e-vendors may employ RSs that offer recommendations that may not be entirely personalised to benefit the consumer; instead, they are skewed in favour of their own interests (Chau et al., 2013; Xiao & Benbasat, 2011, 2015, 2018).

Research has offered limited explanations based on the effect of consumers’ flow experience on their intention to reuse RSs. Yan et al. (2021) argued that a closer examination of mental processes engaged while using a technology (e.g., flow) should be conducted.

The direct and indirect effect of cognitive absorption, which is regarded as on flow in the context of information systems, on RSs reuse intentions remain unexplored.

Despite the usefulness of RSs, a vital yet neglected issue is whether consumer reuse RSs after the initial adoption (Sheng et al., 2014). Studies that investigate RSs reuse or continuous use intentions are somewhat recent (Ashraf et al., 2020; Benlian et al., 2012; He et al., 2021; Yang, 2021), and they only investigate limited determinants of behavioural intentions to reuse RSs, salient determinants are yet to be explored. Several researchers have argued that the success and sustainability of a technology depend more upon the reuse or continuous use of technology than upon its initial adoption (Ashraf et al., 2020; Benlian et al., 2012; Bhattacherjee, 2001; Yan et al., 2021). For instance, The Pokemon Go app quickly became the most downloaded app in the world after its introduction in July 2016, but by mid-September of the same year, it nearly lost 80% of its US players (Yan et al., 2021).

No study has employed MICOM and PLS-MGA, which is considered as more robust method (Hair et al., 2021), to determine the moderating effects of product type and gender. A variation of research methodology is needed to advance understanding or to avoid skewed results (Miles, 2017).

No study investigated the recommender system reuse intentions in Australia where online shopping is constantly rising. Hence, drawing upon various disciplines, this research argues that such gaps can be better addressed by understanding the post-adoption factor influencing of RSs reuse intentions.

2.9 Chapter summary

The chapter presented the literature review in which the recommender systems adoption process and important antecedent factors of information systems reuse or continuous use intentions were discussed. The ResQue Model, trust literature, the technology acceptance model, flow theory and cognitive absorption theory provided understanding of the sparsely researched area in user-centric evaluation of recommender systems. Further, research gaps identified from the relevant literature was discussed. The next chapter presents the design, implementation and findings of Study 1 of the research project.

CHAPTER 3: PAPER 1 - Consumers' behavioural intentions to reuse recommender systems: assessing the effects of trust propensity, trusting beliefs and perceived usefulness

3.1

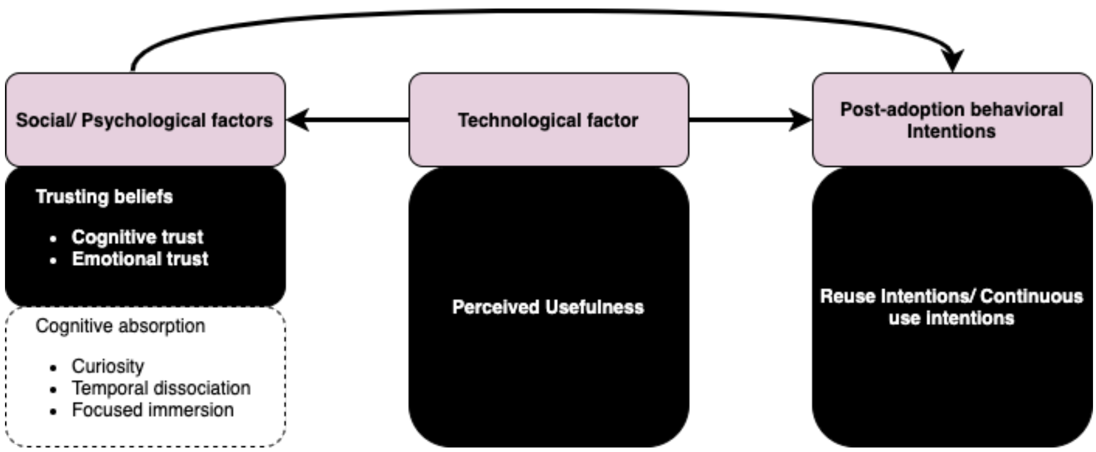


FIGURE 3.1 FRAMEWORK FOR CHAPTER 3

3.2 Preface

This chapter presents an empirical paper that at the time of submitting this thesis is under review by a Q1 journal. The paper is presented as it was last submitted to the journal. This chapter examines the influence of trusting beliefs on behavioural intentions to reuse RSs, emphasising the effects of trust propensity, perceived usefulness and product type.

3.2.1 Highlights of this chapter

- Consumers' trusting beliefs and perceived usefulness of recommender systems positively and significantly affect their intention to reuse RSs.
- Perceived usefulness of RSs is more important compared to trusting beliefs in predicting consumers' behavioural intention to reuse RSs.

- Trusting beliefs partially mediate the impact of perceived usefulness on behavioural intentions to reuse RSs.
- There is an insignificant difference between the effect of different product types on Australian consumers' behavioural intention to reuse RSs.

CONSUMERS' BEHAVIOURAL INTENTIONS TO REUSE RECOMMENDER SYSTEMS: ASSESSING THE EFFECTS OF TRUST PROPENSITY, TRUSTING BELIEFS AND PERCEIVED USEFULNESS

ABSTRACT

Recommender systems (RSs) are widely utilised across industries as tools to provide users with recommendations based on their preferences. This paper reports on an examination of the influence of trusting beliefs on behavioural intentions to reuse RSs, emphasising the effects of trust propensity, perceived usefulness and product type. A distinctive contribution of this study is the research model, which integrated perceived usefulness as an antecedent of trusting beliefs. Data collected in Australia with 366 participants were used. A new approach (MICOM and PLS-MGA) was performed to assess the moderating effect of product type. The research results indicate that trust propensity has a positive and significant direct effect on consumers' trusting beliefs in an ongoing relationship. The results also suggest that consumers' trusting beliefs and the perceived usefulness of RSs positively and significantly affect their intention to reuse RSs. Perceived usefulness of RSs is more important compared to trusting beliefs in predicting consumers' behavioural intentions to reuse RSs. Trusting beliefs partially mediate the impact of perceived usefulness on behavioural intentions to reuse RSs. The results also showed an insignificant difference between the effect of different product types on Australian consumers' behavioural intention to reuse RSs. These results have implications for the design of RSs.

3.2.2 KEYWORDS

Recommender systems (RSs), Trust propensity, Trusting beliefs, Perceived usefulness, Product type, PLS-MGA

3.3 Introduction

Continued growth in internet and e-commerce technology accelerates easy access to large amounts of data at any point, and this access has led to a new issue called 'information overload' that can make it time consuming for an individual to find the specific information required (Roetzel, 2019). Online merchants commonly use information systems (IS) such as recommender systems to minimise information overload by assisting customers with suggestions that allow them to shop based on their preferences and to avoid the often confusing and excessive advice that can be offered (Li & Karahanna, 2015; Xiao & Benbasat, 2007; Yoon et al., 2013). Recommender systems (RSs) not only can reduce search complexity and information overload but also have the ability to enhance decision accuracy (Shani & Gunawardana, 2011; Xiao & Benbasat, 2007). RSs are of significant value for the success of an online business. Netflix estimated that 75% of what people watch is generated using recommendations (Jannach & Jugovac, 2019). Their business value was estimated to be over 11.7 billion USD per year and over 1 billion USD per year associated with the recommendations and personalisation the company offers (Gomez-Uribe & Hunt, 2016). Recommendations contribute 60% of clicks on the YouTube home screen clicks (Davidson et al., 2010). Approximately 35% of Amazon's sales originated from recommendations by RSs (Jannach & Jugovac, 2019).

In contrast to statements extolling the value that RSs contributes to online businesses, several studies have shown that there are negative consequences of applying RSs. Most websites with a recommender system reported low returns on their investments (Wang et al., 2015). Some of these factors are beyond the objective of prediction precision, but the impact on the consumers' experience (i.e., consumers' subjective assessment for

RSs) has resulted in scholars calling for more research in assessing the efficiency of RSs usage (Ghasemaghaei, 2020; Xiao & Benbasat, 2007). Bhattacherjee (2001) noted, "the long-term viability of an IS, and its eventual success depends on its continued use"; behavioural intentions to reuse RSs is crucial for the success of RSs (Benlian et al., 2012). There is a pressing need to understand the effects of subjective factors on their behavioural intentions to reuse RSs. This research aimed to understand the effects of subjective factors such as trust propensity and trusting beliefs using a trust-centred lens to estimate the consumers' behavioural intentions to reuse RSs.

Trust, in the IS literature, is referred to as a set of trusting beliefs (Gefen et al., 2003; Wang & Benbasat, 2005) and is a vital subjective factor that is conceptualised as a multi-dimensional construct that comprises cognitive trust and emotional trust (Komiak & Benbasat, 2004). Cognitive trust refers to a trustee's competence, benevolence and integrity (Wang & Benbasat, 2016; McKnight et al., 2002a), and emotional trust explains how secure and comfortable a person feels when depending on the trustee (Komiak & Benbasat, 2004). Although emotional trust is an important dimension of trust (Komiak & Benbasat, 2006; Glikson & Woolley, 2020), few studies on RSs in IS literature have investigated the effect of emotional trust (Komiak & Benbasat, 2006; Ashraf et al., 2019). There is little empirical evidence detailing how cognitive trust and emotional trust as a component of a comprehensive framework contribute towards behavioural intentions to reuse RSs.

An important antecedent of trusting beliefs is trust propensity (TP) (Murphy, 2003; Wang & Benbasat, 2007). Trust propensity affects both an initial relationship and the effectiveness of an ongoing relationship between the RSs and consumers (Alarcon et al., 2018). Previous studies found trust propensity positively influenced a consumer's trusting beliefs in online shopping (Amin et al., 2015; Chang & Fang, 2013). It was also observed that trust propensity was significant throughout the trust process (Alarcon et al., 2018; Colquitt et al., 2007). Given the importance of trust propensity, it may seem surprising that its influence on the consumers' trusting beliefs in an ongoing relationship with recommender systems is still unknown in the literature. Addressing this unknown in the literature is one of the objectives of this study.

Existing literature has indicated that product type affects consumer buying choices (Xiao and Benbasat, 2007). Researchers have shown that, especially in the context of recommender systems, consumer behaviour varies with product type (search vs experience) (Senecal & Nantel, 2004; Ashraf et al., 2019; Benlian et al., 2012). This further validates the existing knowledge and tries get a broader picture of the effect of product type on the customer's behavioural intention to reuse RSs.

Trust-centred studies have largely avoided improving the design of RSs; instead, they have focused on improving the privacy policy, security, statistic efficiency and reputation of RSs (Zhang & Curley, 2018). In the research reported on in this paper, the aim was to fill the gap and explore the influence of consumers' trusting beliefs on their behavioural intention to reuse RSs, emphasising the design of RSs. In particular, the effects of trust propensity, perceived usefulness, and product type was investigated in an ongoing relationship between RSs and consumers' behavioural intentions. These may contribute to the design of a trusted recommender system for ongoing relationships. To achieve this goal, the present study equipped a trust centred lens and started from the exploitation of the ResQue Model (Pu et al., 2011). The research model of the study used perceived usefulness as an antecedent of trusting beliefs and validated it empirically by using recent approaches (MICOM and PLS-MGA) via a cross-sectional survey involving Amazon customers from Australia. This study also uses the PLSpredict technique to determine whether the inclusion of emotional trust improves the prediction accuracy of consumers' behavioural intentions.

The paper is organised as follows: the next section discusses the salient literature; based on this, a research model has been created to be empirically examined in the research. Following this is the research method adopted for the study. The findings of the study and discussion are presented in the methodology and ad hoc analysis sections, respectively. The paper concludes with the implications, recommendations for further research and conclusions.

3.4 Theoretical background

3.4.1 Recommender systems

Recommender systems (RSs) can be expressed as information processing technology that generates a personalised item recommendation that may interest the target consumer, predict ratings or rank items (including services, products, movies), or both (Ricci et al., 2015). RS tries to persuade a user to follow its recommendation. These recommendations have been utilised in various settings, from accounting (e.g., Esswein et. al., 2020) and finance (e.g., Kanaujia et al., 2016) to e-commerce (e.g., Komiak and Benbasat 2006). Prior literature in IS research has proposed the use of recommender systems as a feasible solution for online merchants to tackle data sparsity and scalability and provide personalised item recommendations that alter consumer buying behaviour (Gretzel & Fesenmaier, 2006; Li et al., 2007; Senecal & Nantel, 2004; Swaminathan, 2003). Such systems also play an essential role in the decision-making process, assisting consumers in reducing risks (Benlian et al., 2012) and maximising profitability (Chen et al., 2008) by enhancing the sales efficiency, making it valuable for both customers and online merchants.

Different kinds of recommendation systems have been developed based on various filtering approaches to try to improve website sales efficiency. In general, recommender systems are classified into different categories based on the filtering method: content-based filtering, context-aware, collaborative filtering, hybrid filtering and random (Logesh et al., 2020; Nilashi et al., 2018; Panniello et al., 2016). Customers' trust and purchasing decisions can be influenced by recommendation systems (RSs) using a variety of filtering techniques, suggestion diversity, and recommendation accuracy (Panniello et al., 2016). In terms of trust (i.e., perceptions of competence, compassion, and honesty), Gorgoglione et al. (2011) found that the context-aware RSs outperformed the content-aware RSs and the one that provides random recommendations. Based on the assumption that context improves accuracy as well as diversity, and that trust is affected by both of these factors, the experiment should also hold true for collaborative filtering algorithms (Panniello et al., 2016).

The collaborative filtering approaches are recognised as popular models, among all the recommendation models, because of their major benefits such as domain independency and requirement of minimum rating information for prediction (Nilashi et al., 2018). Collaborative filtering is similar to word-of-mouth recommendations and tracks the behaviour of consumers that are like-minded to provide suggestions to one particular customer (Ariely et al., 2004; Benlian et al., 2012). These suggestions arise from the statistical analysis of patterns either from data on product ratings specifically provided by other customers or from the implicit monitoring of other customers' purchasing activity by the recommendation system (Montaner et al., 2003). For example, a collaborative filtering recommendation algorithm offers a list of items for customers because the products have been bought or liked by like-minded customers. A group of customers with identical tastes is referred to as like-minded customers (Benlian et al., 2012). Collaborative filtering approaches have been applied by many online merchants (Nilashi, 2016). The research reported in this paper focuses on recommender systems that use collaborative filtering method to elicit the user's preferences or interests both implicitly and explicitly and recommends tailored products or services accordingly. Due to the complexity of recommendation algorithms, it can be difficult to explain to end-users the rationale behind recommendations (Herlocker et al., 2000). It could lead to trust issues when recommendations fail.

3.4.2 Trust

Trust can be defined as "a willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993). Previous studies have stressed that online trust in e-commerce is important as it can make positive leverage e-commerce transactions, lower the amount of perceived risk and increase intention to purchase (Kim et al., 2008). In RSs studies, trust has been extensively studied using both user- and system-centric evaluation approaches (Abumalloh et al., 2020; Knijnenburg et al., 2012; Nilashi et al., 2016; Pu et al., 2011). Pu et al. (2011) presented a balanced measurement framework for evaluating RSs in accord with the technology acceptance model, which they referred to as ResQue (recommender system's quality of user experience). They validated the framework consisting of four layers of high-level construct based on the following influence paths: perceived quality → user beliefs → user attitudes → behavioural intentions.

Knijnenburg et al. (2012) presented a study that adopted an evaluation framework for RSs. Using a user-centric evaluation approach, the framework extended beyond focusing on the algorithm's accuracy to examine the quality of RSs on an objective and subjective level. Users' experiences were analysed using an abstract method that focused on general user experience concepts. In their study subjective system features and experience factors were shown to be critical in understanding and characterizing users' perceptions of RSs. Abumalloh et al. (2020) argued that trust in the RS is an important mediating factor that can increase customer loyalty towards RS. Nilashi et al. (2016) investigated the characteristics that increase user trust in the recommender system on commercial websites such as Amazon and Lazada. Their work indicated the importance of several trust-building factors (such as website quality, recommendation quality and transparency) on the level of adoption of the recommendations. Though the frameworks presented in these studies provide a solid foundation for evaluating user experiences with RSs, a major drawback in these frameworks is the omission of the cognitive and emotional elements of trust as an indicator of behavioural intentions, which could impede our ability to comprehend customer behaviour (Komiak & Benbasat, 2006; Leong et al. 2021). The use of a thorough framework of trusting beliefs, and a robust statistical analysis technique, is required to answer more specific research questions.

Researchers in the information system studies have used the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) to develop a web-based trust model which categorises trust into three categories: (1) trusting beliefs, (2) trusting intentions and (3) trust propensity (Kim et al., 2008, 2009; McKnight et al., 2002a, 2002b; McKnight et al., 1998). Trust in technology (such as recommender systems) is believed to be based on the dimensions of trusting beliefs (Zhang & Curley, 2018). This study applies the concept of trusting beliefs to determine the impact of trust on shoppers' behavioural intentions to reuse RSs.

3.4.2.1 TRUSTING BELIEFS

Much of the trust literature in IS conceptualises trust as trusting beliefs (TB); research findings have indicated that people trust technology in the same way they trust other people (Gefen et al., 2003; Wang & Benbasat, 2005). Since RSs offers interactive functions and personalises advice, like a real person, it can affect shoppers' attitudes and buying intentions (Lankton et al., 2014).

In the context of RSs, Komiak and Benbasat (2004) proposed a model in which they conceptualised that trusting beliefs comprise cognitive trust and emotional trust. The cognitive trust consists of three dimensions, related yet distinct: benevolence, integrity, and competence (Kim et al., 2009; McKnight et al., 2002a; Schlosser et al., 2006; Wang & Benbasat, 2005). Prior literature has recognised that trusting beliefs is a multi-dimensional concept, consisting of cognitive and emotional trust (Komiak & Benbasat, 2004; Ashraf et al., 2019). Prior literature in IS focused primarily on the cognitive dimension of trust and indicated that cognitive trusting beliefs consisted of benevolence, competence and integrity (Kim et al., 2009; McKnight et al., 2002a; Wang & Benbasat, 2005; Wang & Benbasat, 2016; Zhang & Curley, 2018). Benevolence, integrity, and competence are defined as follows:

- Benevolence is defined as "the belief that a trustee cares about a trustor and is motivated to act in the trustor's interest" (McKnight & Chervany, 2001a).

- Integrity is defined as "the belief that a trustee makes good faith agreements, tells the truth, and fulfils promises" (McKnight & Chervany, 2001a).
- Competence is defined as "the belief that a trustee has the ability or power to do for a trustor what the trustor needs to be done" (McKnight & Chervany, 2001a).

Wang and Benbasat (2005) tested an integrated Trust-TAM model and reported on the effects of consumers' initial evaluation of trust, considering only the cognitive dimension of trusting beliefs, on the intention to adopt the RSs. The study found that the consumers' initial evaluation of trust affected the perceived usefulness of RSs and intention to adopt the RSs. Xu et al. (2016) investigated the effect of the cognitive dimension of trusting beliefs on satisfaction and purchase behaviour. Human relationships with RSs rarely address emotional trust, even though emotions are well-known to have a large impact on trusting behaviours (Hoff & Bashir, 2015).

Emotional trust can be defined as how secure and comfortable a person feels when depending on the trustee (Komiak & Benbasat, 2004). It allows a person to go beyond the evidence to ensure that they can rely on the trustee (Komiak & Benbasat, 2006). In online environments, trust is assessed emotionally, and if the level of emotional trust is strong, consumers are more likely to engage in certain behaviours enthusiastically (Komiak & Benbasat, 2004; Leong et al. 2021). Understanding customers' behaviour may be hindered if their emotional trust is ignored (Komiak & Benbasat, 2006; Leong et al. 2021). In determining consumers' RSs adoption intention, emotional trust plays a vital role beyond cognitive trust (Komiak & Benbasat, 2006). The conceptualisation of trusting beliefs proposed by Ashraf et al. (2019) included the emotional trust dimension and found that trusting beliefs significantly affected buying intention based on RSs.

Table 3.1 shows a summary of studies that focus on the concept of trusting beliefs, trust propensity, buying behaviours, buying intentions and use intentions. Although trust-related issues in the field of e-commerce and human-computer interaction have been explored widely, research on the contribution of multiple dimensions of trusting beliefs has lacked sufficient study (See Table 3.1).

TABLE 3.1 RSS STUDIES FOCUSING ON THE CONCEPT OF "TRUST" AND ITS IMPACT ON BUYING BEHAVIOUR, BUYING INTENTION OR USE/REUSE INTENTION

Study	Independent Variables					Dependent Variables		
	Trusting Beliefs				**Trust Propensity**	**Buying Behaviour**	**Intention**	
	Cognitive Trust			**ET**			**Buy**	**Use/ Reuse**
	CT	**BT**	**IT**					
(Wang & Benbasat, 2005)	✓	✓	✓					✓
(Komiak & Benbasat, 2006)	✓		✓	✓				✓
(Benlian et al., 2012)	✓	✓	✓				✓	✓
(Xu et al., 2016)	✓	✓	✓			✓		
(Zhang & Curley, 2018)	✓		✓		✓			✓
(Ashraf et al., 2019)	✓	✓	✓	✓			✓	
This Study	✓	✓	✓	✓	✓			✓

Note: CT = Competence Trust, BT = Benevolence Trust, IT = Integrity Trust, and ET = Emotional Trust

Looking at the independent variables, it is apparent that earlier attempts of trust-centred studies have ignored essential factors such as emotional trust and trust propensity. In most of these studies, initial evaluation of trust has been focused on the space, where consumers first confront specific websites to form a certain degree of trust (Wang et al., 2018). This trust may, however, differ from that of existing consumers, who over the years have established trust with the e-vendor. Consumers' behavioural intentions might be based on rational evaluation (cognitive trust), emotional evaluation (emotional trust) or a combination of both (Komiak & Benbasat, 2006; Chou & Hsu, 2016). An individual's rational evaluation emphasises cognitive assessments of risks and benefits, whereas emotional evaluation focuses on faith and feelings, which can be rational or irrational in nature (Chou & Hsu, 2016). To provide more evidence and obtain a broader picture, the research reported in this paper treats trusting beliefs as part of a comprehensive framework proposed in a previous study by Ashraf et al. (2019) that comprises cognitive and emotional trust.

3.4.2.2 Trust Propensity

Trust Propensity (TP) is an important antecedent of trusting beliefs. It is the degree to which a person is willing to rely upon others (McKnight & Chervany, 2001b). People differ in their tendency to trust others, regardless of whether the other is a person or system. Prior trust research suggests that trust propensity should be significantly related to TB's dimensions (Murphy, 2003; Wang & Benbasat, 2007). Trust propensity has been incorporated as a control variable in past studies (Wang & Benbasat, 2007; Zhang & Curley, 2018). Wang and Benbasat (2007) reported that trust propensity significantly and positively affects competence belief. Individual trust propensity is a critical element that may determine consumers' trust. McKnight and Chervany (2001b) have indicated that consumers' trust propensity would affect their trusting beliefs. Likewise, researchers have shown that trust propensity affects the level of an individual's trust in online shopping (Amin et al., 2015; Chang & Fang, 2013; Lee & Turban, 2001). Trust propensity has an important role in determining online trusting beliefs as it is affected by an individual’s past experience (Lee & Turban, 2001).

Previous studies have consistently demonstrated trust propensity to be an important factor in an initial evaluation of trust, but it becomes less important over time in later evaluations (Alarcon et al., 2016; Jones & Shah, 2016). Alarcon et al. (2016) examined the impact of trust propensity on perceived trustworthiness over time. They ascertained that trust propensity was linked to trustworthiness only in unfamiliar conditions but had no effect over time. Jones and Shah (2016) found that trust propensity was initially dominant for trust, but the influence decreased over time while the trustee became dominant. Although research indicates the significance of trust propensity throughout the trust process (Alarcon et al., 2018; Colquitt et al., 2007), scant research has been conducted to explore its effect in later evaluations. Colquitt et al. (2007) found that trust propensity substantially impacted the trustworthiness dimension on both initial and later evaluations. Alarcon et al. (2018) conducted three studies using the five-factor model of trust. They found that trust propensity was an important predictor of trust action, beliefs and intentions throughout the trust process. The attributes of trustworthiness were similar to the dimensions of trusting beliefs (Vidotto et al., 2012). Taking these issues into account, the proposed study examines the influence of trust propensity on the consumers’ trusting beliefs in an ongoing relationship with RSs.

3.4.3 Perceived Usefulness

In the context of IT use, perceived usefulness is defined as the extent to which a person considers that using a specific system can improve the achievement of its tasks (Davis, 1989). In this research, the perceived usefulness refers to the degree to which a person thinks an RS is useful in online shopping activities. Several previous studies have used perceived usefulness instrumental belief and found it directly linked with behavioural intentions (Ayanso et al., 2015; Lee, 2010; Recker, 2010; Sun et al., 2014). The technology acceptance model posits that individuals' behavioural intentions towards an information system are directly and indirectly impacted by perceived usefulness (Brömmelstroet, 2017; Cheng et al., 2015). Earlier studies indicate that the "usefulness of an online RS" is a critical factor in the intention of consumers to adopt and reuse RSs (Benlian et al., 2012; Kowatsch & Maass, 2010; Wang & Benbasat, 2005; Pu et al., 2011). Kowatsch and Maass (2010) indicate that the perception of the usefulness of online RSs impacts the intention of individuals to use the RSs and their intention to buy after using them.

3.4.4 Behavioural Intention

The likelihood of whether a person will perform or execute a particular behaviour is defined as behavioural intention (BI) (Fishbein & Ajzen, 1975). The research reported in this paper measured the behavioural intention to reuse recommender systems and focused on exploring the factors that influence doing so. In this study, behavioural intention indicates the consumers' intention to continue using recommender systems whenever they need to buy a product in the future.

3.4.5 Product type as a moderator

Alteration in product type changes RSs usage behaviour and decision outcomes (Ashraf et al., 2019; Benlian et al., 2012; Huang et al., 2013). Product type moderates the impact of RSs use on consumer beliefs (Huang et al., 2013; Xiao & Benbasat, 2007). Different types of information are required in evaluating different products (Mudambi & Schuff, 2010).

This research examined the moderating effect of product type on the relationship between consumers' intentions to reuse RSs and their trusting beliefs, as well as their perceived usefulness. Nelson's (1970) theory on "search" and "experience" goods has been widely accepted in decision-making literature and has been linked extensively to recommendations in previous studies (Aggarwal & Vaidyanathan, 2005; Ashraf et al., 2019; Ochi et al., 2010; Senecal & Nantel, 2004), and has been used in this research. According to the theory, a product whose quality can be measured based on its objective characteristics can be considered a search product. On the other side of the spectrum is a well-known product, which refers to a product whose quality is not calculated based on technical criteria but which relies more on subjective interpretation, subject to personal taste (Nelson, 1970). Table 3.2 shows examples of different product types that have been considered in prior literature. Most previous studies have used limited varieties of products that may not embody all kinds of products and e-vendors in general. As suggested by Wang and Benbasat (2007), to further validate the existing literature and to get a broader picture of the effect of product type, this study used a greater variety of products (see Table 3.2) and used up to date statistical measures to assess the moderation effect.

TABLE 3.2 EXAMPLES OF SEARCH AND EXPERIENCE GOODS

Product Type	Examples
Search Goods (Ashraf et al., 2019; Huang et al., 2013; Willemsen et al., 2011)	Eyeglass, Cell phone, Laptop, Home Electronics, Digital Camera, Kitchen Utensils, Motorcycle Parts, Photographic Equipment, Printer, DVD Player, Network Equipment, and Electronic Accessories
Experience Goods (Ashraf et al., 2019; Huang et al., 2013; Willemsen et al., 2011)	Movies/Music CDs, Books/Magazine, Cleaning Products, Clothing, Leather Purse, Shoes, Perfume, Cosmetics, Software, Watch, Pet Supplies and recreational services.

3.5 Research model and hypotheses

The research model proposed in this paper to explain the consumers’ intention to reuse RSs is presented in Figure 3.2.

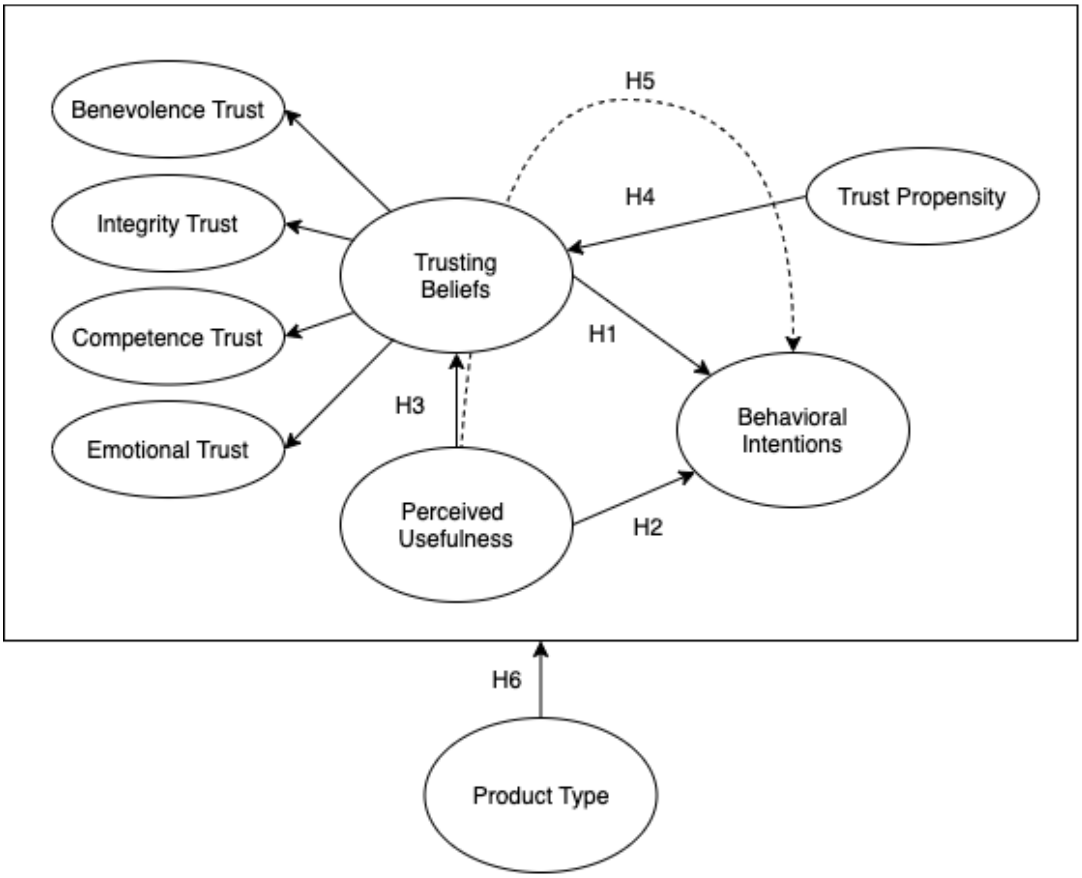


FIGURE 3.2 OVERVIEW OF THE RESEARCH MODEL AND HYPOTHESES

Pu et. al. (2011) proposed a balanced measuring approach for assessing recommendation systems, which they termed ResQue (recommender system’s quality of user experience). They investigated both users' attitudes towards the recommendation systems and the influences of users' attitudes on users' behavioural intentions in the proposed framework. Their research did not account for trust propensity, trusting beliefs, or reuse behaviour. Despite the fact that their model includes the trust construct, they only employed a small number of questionnaire items to measure trust, making it impossible to capture the various dimensions of trusting beliefs. It is also challenging to address more specific research questions solely using the ResQue Model with the main objective of exploring the influence of consumers' trusting beliefs on their behavioural intention to reuse RSs. The rationale of the interrelation between the underlying construct in the proposed model is derived from strong theoretical foundation of ResQue model and trust literature, as stated below.

The rationale of the relation between the trusting beliefs and behavioural intentions is based on the fundamental tenet of the ResQue Model (Pu et al., 2011) of user centric evaluation that argues that user attitudes are positively linked with behavioural intentions. Prior research has also indicated the impact of trusting beliefs on behavioural intentions (Benlian et al., 2012; Wang & Benbasat, 2005; Komiak and Benbasat, 2006). Benlian et al. (2012) revealed that consumers using RSs expressed significantly higher perceived usefulness. Consumers' perceived usefulness and initial trust significantly affected their intentions to adopt RSs (Wang & Benbasat, 2005). An increase in trusting beliefs increase adoption intentions (Komiak and Benbasat, 2006).

The underlying argument of the relation between trusting beliefs and trust propensity is guided by studies that have identified trust propensity as an important antecedent of trusting beliefs throughout the trust process (Alarcon et al., 2018; Colquitt et al., 2007).

In various technology contexts, perceived usefulness was found to be a cognitive belief that is salient to technology acceptance (Davis, 1989) and reuse (Benlian et al., 2012). Contrary to the Trust-TAM studies in the field of RSs that argue that trust stimulates usefulness (Benlian et al., 2012; Wang & Benbasat, 2005), the current study argues that the increase in perceived usefulness of RSs can positively influence trusting beliefs. The relationship can be explained based on the ResQue model that asserts that user beliefs (i.e., perceived usefulness) affects user attitudes (i.e., trust and confidence) (Pu et al., 2011). A recent decision-making study in the field of IS has also linked perceived usefulness with trust and inferred that perceived usefulness influenced trust (Harrigan et.al., 2021). No study has linked perceived usefulness with trusting beliefs in the context of RSs. The underlying argument of the indirect effect of perceived usefulness on behavioural intention through trusting beliefs can be based on the relationship between the constructs as classified in the ResQue model (user beliefs) → (user attitudes) → (behavioural intentions) (Pu et al., 2011).

In line with the literature review and the findings discussed above, the following six hypotheses were developed to outline how consumers' trust propensity, trusting beliefs, perceived usefulness, and product type could directly and/or indirectly relate to the behavioural intentions to reuse RSs.

H1: Consumers' trusting beliefs will directly affect the behavioural intentions to reuse RSs.

H2: Perceived usefulness of RSs will directly affect the consumers' behavioural intentions to reuse RSs.

H3: Perceived usefulness of RSs will have a direct effect on consumers' trusting beliefs.

H4: Consumers' trust propensity will have a direct effect on their trusting beliefs.

H5: Consumers' trusting beliefs will mediate the direct effect of perceived usefulness of RSs on intentions to reuse RSs.

H6: The strength of the relationship between the constructs is significantly different in search and experience products.

3.6 Methodology

A cross-sectional survey of Amazon consumers was undertaken to test the research model presented in Figure 3.2. The research was approved by the University of Southern Queensland's ethics committee (approval number H20REA201). Instead of a laboratory experiment with a fictitious online store and an ad hoc recommender system (Cooke et al., 2002), the methods involved using a real website and an e-vendor. This was consistent with previous studies (Gefen & Straub, 2000; Huang & Zhou, 2019; Martínez-López, 2015; Mudambi & Schuff, 2010). Amazon is a leading e-vendor that stocks a wide variety of products and implements personalisation, such as a recommender system that suits the need of this research (Huang & Zhou, 2019).

3.6.1 Survey instruments and measurements

All items were assessed on a 5-point Likert scale with endpoints: '1 for strongly disagree' and '5 for strongly agree'. The survey instruments for all the constructs were adopted from valid scales with minor verbal adjustments in accordance with the study context (Seale, 2004) (See Appendix B).

The trust propensity construct comprised four items adapted from Wang and Benbasat (2007). Measures for the trusting beliefs construct consist of thirteen items and was adopted from Ashraf et al. (2019). The perceived usefulness construct was adopted from the study of Wang & Benbasat (2005). The behavioural intentions construct comprises three items based on Benlian et al. (2012). In keeping with the advice of Kamis, Koufaris, and Stern (2008), binary values were constructed for product type; it was coded as 0 for the search products (N = 171) and 1 for the experience products (N = 195).

3.6.2 Data collection and descriptive statistics

Selected Amazon (amazon.com.au) clients from Australia were sent an online survey using the Zoho Survey Platform (survey.zoho.com.au). The study adopted a non-probability sampling method as it is a commonly used technique in IS research (Loehlin & Beaujean, 2016). Zoho was contracted to perform the online survey, and 1361 responses were obtained. An explanation of recommender systems was provided. Respondents were briefed that Amazon typically offers recommendations under the labels "Frequently bought together" or “Compare to similar items” or "Customers who bought... also bought". The respondents were then subject to two screening questions to determine whether the respondents were current active users of Amazon and whether they had purchased at least one of the products listed in Table 3.2 from amazon.com.au using RSs over the last six months of responding to the survey. Using the purchased product responses, this study followed the pretested classification of product type by Ashraf et al. (2019) and categorised the respondents into search product and experience product groups. This approach was consistent with previous studies based on online shopping (Lim et al., 2015; Sun et al., 2019). Based on the survey questionnaire’s screening criteria, 452 responses were considered usable and valid. An additional 86 responses were discarded for a number of reasons: acquiescence response bias was detected, where respondents answered questions without any significant variation (Podsakoff et al., 2003); either a univariant outlier or multivariant outlier was evident (Ho, 2013). Accordingly, only 366 of the responses were used for subsequent analysis.

Table 3.3 indicates the study’s demographic profile showing that 49.7% were males, 27.9, 28.4, 27% of respondents were 20-25 years, 26-35 years, 36-45 years, respectively. The majority of respondents were married (52.2%), held a bachelor's degree (33.6%) and were from NSW (33.3%) and VIC (31.1%). On average, respondents had used the internet for over six years, had been purchasing online for 4–5 years and had been using RSs for more than a year (mean = 3.23, SD = 1.748).

TABLE 3.3 DESCRIPTIVE STATISTICS

Variable	Frequency	%	Mean	SD
Gender				
Male	182	49.7		
Female	184	50.3		
Age Group				
Less than 20 years	16	4.4		
20-25 years	102	27.9		
26-35 years	104	28.4		
36-45 years	99	27		
Over 45 years	45	12.3		
Marital Status				
Single	156	42.6		
Married	191	52.2		
Widowed	1	0.3		
Divorced	10	2.7		
Other	8	2.2		
Education				
Certificate	86	23.5		
Diploma	39	10.7		
Bachelor Degree	123	33.6		
Master Degree	92	25.1		
Doctorate/PhD	24	6.6		
Other	2	0.5		
Geographic Location				
VIC	114	31.1		
NSW	122	33.3		
QLD	65	17.8		
WA	32	8.7		
SA	15	4.1		
TAS	7	1.9		
ACT	10	2.7		
NT	1	0.3		
Internet usage, online purchasing experience and RSs usage experience				
Internet usage experience*			7.42	1.406
Online purchasing experience**			4.85	1.477
RSs usage experience***			3.23	1.748

* Anchored at 1 = "Less than 1 year" and 8 = "more than 7 years"
**Anchored at 1 = "Less than 1 year" and 6 = "more than 5 years"
***Anchored at 1 = "Less than 6 months" and 7 = "more than 5 years"

3.7 Results

Partial least squares structural equation modelling (PLS-SEM) inspection of the research model was executed with SmartPLS (v3.3.3) software (Ringle et al., 2015). Evaluating PLS-SEM findings entailed two stages: analysis of the measurement model in stage one and analysis of structural model in stage two (Sarstedt et al., 2021). To assess the possible moderating effect of the product type, PLS-MGA was performed as it was considered the most efficient way of determining moderation across multiple relationships (Hair et al., 2021).

3.7.1 Analysis of measurement model

The scales' reliability, convergent validity and discriminant validity were tested as part of the measurement model evaluation based on the recommendation of Hair et al. (2019) and Hair et al. (2021). As shown in the outcomes of the evaluations (see Table 3.4), all the item loadings met the cut-off value of 0.70 (Hair et al., 2019), all the constructs' Cronbach's alpha (ɑ), composite reliability (CR), Dijkstra–Henseler's rho (ρ_A) and the average variance extracted (AVE), were above the accepted thresholds of 0.70 (Chin, 2010), 0.70 (Hair et al., 2019), 0.70 (Hair et al., 2021) and 0.50 (Fornell & Larcker, 1981), respectively. Internal consistency was achieved.

Heterotrait Monotrait (HTMT) Ratio procedure was assessed to determine the discriminant validity of the constructs. The threshold value of the HTMT ratio was 0.90 (Henseler et al., 2015). As depicted in Table 3.5, all the values of HTMT in this study are less than the threshold value of 0.90. This study ran a bootstrap routine to assess the confidence interval for HTMT, and the upper confidence interval limit was below 1 (Hair et al., 2017) (see Table 3.6). Discriminant validity was attained.

TABLE 3.4 FACTOR LOADINGS, RELIABILITY AND VALIDITY

	Item loadings	α	ρ_A	CR	AVE
Trust Propensity		0.877	0.881	0.915	0.730
TP1	0.880				
TP2	0.857				
TP3	0.865				
TP4	0.815				
Trusting Beliefs		0.952	0.953	0.958	0.637
BT1	0.756				
BT2	0.785				
BT3	0.720				
CT1	0.785				
CT2	0.820				
CT3	0.801				
ET1	0.833				
ET2	0.822				
ET3	0.828				
IT1	0.814				
IT2	0.772				
IT3	0.811				
IT4	0.820				
Perceived Usefulness		0.923	0.923	0.936	0.618
PU1	0.764				
PU2	0.782				
PU3	0.782				
PU4	0.801				
PU5	0.787				
PU6	0.745				
PU7	0.804				
PU8	0.815				
PU9	0.792				
Behavioural Intentions		0.878	0.878	0.925	0.804
BI1	0.886				
BI2	0.897				
BI3	0.907				

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity
Trusting Beliefs includes: BT: Benevolence Trust, CT: Competence Trust, IT = Integrity Trust, and ET = Emotional Trust

TABLE 3.5 DISCRIMINANT VALIDITY USING HTMT

	BI	PU	TB	TP
BI				
PU	0.885			
TB	0.804	0.846		
TP	0.639	0.652	0.743	

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity

TABLE 3.6 HTMT INFERENCE

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%
PU -> BI	0.885	0.887	0.836	0.930
TB -> BI	0.804	0.804	0.720	0.874
TB -> PU	0.846	0.846	0.789	0.894
TP -> BI	0.639	0.638	0.560	0.713
TP -> PU	0.652	0.650	0.573	0.724
TP -> TB	0.743	0.743	0.672	0.803

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity

3.7.2 Analysis of structural model

An examination of collinearity is essential prior to the structural model analysis to ensure it does not prejudice the regression result (Hair et al., 2021). In this study, there were no collinearity issues, as the multi-collinearity test result revealed that all the VIF values ranged from 1.531 to 2.715 and were below the recommended threshold of 3.3 (Kock, 2015).

The structural model's explanatory capabilities were evaluated using R^2 values to reflect the explained variance of the dependent constructs (Hair et al., 2019). The R^2 values were 0.701 for trusting beliefs and 0.664 for behaviour intentions, which explained more than 70.1% and 66.4% of the construct, respectively. All of these R^2 values that were reported signified a substantial model (Hair et al., 2017). Using the blindfolding procedure, the Stone–Geisser's Q^2 value for the complete model was obtained to determine the model's predictive relevance. The value of 0.529 for BI revealed the large predictive accuracy of the PLS path model (Hair et al., 2019). A bootstrapping routine of 5000 subsamples (Hair et al., 2021) was used to explore the significance of the path coefficients. Figure 3.3 shows the result of the structural model inspection for better illustration.

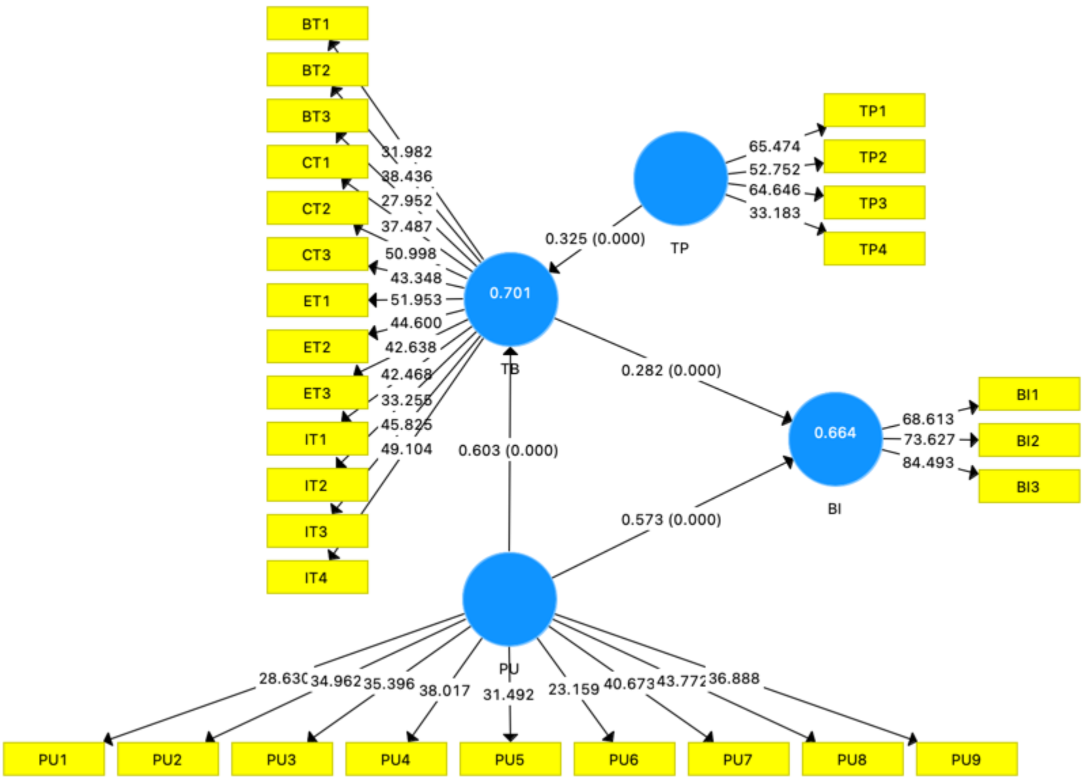
As exhibited in Table 3.7, all four direct effect hypotheses were supported. Trust propensity was observed to have a positive impact on trusting beliefs ($\beta = 0.325$, $t = 8.035$, $p < 0.001$). Perceived usefulness was positively linked to trusting beliefs (β = 0.603, t = 16.196, p < 0.001). Behavioural intentions to reuse RSs was found to be positively affected by perceived usefulness (β = 0.573, t = 7.644, p < 0.001) and trusting beliefs (β = 0.282, t = 3.483, p < 0.001).

TABLE 3.7 RESULTS FOR DIRECT RELATIONSHIPS (COMPLETE SAMPLE)

	Path coefficient	Standard Deviation	T statistics	P values
TB -> BI	0.282	0.081	3.483	0.000
PU -> BI	0.573	0.075	7.644	0.000
PU -> TB	0.603	0.037	16.196	0.000
TP -> TB	0.325	0.040	8.035	0.000

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity

FIGURE 3.3 RESULT OF STRUCTURAL MODEL INSPECTION (COMPLETE SAMPLE)



Note: BI: Behavioural Intentions, PU: Perceived usefulness, TB: Trusting Beliefs, TP: Trust Propensity. (0.000) indicates all direct paths are (Sig. at p < 0.001).

3.7.3 Mediation Analysis

The results indicated that the total effect of perceived usefulness on behavioural intentions was found to be significant and positive (β = 0.743, t = 25.522, $p < 0.001$). When the mediator was integrated into the model, the effect was reduced, but the direct relationship remained significant (β = 0.573, t = 7.644, $p < 0.001$). Furthermore, the inclusion of the mediator (trusting beliefs) in the analysis was also found to be significant (β = 0.170, t = 3.329, $p < 0.05$). The result reveals a partial mediation. Consequently, H5 was accepted (see Table 3.8).

TABLE 3.8 MEDIATION ANALYSIS (COMPLETE SAMPLE)

	Total effects		Direct effects			Indirect effects		
	β	**t-value**	**β**	**t-value**		**β**	**t-value**	**p-value**
PU -> BI	0.743	23.522	0.573	7.644	PU -> TB -> BI	0.170	3.329	0.001

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs

3.7.4 MULTI-GROUP ANALYSIS

An essential and logical step prior to conducting PLS-MGA is to estimate the invariance of composite models (Henseler et al., 2016). This step is important to evaluate whether the composition has different meanings in each group, as it can otherwise mislead the structural coefficients' group-specific results. MICOM was assessed to establish the measurement invariance (Henseler et al., 2016).

The steps involved in the MICOM process were: assessment of configural invariance (Step 1), assessment of compositional invariance (Step 2), and finally, determination of the equality of composite mean values (Step 3a) and variances (Step 3b) (Henseler et al., 2016). To perform a multi-group analysis, at least partial measurement invariance needs to be established (Henseler et al., 2016).

First, the assessment of configural invariance was executed. In smartpls 3, running micom automatically accomplishes configural invariance (hair et al., 2021). Second, compositional invariance was assessed, focusing on the creation of identical composite scores throughout the groups. Smartpls was used to perform a permutation analysis with 5000 resamples (chin et al., 2010). As illustrated in Table 3.9, the correlation of the composite scores between the indicator weights obtained from the search products and experience products groups were equal to 1 or greater than 5%-quantile. It can be concluded that both groups were compositionally invariant. The third step was to assess the equality of composite mean values and variances. Equality of composite mean and variances can be confirmed, and full measurement invariance is attained if the confidence intervals of the differences of mean values and variances between the two groups contain zero (henseler et al., 2016). To validate this step, permutation results were analysed to determine the mean values and variances between the construct scores of the search products and experience products groups that differ from each other. As illustrated in Table 3.9, the equality of means and variances was successfully verified; hence full measurement invariance was attained.

TABLE 3.9 RESULTS OF 3-STEP MEASUREMENT INVARIANCE TESTING USING PERMUTATION.

	Step 1	Step 2			Step 3(a)			Step 3(b)			
Constructs	Configural Invariance	C = 1	5% quantile of C_u	Compositional Invariance	Differences	Confidence Interval (CIs) - Mean Value	Equal mean value	Differences	Confidence Interval (CIs) - variances Value	Equal mean value	Measurement Invariance
BI	**Yes**	1.000	1.000	**Yes**	0.228	[-0.210; 0.204]	**Yes**	-0.113	[-0.305; 0.308]	**Yes**	**Full**
PU	**Yes**	1.000	1.000	**Yes**	0.189	[-0.209; 0.203]	**Yes**	0.123	[-0.321; 0.324]	**Yes**	**Full**
TB	**Yes**	1.000	1.000	**Yes**	0.253	[-0.216; 0.204]	**Yes**	0.107	[-0.253; 0.252]	**Yes**	**Full**
TP	**Yes**	0.999	0.999	**Yes**	0.405	[-0.213; 0.199]	**Yes**	0.073	[-0.245; 0.251]	**Yes**	**Full**

Note: TB: Trusting Beliefs, PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity

After full measurement invariance was attained, PLS-MGA was performed to detect the differences between search products and experience products using the Welch-Satterthwait test (Hair et al., 2021). Table 3.10 illustrates the differences between the path coefficients of the two groups. None of the paths between the two data sets (Search products and experience products) was found to be significantly different; H6 was not supported.

TABLE 3.10 MULTI-GROUP ANALYSIS (PLS-MGA) USING WELCH-SATTERTHWAIT TEST

Relationship	Search Product Path (N = 171)	Experience Product Path (N = 195)	Path Coefficients difference	t-Value	p-Value
TB -> BI	0.339	0.248	0.091	0.547	0.585
PU -> BI	0.528	0.597	-0.069	0.441	0.660
PU -> TB	0.665	0.571	0.095	1.293	0.198
TP -> TB	0.261	0.356	-0.095	1.151	0.251

Note: TB: Trusting Beliefs, PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity

The research further uses PLSpredict (see Shmueli et al., 2016) to generate holdout sample-based point predictions in PLS path models to see whether integrating emotional trust improves prediction accuracy over using the model without emotional trust. Table 3.11 shows that integrating emotional trust into the model improves prediction compared to the one that does not include it. This is evident in the results; the inclusion of emotional trust improves the Q^2_predict values of a model's constructs over a model without it (Shmueli et al., 2019). To summarise, while the model without the inclusion of emotional trust remains impactful, the model with the inclusion of emotional trust is more efficient in explaining consumers' behavioural intentions to reuse RSs.

TABLE 3.11 PLSPREDICT ASSESSMENT

With Emotional Trust				**Without Emotional Trust**			
Constructs	**RMSE**	**MAE**	**Q²_predict**	**Constructs**	**RMSE**	**MAE**	**Q²_predict**
BI	0.606	0.439	0.643	**BI**	0.604	0.438	0.640
TB	0.558	0.389	0.694	**TB**	0.566	0.398	0.684

Note: BI: Behavioural Intentions, TB: Trusting Beliefs

3.8 POST HOC ANALYSES

In the research reported on in this paper, the aim was to examine the influence of trusting beliefs on behavioural intentions to reuse recommender systems, emphasising the effect of trust propensity, perceived usefulness and product type. To accomplish the present study's objective, a cross-sectional questionnaire survey was undertaken using an integrated model (Figure 3.2), which included six accompanying hypotheses.

As predicted by the hypotheses associated with the direct effect of trusting beliefs and perceived usefulness (i.e., H1 and H2), the results revealed that trusting beliefs and perceived usefulness were significant and positive indicators of the behavioural intentions to reuse RSs. These results substantiate prior findings in the literature (Benlian et al., 2012; Wang & Benbasat, 2005).

In accordance with the prediction of H3, it was found that perceived usefulness has a significant and positive effect on the consumers' trusting beliefs. The PLS-SEM result has indicated that the effect of perceived usefulness is more significant than trusting beliefs in predicting consumers' intentions to reuse a recommender system. The most remarkable result that emerged from the data was the direct relation of trust propensity on trusting beliefs, confirming our hypothesis H4. The result widens our knowledge on the effect of trust propensity in later evaluations.

As predicted by H5, trusting beliefs significantly and positively mediate the direct effect of consumers' perceived usefulness of RSs on behavioural intention to reuse RSs. This result supports the existing body of literature (Benlian et al., 2012; Wang & Benbasat, 2005).

Surprisingly, contradicting H6, the relationship between the constructs is statistically insignificant in search and experience products and deserves a much-extended comprehensive discussion in future studies. This finding contradicts earlier results reported in the literature (Ashraf et al., 2019; Benlian et al., 2012; Choi et al., 2011). Consumers perceived lower trusting beliefs in the context of experience products as compared to search products (Ashraf et al., 2019). Perceived usefulness was more significantly affected in the search product than the experience product (Benlian et al., 2012). Choi et al. (2011) identified differences in the effects of social presence on RSs reuse intentions concerning product type. The nature of the shopping environment online can provide a possible explanation for the result of the current study. Hedonic excitement occurs mainly when the consumer uses a product (Hirschman & Holbrook, 1982). This can be particularly the case in the context of the online environment in which search and experience products are quite unlikely to be experienced before the purchase; a consumer cannot feel any noticeable differences. Building on this view, the online shopping environment can explain why the product type has no moderating effect on consumers' intentions to reuse recommender systems. A number of experts have provided further support for our argument (Van der Heijden, 2004; Wang et al., 2015).

3.9 Contributions

3.9.1 Theoretical contributions

The current study aimed to address the ignorance of important factors such as emotional trust and trust propensity in the past trust-centred studies based on RSs by empirically testing a model that estimates the effect of a comprehensive framework of trusting beliefs on customers' reuse of RSs. In the current study, an important antecedent of trust, i.e., trust propensity, indicated a significant and direct relationship with trusting beliefs. The current research bridges the literature gap, illustrating how an antecedent of trusting beliefs, i.e., consumers' trust propensity is related to trusting beliefs of the recommender system in an ongoing relationship. The empirical results of the study indicated that the proposed model has good explanatory as well as good predictive power. It indicates that the integration of subjective factors such as trust propensity and trusting beliefs provides a theoretical basis for explaining the customers' behavioural intentions to reuse recommender systems. The significant strength of the mediating effects was also shown to be an intriguing finding; the results revealed that trusting beliefs was an important mediator of reuse intentions. The research model which integrated perceived usefulness as an antecedent of trusting beliefs, is a distinctive contribution of this study. Another contribution of this study also included a typical combination novelty that incorporates concepts from IS literature (recommender systems, perceived usefulness), trust literature (trust propensity, trusting beliefs) and the use of up-to-date as well as the most efficient statistical approach (PLS-MGA) to test the moderation effect of product type. This study also used the PLSpredict technique that focuses on the predictive model assessment, most notably a model's predictive validity or out-of-sample predictive power (Shmueli et al., 2016). It is evident that the model with the inclusion of emotional trust is more efficient in explaining consumers' behavioural intentions to reuse RSs. An emotional trust can extend a relationship much beyond a typical business or transactional relationship as it is built on a strong foundation of social-emotional relationships (Kim, 2005). A strong favourable feeling towards a trustworthy object, i.e., emotional trust, may motivate trust in addition to good rational reasoning that builds cognitive trust (Punyatoya, 2019).

Both the theory and the extant literature guided the inclusion of the product type as a moderator. Surprisingly, the result of PLS-MGA showed an insignificant difference between the effect of search products and experience products regarding consumers' behavioural intentions to reuse the recommender system. Although the outcome did not find support for the hypotheses of product type as moderator, this result may contribute to our understanding of Australian consumers' intentions to reuse the recommender system.

More significantly, perhaps, this study can also be used by researchers and academicians to improve the understanding of customers' intentions to reuse RSs.

In terms of methodology, this paper is among the first to apply MICOM and PLS-MGA to investigate the moderation effect of product type on the consumers' behavioural intentions to reuse the recommender systems. This study also uses the PLSpredict technique to determine the appropriate causal-predictive model.

3.9.2 Practical contributions

The present study also has implications for practice. The findings of the research suggest that e-vendors should design recommender systems that are not only useful and convenient, but also trustworthy. Trustworthiness in RSs can be strengthened by providing the reason for proposing a certain recommendation or recommendation set in the form of textual explanations (Felfernig & Gula, 2006; Herlocker et al., 2000; Pu & Chen, 2007). An example of textual explanation used by Amazon is the "Frequently Bought Together" section. Higher degrees of trusting beliefs in recommender systems can also trigger a higher degree of consumer intentions to reuse recommender systems. The finding of this research also suggests improving emotional trust formation as it contributes to behavioural intentions to reuse recommender systems. Emotional trust can be fostered more effectively by incorporating RSs that provide immediate feedback (e.g., those that incorporate elements of the phone conversation) and available channels for interpreting communication cues (such as sound, video, text) (Gallié & Guichard, 2005; Rocco et. al., 2001). E-vendors may exploit useful techniques such as providing textual explanations for the recommended items, explanations indicating a high average rating of a recommendation or using natural language to provide an explanation based on the content features to improve customer trust in recommender systems (Berkovsky, Taib, & Conway, 2017; Felfernig & Gula, 2006; Kunkel et al., 2019). E-vendors may also equip recommender systems with explanatory components to more closely imitate the flow of information between humans to encourage a customer to feel trusted and reduce customers' utilisation concerns (Kunkel et al., 2019). Trust is highlighted as a key antecedent in the online environment for other behaviours including loyalty (Huang et al., 2014) and purchase intentions (Sahi et al., 2016). There exist significant possibilities for this to influence other customers' behaviour if such design aspects of the RSs can affect trusting beliefs and trusting intentions. Trust propensity is an important determinant of consumer trusting beliefs on the recommender system in an ongoing relationship. Even if some customer groups may be targeted, it is clearly beyond the control of an e-vendor to manipulate a consumer's trust propensity.

E-vendors before expecting purchase behaviour must understand the need of establishing consumer trust, because this makes e-commerce marketing efforts long-term and more relational instead of transactional. This changes potential key performance indicators (KPIs) from being solely a sales-based approach to an engagement-based approach.

3.10 Limitations and future research

Notwithstanding the contributions of the research, it is not without limitations. First, the data have been collected from users of Amazon of Australia; the model should be replicated in other contexts for results triangulation and better generalizability. Second, this research was restricted to Amazon's recommender systems that use collaborative filtering methods. Third, the omission of actual behaviour is another impediment, as some scholars disagree with intentions as a proxy for reuse behaviour. Some academics postulate that the causal association between intentions and behaviour is unpredictable (Venkatesh et al., 2006). Fourth, a major source of contamination is in the reliance on self-reports to assess trust propensity resulting in common method variance. While it may affect the strength of the relationships, certain studies suggest that the problem is not as typical as assumed (Spector, 2006).

Further research should explore the proposed model using a less famous e-commerce platform that uses recommender systems with a different underlying method of algorithms such as content-based filtering or hybrid filtering. Future research should determine actual reuse and consider a comparison of male and female online shoppers in a cross-group study. Prospective research may also examine other possible factors such as perceived risk, different recommender systems, discounted products, and attitudes towards the e-vendor's recommender systems. Future research should assess the impact of dimensions of trusting beliefs differently on consumers' intentions to reuse RSs. Further, even though the current study showed no moderating effect of product type on consumers' behavioural intentions to reuse RSs, future studies might examine other variables and contexts that could have a strong moderating effect on behavioural intentions in the product type.

3.11 CONCLUSIONS

The present study used a trust centred lens to address an important gap in the IS literature. The present study estimated the role of trust propensity on the influence of consumers' trusting beliefs of RSs in a continuing relationship, a novel aspect not previously considered in RSs research. The influence of consumers' trusting beliefs and perceived usefulness of RSs on behavioural intentions to use RSs in a continuing relationship was also assessed.

Building consumers' trusting beliefs is a crucial element for e-commerce companies to succeed. The study also explored the moderating effect of product type. Contrary to our expectations this study finds that the consumers do not perceive search products or experience products differently. The somewhat contradictory result could be attributed to the assumption that customers could not perceive any difference between search products and experience products due to the influence of the nature of the online shopping environment. This research is a small but significant step towards understanding the effects of subjective factors such as consumers' trust propensity and trusting beliefs and their effect on intentions to use recommender systems in an ongoing relationship. Finally, several recommender systems are now available on mobile apps (Ickin et al., 2012). It is hoped that the present study would prompt new questions and further research that will lead to guidance for e-vendors seeking to increase their customers' trust and ultimately their sales. Future research should extend our research to the context of the mobile application.

3.12 References

Amin, M., Rezaei, S., & Tavana, F. S. (2015). Gender differences and consumer's repurchase intention: the impact of trust propensity, usefulness and ease of use for implication of innovative online retail. International Journal of Innovation and Learning, 17(2), 217-233. doi: 10.1504/IJIL.2015.067409

Aggarwal, P., & Vaidyanathan, R. (2005). Perceived effectiveness of recommendation agent routines: search vs. experience goods. *International Journal of Internet Marketing and Advertising, 2*(1-2), 38-55. doi: 10.1504/IJIMA.2005.007503

Alarcon, G. M., Lyons, J. B., & Christensen, J. C. (2016). The effect of propensity to trust and familiarity on perceptions of trustworthiness over time. *Personality and Individual Differences, 94*, 309-315. doi: 10.1016/j.paid.2016.01.031

Alarcon, G. M., Lyons, J. B., Christensen, J. C., Bowers, M. A., Klosterman, S. L., & Capiola, A. (2018). The role of propensity to trust and the five factor model across the trust process. *Journal of Research in Personality, 75*, 69-82. doi: 10.1016/j.jrp.2018.05.006

Abumalloh, R. A., Ibrahim, O., & Nilashi, M. (2020). Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce. *Technology in Society, 61*, 101253. doi: 10.1016/j.techsoc.2020.101253

Ariely, D., Lynch Jr, J. G., & Aparicio IV, M. (2004). Learning by collaborative and individual-based recommendation agents. *Journal of Consumer Psychology, 14*(1-2), 81-95. doi: 10.1207/s15327663jcp1401&2_7

Ashraf, M., Ismawati Jaafar, N., & Sulaiman, A. (2019). System- vs. consumer-generated recommendations: affective and social-psychological effects on purchase intention. *Behaviour and Information Technology, 38*(12), 1259-1272. doi:10.1080/0144929X.2019.1583285

Ayanso, A., Herath, T. C., & O'Brien, N. (2015). Understanding continuance intentions of physicians with electronic medical records (EMR): An expectancy-confirmation perspective. *Decision Support Systems, 77*, 112-122. doi: 10.1016/j.dss.2015.06.003

Berkovsky, S., Taib, R., & Conway, D. (2017). How to Recommend? User Trust Factors in Movie Recommender

Systems. Paper presented at the Proceedings of the 22nd International Conference on Intelligent User Interfaces, Limassol, Cyprus. doi 10.1145/3025171.3025209

Benlian, A., Titah, R., & Hess, T. (2012). Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study. *Journal of Management Information Systems, 29*(1), 237-272. doi:10.2753/MIS0742-1222290107

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. MIS quarterly, 25(3), 351-370. doi:10.2307/3250921

Brömmelstroet, M. t. (2017). PSS are more user-friendly, but are they also increasingly useful? *Transportation Research Part A: Policy and Practice, 104*, 96-107. doi: 10.1016/j.tra.2016.08.009

Chang, Y.-S., & Fang, S.-R. (2013). Antecedents and distinctions between online trust and distrust: Predicting high-and low-risk internet behaviors. *Journal of Electronic Commerce Research, 14*(2), 149-166.

Chen, L.-S., Hsu, F.-H., Chen, M.-C., & Hsu, Y.-C. (2008). Developing recommender systems with the consideration of product profitability for sellers. *Information Sciences, 178*(4), 1032-1048. doi: 10.1016/j.ins.2007.09.027

Cheng, S.-I., Chen, S.-C., & Yen, D. C. (2015). Continuance intention of E-portfolio system: A confirmatory and multigroup invariance analysis of technology acceptance model. *Computer Standards & Interfaces, 42*, 17-23. doi: 10.1016/j.csi.2015.03.002

Chin, W. W. (2010). How to write up and report PLS analyses. In *Handbook of partial least squares* (pp. 655-690). Berlin, Heidelberg: Springer.

Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares: Concepts, methods and applications*: Berlin, Heidelberg: Springer.

Choi, J., Lee, H. J., & Kim, Y. C. (2011). The influence of social presence on customer intention to reuse online recommender systems: The roles of personalization and product type. *International journal of electronic commerce, 16*(1), 129-154. doi: 10.2753/JEC1086-4415160105

Chou, S.-W., & Hsu, C.-S. (2016). Understanding online repurchase intention: social exchange theory and shopping habit. *Information Systems and e-Business Management*, 14(1), 19-45. doi:10.1007/s10257-015-0272-9

Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of applied psychology, 92*(4), 909. doi: 10.1037/0021-9010.92.4.909

Cooke, A. D., Sujan, H., Sujan, M., & Weitz, B. A. (2002). Marketing the unfamiliar: the role of context and item-specific information in electronic agent recommendations. *Journal of Marketing Research, 39*(4), 488-497. doi: 10.1509/jmkr.39.4.488.19121

Davidson, J., Liebald, B., Liu, J., Nandy, P., Van Vleet, T., Gargi, U., ... & Sampath, D. (2010, September). The YouTube video recommendation system. In Proceedings of the fourth ACM conference on Recommender systems (pp. 293-296).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 13(3), 319-340. doi:10.2307/249008

Esswein, M., Mayer, J. H., Sedneva, D., Pagels, D., & Albers, J.-P. (2020). Improving Invoice Allocation in Accounting—An Account Recommender Case Study Applying Machine Learning. In *Digital Business Transformation* (pp. 137-153): Springer, Cham.

Felfernig, A., & Gula, B. (2006, June). An empirical study on consumer behavior in the interaction with knowledge-based recommender applications. In The 8th IEEE International Conference on E-Commerce Technology and The 3rd IEEE International Conference on Enterprise Computing, E-Commerce, and E-Services (CEC/EEE'06) (pp. 37-37). ieee.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric*, *10*(2).

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50. doi:10.1177/002224378101800104

Gallié, E.-P., & Guichard, R. (2005). Do collaboratories mean the end of face-to-face interactions? An evidence from the ISEE project. *Economics of Innovation and New Technology*, 14(6), 517-532. doi:10.1080/1043859042000304052

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly, 27*(1), 51-90.

Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information Systems, 1*(8), 1-30.

Ghasemaghaei, M. (2020). The impact of in-depth online recommendation agents on consumer disorientation and cognitive absorption perceptions. *Behaviour and Information Technology, 39*(4), 414-430. doi:10.1080/0144929X.2019.1598496

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, 14(2), 627-660. doi:10.5465/annals.2018.0057

Gomez-Uribe, C. A., & Hunt, N. (2016). The Netflix Recommender System: Algorithms, Business Value, and Innovation. *ACM Trans. Manage. Inf. Syst., 6*(4), Article 13. doi:10.1145/2843948

Gorgoglione, M., Panniello, U., & Tuzhilin, A. (2011). *The effect of context-aware recommendations on customer purchasing behavior and trust* Proceedings of the fifth ACM conference on Recommender systems, Chicago, Illinois, USA. doi:10.1145/2043932.2043951

Gretzel, U., & Fesenmaier, D. R. (2006). Persuasion in Recommender Systems. *International journal of electronic commerce, 11*(2), 81-100. doi:10.2753/JEC1086-4415110204

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442-458. doi:10.1108/IMDS-04-2016-0130

Hair, J., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Thousand Oaks, CA: Sage Publications, Inc.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. doi:10.1108/EBR-11-2018-0203

Hair Jr, J. F., Hult, G. T. M., Ringle, C.M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks, CA: Sage publications.

Harrigan, M., Feddema, K., Wang, S., Harrigan, P., & Diot, E. (2021). How trust leads to online purchase intention founded in perceived usefulness and peer communication. Journal of Consumer Behaviour, 1-16. doi:10.1002/cb.1936

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. doi:10.1007/s11747-014-0403-8

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405-431. doi:10.1108/IMR-09-2014-0304

Herlocker, J. L., Konstan, J. A., & Riedl, J. (2000, December). Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp. 241-250).

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: emerging concepts, methods and propositions. *Journal of Marketing, 46*(3), 92-101.

Ho, R. (2013). *Handbook of univariate and multivariate data analysis with IBM SPSS*. Boca Raton, FL: CRC press.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human factors*, 57(3), 407-434. doi:10.1177/0018720814547570

Huang, C.-C., Fang, S.-C., Huang, S.-M., Chang, S.-C., & Fang, S.-R. (2014). The impact of relational bonds on brand loyalty: the mediating effect of brand relationship quality. Managing Service Quality*, 24*(2).

Huang, J., & Zhou, L. (2019). The dual roles of web personalization on consumer decision quality in online shopping: The perspective of information load. *Internet Research, 29*(6), 1280-1300. doi:10.1108/INTR-11-2017-0421

Huang, L., Tan, C.-H., Ke, W., & Wei, K.-K. (2013). Comprehension and assessment of product reviews: A review-product congruity proposition. *Journal of Management Information Systems, 30*(3), 311-343.

Ickin, S., Wac, K., Fiedler, M., Janowski, L., Hong, J.-H., & Dey, A. K. (2012). Factors influencing quality of experience of commonly used mobile applications. *IEEE Communications Magazine, 50*(4), 48-56.

Jannach, D., & Jugovac, M. (2019). Measuring the Business Value of Recommender Systems. *ACM Trans. Manage. Inf. Syst., 10*(4), Article 16. doi:10.1145/3370082

Jones, S. L., & Shah, P. P. (2016). Diagnosing the locus of trust: A temporal perspective for trustor, trustee, and dyadic influences on perceived trustworthiness. *Journal of applied psychology, 101*(3), 392.

Kamis, A., Koufaris, M., & Stern, T. (2008). Using an Attribute-Based Decision Support System for User-Customized Products Online: An Experimental Investigation. *MIS quarterly, 32*(1), 159-177. doi:10.2307/25148832

Kanaujia, P. K. M., Behera, N., Pandey, M., & Rautaray, S. S. (2016). Recommendation system for financial analytics. 2016 International Conference on ICT in Business Industry & Government (ICTBIG), 1-5. doi: 10.1109/ICTBIG.2016.7892673

Kim, D. (2005). *Cognition-Based Versus Affect-Based Trust Determinants in E-Commerce: Cross-Cultural Comparison Study.* Paper presented at the ICIS 2005 Proceedings.

Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems. *User Modeling and User-Adapted Interaction, 22*(4), 441-504. doi: 10.1007/s11257-011-9118-4

Kock, N. (2015). Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *International journal of e-collaboration, 11*(4), 1-10. doi:10.4018/ijec.2015100101

Komiak, S. X., & Benbasat, I. (2004). Understanding customer trust in agent-mediated electronic commerce, web-mediated electronic commerce, and traditional commerce. *Information technology and management, 5*(1-2), 181-207.

Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS quarterly, 30*(4), 941. doi:10.2307/25148760

Kowatsch, T., & Maass, W. (2010). In-store consumer behavior: How mobile recommendation agents influence usage intentions, product purchases, and store preferences. *Computers in Human Behavior, 26*(4), 697-704.

Kunkel, J., Donkers, T., Michael, L., Barbu, C. M., & Ziegler, J. (2019, May). Let me explain: Impact of personal and impersonal explanations on trust in recommender systems. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems,* 1-12. doi: 10.1145/3290605.3300717.

Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into Expectation Disconfirmation Theory. *The Journal of Strategic Information Systems, 23*(2), 128-145.

Lee, M.-C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education, 54*(2), 506-516.

Lee, M. K., & Turban, E. (2001). A trust model for consumer internet shopping. *International journal of electronic commerce, 6*(1), 75-91.

Li, Q., Myaeng, S. H., & Kim, B. M. (2007). A probabilistic music recommender considering user opinions and audio features. *Information Processing & Management, 43*(2), 473-487. doi: 10.1016/j.ipm.2006.07.005

Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the Association for Information Systems, 16*(2), 72.

Lim, J.-S., Al-Aali, A., & Heinrichs, J. H. (2015). Impact of satisfaction with e-retailers' touch points on purchase behavior: the moderating effect of search and experience product type. *Marketing Letters*, 26(2), 225-235. doi: 10.1007/s11002-014-9334-x

Loehlin, J. C., & Beaujean, A. A. (2016). *Latent variable models: An introduction to factor, path, and structural equation analysis*. New York: Taylor & Francis.

Logesh, R., Subramaniyaswamy, V., Malathi, D., Sivaramakrishnan, N., & Vijayakumar, V. (2020, 2020/04/01). Enhancing recommendation stability of collaborative filtering recommender system through bio-inspired clustering ensemble method. *Neural Computing and Applications, 32*(7), 2141-2164. doi: 10.1007/s00521-018-3891-5

Martínez-López Francisco, J. (2015). Psychological factors explaining consumer adoption of an e-vendor's recommender. *Industrial Management & Data Systems, 115*(2), 284-310. doi:10.1108/IMDS-10-2014-0306

McKnight, D. H., & Chervany, N. L. (2001a). Conceptualizing trust: A typology and e-commerce customer relationships model. *Paper presented at the Proceedings of the 34th Annual Hawaii International Conference on System Sciences*. 1-10. doi: 10.1109/HICSS.2001.927053.

McKnight, D. H., & Chervany, N. L. (2001b). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International journal of electronic commerce, 6*(2), 35-59.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002a). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research, 13*(3), 334-359.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002b). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The Journal of Strategic Information Systems*, 11(3-4), 297-323.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, 23(3), 473-490.

Montaner, M., López, B., & De La Rosa, J. L. (2003). A taxonomy of recommender agents on the internet. *Artificial intelligence review, 19*(4), 285-330. doi: 10.1023/A:1022850703159

Moorman, C., Deshpandé, R., & Zaltman, G. (1993). Factors Affecting Trust in Market Research Relationships. *Journal of Marketing*, 57(1), 81-101. doi:10.1177/002224299305700106

Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on

Amazon. com. *MIS quarterly*, 34(1), 185-200. doi:10.2307/20721420

Murphy, G. B. (2003). Propensity to trust, purchase experience, and trusting beliefs of unfamiliar e-commerce ventures. *New England Journal of Entrepreneurship, 6*(2), 53-64. doi: 10.1108/NEJE-06-02-2003-B008

Nelson, P. (1970). Information and consumer behavior. *Journal of political economy, 78*(2), 311-329.

Nilashi, M. (2016). An overview of data mining techniques in recommender systems. *J. Soft Comput. Decision Support Syst., 3*(6), 16-44.

Nilashi, M., Ibrahim, O., & Bagherifard, K. (2018). A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. *Expert Systems with Applications, 92*, 507-520. doi: 10.1016/j.eswa.2017.09.058

Nilashi, M., Jannach, D., Ibrahim, O. b., Esfahani, M. D., & Ahmadi, H. (2016). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. *Electronic Commerce Research and Applications, 19*, 70-84. doi: 10.1016/j.elerap.2016.09.003

Ochi, P., Rao, S., Takayama, L., & Nass, C. (2010). Predictors of user perceptions of web recommender systems: How the basis for generating experience and search product recommendations affects user responses. *International Journal of Human-Computer Studies, 68*(8), 472-482.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology, 88*(5), 879-903.

Panniello, U., Gorgoglione, M., & Tuzhilin, A. (2016). Research note—In CARSs we trust: How context-aware recommendations affect customers’ trust and other business performance measures of recommender systems. *Information systems research*, *27*(1), 182-196.

Pu, P., & Chen, L. (2007). Trust-inspiring explanation interfaces for recommender systems. Knowledge-Based Systems, 20(6), 542-556. doi: 10.1016/j.knosys.2007.04.004

Pu, P., Chen, L., & Hu, R. (2011). *A user-centric evaluation framework for recommender systems* Proceedings of the fifth

ACM conference on Recommender systems, Chicago, Illinois, USA. doi: 10.1145/2043932.2043962

Punyatoya, P. (2019). Effects of cognitive and affective trust on online customer behavior. *Marketing Intelligence & Planning, 37*(1), 80-96. doi:10.1108/MIP-02-2018-0058

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145-182.

Recker, J. (2010). Continued use of process modeling grammars: the impact of individual difference factors. *European Journal of Information Systems, 19*(1), 76-92.

Ricci, F., Rokach, L., & Shapira, B. (2015). *Recommender Systems Handbook* (2nd ed.). Berlin/Heidelberg: Springer Publishing Company.

Ringle, C. M., Wende, S., and Becker, J.-M. 2015. SmartPLS 3.0 (version 3.3.3). Boenningstedt: SmartPLS GmbH, http://www.smartpls.com.

Rocco, E., Finholt, T. A., Hofer, E. C., & Herbsleb, J. (2001). *Out of sight, short of trust*. Paper presented at the Presentation at the Founding Conference of the European Academy of Management. Barcelona, Spain.

Roetzel, P. G. (2019). Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. Business Research, 12(2), 479-522. doi:10.1007/s40685-018-0069-z

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), Handbook of Market Research (pp. 1-47). Springer, Cham. doi:10.1007/978-3-319-05542-8_15-2

Sahi, G. K., Sekhon, H. S., & Quareshi, T. K. (2016). Role of trusting beliefs in predicting purchase intentions. International Journal of Retail & Distribution Management, 44(8), 860-880. doi:10.1108/IJRDM-10-2015-0157

Schlosser, A. E., White, T. B., & Lloyd, S. M. (2006). Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase

Intentions. *Journal of Marketing, 70*(2), 133-148. doi:10.1509/jmkg.70.2.133

Seale, C. (2004). Using data archives for secondary analysis. In Seale, C. (Eds.), *Researching society and culture*(pp. 356-365)., Sage Publications, Thousand Oaks, California.

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of retailing, 80*(2), 159-169.

Shani, G., & Gunawardana, A. (2011). Evaluating Recommendation Systems. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender Systems Handbook* (pp. 257-297). Boston, MA: Springer.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, 69(10), 4552-4564. doi:10.1016/j.jbusres.2016.03.049

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322-2347. doi:10.1108/EJM-02-2019-0189

Spector, P. E. (2006). Method Variance in Organizational Research: Truth or Urban Legend? *Organizational Research Methods, 9*(2), 221-232. doi:10.1177/1094428105284955

Sun, X., Han, M., & Feng, J. (2019). Helpfulness of online reviews: Examining review informativeness and classification thresholds by search products and experience products. *Decision Support Systems*, 124, 113099. doi: 10.1016/j.dss.2019.113099

Sun, Y., Liu, L., Peng, X., Dong, Y., & Barnes, S. J. (2014). Understanding Chinese users' continuance intention toward online social networks: an integrative theoretical model. *Electronic Markets, 24*(1), 57-66.

Swaminathan, V. (2003). The Impact of Recommendation Agents on Consumer Evaluation and Choice: The Moderating Role of Category Risk, Product Complexity, and Consumer Knowledge. *Journal of Consumer Psychology, 13*(1), 93-101. doi: 10.1207/S15327663JCP13-1&2_08

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS quarterly*, 28(4), 695-704. doi:10.2307/25148660

Venkatesh, V., Maruping, L. M., & Brown, S. A. (2006). Role of time in self-prediction of behavior. *Organizational Behavior and Human Decision Processes, 100*(2), 160-176.

Vidotto, G., Massidda, D., Noventa, S., & Vicentini, M. (2012). Trusting Beliefs: A Functional Measurement Study. *Psicologica: International Journal of Methodology and Experimental Psychology*, *33*(3), 575-590.

Wang, W., & Benbasat, I. (2005). Trust in and Adoption of Online Recommendation Agents. *Journal of the Association of Information Systems, 6*(3), 72-101. doi:10.17705/1jais.00065

Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems, 23*(4), 217-246.

Wang, W., & Benbasat, I. (2016). Empirical assessment of alternative designs for enhancing different types of trusting beliefs in online recommendation agents. *Journal of Management Information Systems, 33*(3), 744-775.

Wang, Y. Y., Luse, A., Townsend, A. M., & Mennecke, B. E. (2015). Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems. *Information Systems and e-Business Management, 13*(4), 769-799. doi:10.1007/s10257-014-0269-9

Wang, W., Xu, J., & Wang, M. (2018). Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust vs. Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations. Management Science, 64(11), 5198-5219. doi:10.1287/mnsc.2017.2906

Willemsen, L. M., Neijens, P. C., Bronner, F., & De Ridder, J. A. (2011). "Highly recommended!" The content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication, 17*(1), 19-38.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. *MIS Q., 31*(1), 137-209.

Xu, J. D., Cenfetelli, R. T., & Aquino, K. (2016). Do different kinds of trust matter? An examination of the three trusting beliefs on satisfaction and purchase behavior in the buyer–seller context. *The Journal of Strategic Information Systems, 25*(1), 15-31.

Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems, 55*(4), 883-893. doi:10.1016/j.dss.2012.12.024

Zhang, J., & Curley, S. P. (2018). Exploring Explanation Effects on Consumers' Trust in Online Recommender Agents. *International Journal of Human–Computer Interaction, 34*(5), 421-432. doi:10.1080/10447318.2017.1357904

CHAPTER 4: PAPER 2 - The effect of cognitive absorption on online shoppers' intentions to reuse recommender systems

4.1

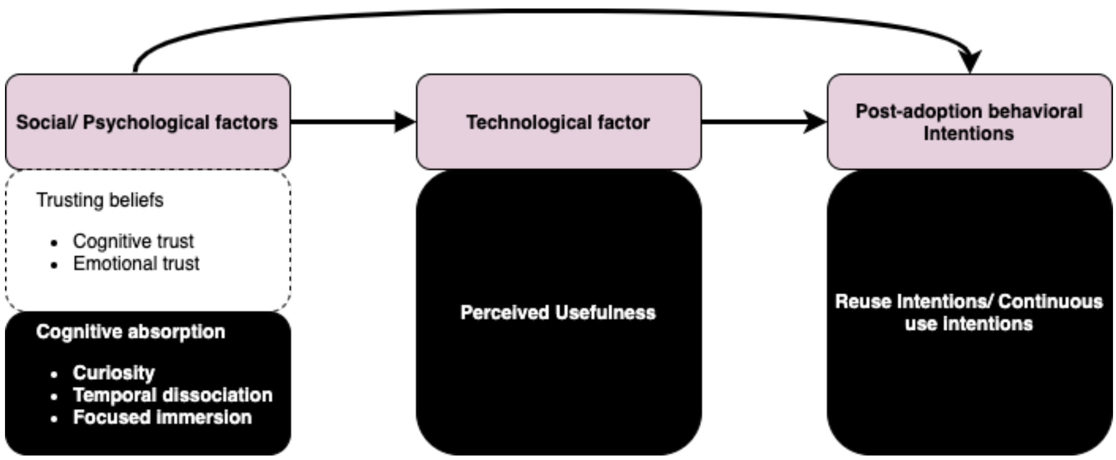


FIGURE 4.1 FRAMEWORK FOR CHAPTER 4

4.2 PREFACE

This chapter presents an empirical paper that at the time of submitting this thesis is under review by a Q1 journal. The paper is presented as it was last submitted to the journal. This chapter investigates the effect of cognitive absorption to estimate holistic experience of recommender systems on shoppers' intentions to reuse recommender systems.

4.2.1 HIGHLIGHTS OF THIS CHAPTER

- High levels of cognitive absorption in recommender systems are associated with an interaction dominated by curiosity, focused immersion, and temporal dissociation.
- Cognitive absorption directly and indirectly affect shoppers' behavioural intentions to reuse recommender systems.

- Cognitive absorption should be given more priority as compared to perceived usefulness to further increase the performance of behavioural intentions to reuse recommender systems
- Gender plays a moderating role on shoppers' behavioural intentions to reuse recommender systems.
- Cognitive absorption significantly influences behavioural intentions to reuse recommender systems in females than males.

THE EFFECT OF COGNITIVE ABSORPTION ON ONLINE SHOPPERS' INTENTIONS TO REUSE RECOMMENDER SYSTEMS

ABSTRACT

E-commerce is the trade of services and goods via electronic means such as the Internet. It is critical in today's business and user experience. Most current e-commerce websites employ various technologies such as recommender systems to provide customers with personalised recommendations. Taking this as a cue, this study investigates the effect of cognitive absorption to estimate holistic experience of recommender systems on shoppers' intentions to reuse recommender systems. Data collected from 366 online shoppers was analysed using structural equation modelling to test the proposed hypotheses. The findings highlight that cognitive absorption directly and indirectly affect shoppers' behavioural intentions to reuse recommender systems. The results also exposed the moderating effect of gender on shoppers' behavioural intentions to reuse recommender systems. An Importance-Performance Map Analysis was also conducted to identify significant areas of improvement for e-vendors. This study contributes to advancing existing knowledge relevant to shoppers' behavioural intentions to reuse recommender systems. The study also provides e-vendor managers with insights into online shoppers' decision-making.

4.2.2 KEYWORDS

Recommender systems, cognitive absorption, reuse intention, perceived usefulness, PLS-MGA, PLS-IPMA

4.3 INTRODUCTION

Recommender systems (RSs) are personalised agents that improve shoppers' decision quality by offering suggestions for what to buy based on each individual's needs (Komiak and Benbasat, 2006, Benlian et al., 2012). They use complex techniques to consider information from a diverse set of input such as product information, design, function or category, and personal information of shoppers, such as gender, age, or history of purchase, to generate personalised suggestions (Whang and Im, 2018). RSs have been crucial to the success of digital platforms such as Amazon, Netflix, Spotify and Alibaba (Schrage, 2021).

Research in RSs mainly focuses on improving the algorithms to select and rank items (Jugovac and Jannach, 2017, Zhao, 2019, da Silva et al., 2016, Zhang et al., 2016). Algorithms do not contribute to positive shopper perceptions (Whang and Im, 2018). Positive shopper perceptions are important as they drive business outcomes (Yang and Jun, 2002). Particularly, perceived sales motives and the absence of convincing connections resulted in consumers' dissatisfaction and distrust with RSs (Shen, 2014), and RSs are considered as tools to drive, engagement, insight and innovation (Schrage, 2021). RSs can alter shoppers' decision-making and behaviour (Häubl and Trifts, 2000, Bharati and Chaudhury, 2004). A few empirical investigations have studied the influence of RSs on the behavioural intentions of users (Wang et al., 2016, Wang and Benbasat, 2005, Benlian et al., 2012, Abumalloh et al., 2020), but the effect of RSs on customer experience is scant has led scholars to request further study in estimating the perceptions and beliefs on behavioural intentions to use RSs.

These findings suggest that the success of e-commerce platforms requires an understanding of the shoppers' decision processes, particularly the effect of their perceptions and beliefs on behavioural intentions to use RSs. There remains a need to emphasise the potential effect of shopper’s interactions with RSs and their willingness to use/ accept RSs (Abumalloh et al., 2020).

The current study applied the technology acceptance model (TAM) to assess the shoppers’ behavioural intention to reuse RSs, as the TAM has been widely applied to understand the shopper decision making, especially the adoption intentions of the RSs (Wang and Benbasat, 2005, Benlian et al., 2012, Zhu et al., 2014). Prior research based on a generalised model such as the technology acceptance model (TAM) provide a limited explanation of behavioural intentions, as shoppers’ decision-making processes include factors such as online shopping experience that perceived usefulness and ease of use alone do not capture. Although such generalised models have an important part to play in explaining technology acceptance, scholars often have to integrate multiple models or theories to develop a pertinent model. Due to the efficient decision supports that RSs tend to bring to e-shoppers, e-vendor managers should know ways to improve shoppers’ immersive or flow experience to build a “convincing connection”. It is particularly promising to study the effect of shoppers' flow experiences and technological beliefs on their decision to shop using RSs, as the majority of previous research has investigated the significance of flow in e-commerce platforms (Koufaris, 2002, Shang et al., 2005, Suki et al., 2008, Ghasemaghaei, 2020, Mahnke et al., 2015). Flow theory can be utilized to capture the holistic or optimal experience of a user (Balakrishnan and Dwivedi, 2021). The holistic experience of an information system (IS) can best be captured using cognitive absorption (Agarwal and Karahanna, 2000, Mpinganjira, 2019), which is defined as a state of deep involvement with an information system (Agarwal and Karahanna, 2000, Salimon et al., 2021) and is usually conceptualised as flow (Valinatajbahnamiri and

Siahtiri, 2021). To develop a strong RSs adoption, a recent study in RSs encouraged the exploration of users' cognitive absorption perceptions (Ghasemaghaei, 2020). The impact of cognitive absorption in recommender systems is a sparse research area, and there is very little scientific understanding of how cognitive absorption contribute to the shoppers' behavioural intentions to reuse RSs or on the impact on shoppers' decision outcomes. This research, appeals to utilise cognitive absorption to estimate the holistic experience of RSs.

A growing body of research has raised concerns about the inconsistency in the precision of recommendations across genders (Mansoury et al., 2020, Zhu et al., 2018, Ekstrand et al., 2018). Lack of empirical investigation on the impact of gender has been reported (Midha, 2012), despite the presence of substantial gender variations in online shopping speculated by IS scholars, behaviours (e.g., online purchases) and attitudes (e.g., online trust) (Cyr and Bonanni, 2005, Riedl et al., 2010, Hwang, 2010). Limited empirical studies are available to reveal the effect of cognitive absorption on shoppers' behavioural intentions to reuse RSs across gender. This indicates the need to understand the effect of cognitive absorption across gender. The research reported in this paper aims to advance our understanding of the effect of cognitive absorption across gender.

Bearing this in mind, the current research aimed to address this void in the literature by utilising a new theoretical lens. A conceptual framework was proposed by extending TAM by combining it with flow theory to estimate the holistic experience of RSs. The main goal of the paper was to examine the role of shoppers' cognitive absorption perception on their behavioural intentions to reuse RSs. Part of the aim of this was to ascertain the moderating effect of gender across paths in the proposed conceptual model. This study further contributes methodologically by implementing modern PLS-SEM procedures such as PLS-MGA and PLS-IPMA defying classical methods.

It is crucial to evaluate the predictors of the intentions to reuse RSs to achieve superior customer loyalty. Superior loyalty and growth, amplify customer lifetime value (Schrage, 2021). In contrast to existing studies which focused primarily on the development of high-performance RSs, the finding of this research would provide insight into the shoppers' perception and evaluation of RSs. This research also expands our understanding of RSs from the shoppers' perspective.

4.4 Theoretical background

4.4.1 Technology acceptance model (TAM)

IS usage and acceptance are widely investigated using TAM. TAM encompasses two major instrumental factors: perceived ease of use (user attitude) and perceived usefulness (user belief) (Davis, 1989). Perceived usefulness (PU) is one of TAM's core factors. Although prior research has revealed the TAM to be a robust and efficient model, the TAM uses only two instrumental factors (user attitude and user belief) to explain behavioural intentions.

4.4.1.1 Perceived usefulness

Perceived usefulness is regarded as the extent to which shoppers believe that using RSs would enhance the achievement of their shopping tasks (Davis, 1989). Several studies in the RSs literature used TAM to show recommendations increase shoppers' perceived usefulness (Kumar and Benbasat, 2006, Ashraf et al., 2020, Benlian et al., 2012). RSs frequently provides convincing and extensive product-related information that may all be considered to be helpful in evaluating and analysing the performance of various product attributes (Benlian et al., 2012, Kumar and Benbasat, 2006). RSs provides appropriate cues to enhance the shoppers' utilitarian value and that can lead to increased perceived usefulness (Parboteeah et al., 2009). Shoppers' may view and assess the main qualities (e.g., brief descriptions, key features) and values of the product (e.g., price) immediately. By analysing the content provided by RSs, shoppers may determine which attributes are most essential and different values for each attribute. This information is therefore perceived to be more useful by shoppers (Benlian et al., 2012). Ashraf et al. (2020) studied the effects of customers' continuous trust, perceived confirmation, satisfaction with RSs, and perceived usefulness of RSs and found it subsequently affected their behavioural intentions to reuse RSs. Benlian et al. (2012) suggested a model that linked RSs to four consumer beliefs (perceived ease of use, perceived usefulness, trust and perceived affective quality) and found it to be important predictors of behavioural intentions to reuse RSs.

4.4.1.2 Perceived ease of use

Another factor of TAM is perceived ease of use. The term perceived ease of use means the extent to which the shoppers think the RSs is free of physical and mental rigour (Davis, 1989). To purchase a product using a recommender system is a task that is free of physical and mental rigour. The research reported in this paper only focused on the people who were active shoppers at Amazon. The respondents were assumed to be already knowledgeable and were able to use RSs to buy a product. The conceptual model proposed in the research to explore shoppers' intentions to reuse RSs has not incorporated perceived ease of use.

4.4.2 Flow theory

In a flow state, people appear so focused on their task that nothing else seemed to matter (Csikszentmihalyi and Csikzentmihaly, 1990). Flow theory helps scholars and professionals to understand customer experiences (Hoffman and Novak, 1996). Flow is likely to occur during the product information process in the online shopping experience (Mahnke et al., 2015), which cannot be captured using traditional technology acceptance models.

Over the years, flow theory has been extended to a number of subject areas related to an online environment, in order to understand the holistic or optimal experience (Huang et al., 2019, Zhu and Morosan, 2014, Balakrishnan and Dwivedi, 2021). Arguably, these arguments related to the online environment also applies to the context of RSs. Asserted by (Wang et al., 2015, Li, 2015, Chang and Wang, 2008, Lu et al., 2009), in the current study, flow experience is predicted to function as an antecedent of shoppers' behavioural intentions to reuse RSs.

4.4.2.1 Cognitive absorption

In information technology, cognitive absorption is usually conceptualised like the flow construct (Balakrishnan and Dwivedi, 2021, Csikszentmihalyi and Csikzentmihaly, 1990, Valinatajbahnamiri and Siahtiri, 2021) and denotes holistic experience (Agarwal et al., 1997, Mpinganjira, 2019). Cognitive absorption stems from the absorption characteristic that indicates an individual's willingness to participate in an activity or towards an object with entire concentration. Initially conceived as a trait, the concept of absorption was ultimately seen as a trait and a state (Kulviwat et al., 2007). Cognitive absorption is a condition of profound involvement with information technology (Agarwal and Karahanna, 2000, Salimon et al., 2021). Guo and Ro (2008) and

Chandra et al. (2009) defined cognitive absorption as the state holistic experience or deep involvement an individual has with information technology.

In information systems literature, cognitive absorption was primarily used to study the formation of user's intentions to use new technologies (Ghasemaghaei, 2020). Table 1 lists key studies focusing on cognitive absorption in IS. Several IS studies confirmed that cognitive absorption increased the perceived usefulness of the respective information systems (Agarwal and Karahanna, 2000, Agarwal et al., 1997, Lee, 2018, Lin, 2009, Shang et al., 2005, Salimon et al., 2021). Prior literature into cognitive absorption concerning the intention to use has been inconsistent and contradictory. Lin (2009) extended TAM to estimate the influences of cognitive absorption on user beliefs (perceived ease of use, perceived usefulness and speciality) as well as behavioural intentions and found no significant link between cognitive absorption and the intentions to use the virtual community but cognitive absorption significantly affects behavioural intentions through perceived ease of use and perceived usefulness of the virtual community. Zhu and Morosan (2014) also extended TAM with the constructs of cognitive absorption in the context of interactive mobile technologies (IMC) in hotels to capture the holistic experiences of users and found cognitive absorption as the most significant predictor of IMC adoption attitudes and behaviour. It was also concluded that cognitive absorption had a stronger effect on perceived ease of use than perceived usefulness.

Few studies explored cognitive absorption's direct effect on actual behaviour. Curiously, despite the cognitive involvement, different researchers have reported conflicting findings concerning cognitive absorption's impact on actual behaviour (Jia et al., 2007, Lin, 2009, Shang et al., 2005, Suki et al., 2008). Shang et al. (2005) investigated the effect of cognitive absorption, perceived usefulness and perceived ease of use with regards to online shopping believes and behaviour and concluded that cognitive absorption does not have a positive direct effect on actual behaviour. Jia et al. (2007) demonstrated that cognitive absorption influenced actual use, and the actual use of technology was significantly higher for deeply absorbed individuals. Comparing technology usage for social/recreation and work/study purposes, they considered cognitive absorption to be a more meaningful indicator for social/recreational purposes. The study explained its results on the assumption that many individuals may have lower intrinsic motivation to use IS for work, and therefore to have a lower level of cognitive absorption. Suki et al. (2008) reported that online shopping behaviour was not directly affected by cognitive absorption. Lee (2018), by contrast, concluded that cognitive absorption acted as an intrinsic motivator, and affected perceived usefulness and perceived ease of use. Perumal et al. (2021) demonstrated that cognitive absorption directly and positively impacted the perceived usefulness of e-learning platforms. Ghasemaghaei (2020) concluded that online shoppers with high product knowledge perceived greater cognitive absorption when they were using RSs that provided a high level of detail. This holds that cognitive absorption is the intrinsic motivator that expresses the entire pleasure and enjoyment that a person experiences when interacting with information technology.

TABLE 4.1 KEY STUDIES FOCUSING ON COGNITIVE ABSORPTION IN IS

Author(s) (Year)	**Focus (IS)**	**Direct Outcomes of cognitive absorption**
(Balakrishnan and Dwivedi, 2021)	Trust, Experience and continuance intentions in the context of services (AI chatbots)	Positive effect on user experience, trust and technology continuance intentions
(Salimon et al., 2021)	E-learning satisfaction and retention (E-learning platforms)	Positive effect on PU and PEOU
(Jumaan et al., 2020)	Mobile internet users' continuance intentions (Internet)	Positive effect on mobile internet services continuance intentions and PU.
(Ghasemaghaei, 2020)	Intentions to use online in-depth RA in consumer shopping experience (Internet)	Positive effect on in-depth RA effectiveness and intentions to use the in-depth RA in their shopping experience.
(Lee, 2018)	Impulse buying tendency in mobile shopping (Internet)	Positive effect on PU, PEOU and impulse buying tendency in mobile shopping.
(Zhu and Morosan, 2014)	Adoption of interactive mobile technologies (IMC) in hotels (Internet)	Positive effect on PU, PEOU and IMC adoption attitudes and behaviour.
(Chandra et al., 2012)	Workplace Collaboration in Virtual Worlds (Virtual community website)	Positive effect on trust and adaptive use intentions.
(Lin, 2009)	Intentions to use virtual communities (Virtual community website)	Positive effect on PU, PEOU but does not have a positive direct effect on the intentions to use.
(Suki et al., 2008)	Internet shopping acceptance (Internet)	Positive effect on PU, PEOU but do not have a

		positive direct effect on online shopping behaviour.
(Jia et al., 2007)	Antecedents of problematic IS usage (Internet)	Positive effect on actual usage, Problematic usage, Social/Leisure use but does not have a positive direct effect on social/work use.
(Shang et al., 2005)	Online shopping beliefs and behaviour (Internet)	Positive effect on PU, PEOU but do not have a positive direct effect on actual behaviour.
(Agarwal and Karahanna, 2000)	Beliefs about IS usage (Internet)	Positive effect on PU and PEOU.
(Agarwal et al., 1997)	IT adoption, software usage (Windows 95, Lotus 1-2-3)	Positive effect on PU.

Note: PU: Perceived usefulness, PEOU: Perceived ease of use.

The research reported in this paper used cognitive absorption as a higher-order construct consisting of focused immersion (FI), temporal dissociation (TD), and curiosity (CU) as Zhu and Morosan (2014) identifies these dimensions as the core dimensions. The definition of focused immersion, temporal dissociation, and curiosity are as follows:

- Focused immersion is defined as "an immersed engagement when other important attentions are ignored" (Balakrishnan and Dwivedi, 2021).
- Temporal dissociation is defined as "an engaged interaction without noticing the passage of time" (Balakrishnan and Dwivedi, 2021).
- Curiosity is defined as "the user's expectation and cognitive curiosity to explore more in the interaction" (Balakrishnan and Dwivedi, 2021).

In summary, studies exploring cognitive absorption's effect, highlights the dynamic and diversified correlation between cognitive absorption and users' intentions to use IT, their beliefs, and their actual usage behaviour (see Table 4.1). No studies have been conducted linking the investigation of consumers' intentions to reuse RSs on their holistic experience of the RSs, being necessary an improvement of the research on the topic. To fill the gap, the research reported in this paper utilised cognitive absorption to understand the effect of holistic experience on perceived usefulness and their behavioural intentions to reuse recommender systems (RSs).

4.4.3 Intentions to reuse recommender systems

In this research, behavioural intentions are referred to as the shoppers' intentions to reuse RSs. The current research used shoppers' intentions to reuse RSs to measure the impact of RSs use on the decision outcomes. It has been widely used for research into business to consumer e-commerce (Hampton-Sosa and Koufaris, 2005, Koufaris, 2002, Benlian et al., 2012). Intentions to reuse RSs indicates the loyalty and satisfaction of customers (Bhattacherjee, 2001). Scholars have emphasised the importance of shoppers' intentions to reuse RSs and recognized that it is crucial for the success of RSs (Ashraf et al., 2020, Benlian et al., 2012).

4.4.4 Moderating effect of gender

Gender's effect in the e-commerce setting is still very nascent (Lin et al., 2019). Particularly in the RSs literature scholars have expressed concerns about inconsistencies in the accuracy of recommendations between different genders (Mansoury et al., 2020, Zhu et al., 2018, Ekstrand et al., 2018). For instance, Mansoury et al. (2020) argued that women get less accurate recommendations than men.

Previous studies have reported that online information searching differences exist between males and females (Li and Kirkup, 2007). In encoding information and solving problems, males and females use different socially cognitive attributes (Bem, 1981); males are thought to emphasise task-orientation while females are regarded as socially-driven and people-oriented usage motive (Claisse and Rowe, 1987). This means that, due to their gender, males and females can take unconscious or internalized actions. The user's interaction with RSs and cognitive absorption is significantly moderated by gender (Ghasemaghaei, 2020). The cognitive absorption perception of the females significantly increased when using a RSs that provided high levels of details. Males, on the other hand, have no differences in cognitive absorption perceptions irrespective of RSs type (Ghasemaghaei, 2020).

4.5 Research model and hypotheses development

The research model developed to empirically test the hypotheses in this research is shown in Figure 4.2. Prior studies have examined the TAM with the inclusion of constructs such as prior experience and training with technology (Davis, 1989), trust (Wang and Benbasat, 2005), gender (Gefen and Straub, 1997), loyalty (Jarvenpaa et al., 2000), playfulness (Li, 2015), and flow (Wang et al., 2015) to account for user characteristics and considering the nature of the online environments. Several scholars also integrated TAM and flow theory and found it an important predictor of behavioural intentions (Wang et al., 2015, Li, 2015, Chang and Wang, 2008, Lu et al., 2009). Lu et al. (2009) highlighted the importance of intrinsic and extrinsic motivations in instant messaging (IM) adoptions. The study found that in addition to IM being seen as utilitarian and user-friendly, users desire an enjoyable and fun flow experience. Flow mediates the association between attitudinal factor as well as behavioural intentions and it also directly affects behavioural intentions (Chang and Wang, 2008). Li (2015) integrated the Elaboration Likelihood Model (ELM) and the TAM with flow theory constructs and found a stronger effect of argument quality as well as source quality on attitude and through it on behavioural intentions, compared to playfulness. Wang et al. (2015) studied the user experience in the Chinese tourism industry and concluded that both motivation and flow components are responsible for developing behavioural intentions. Considering the nature of online shopping, the research model integrates the TAM with cognitive absorption, which is commonly referred to as a flow construct as a measure of holistic experience (Balakrishnan and Dwivedi, 2021), to estimate the holistic experience of RSs.

The specific factors of the model and related hypotheses are detailed below.

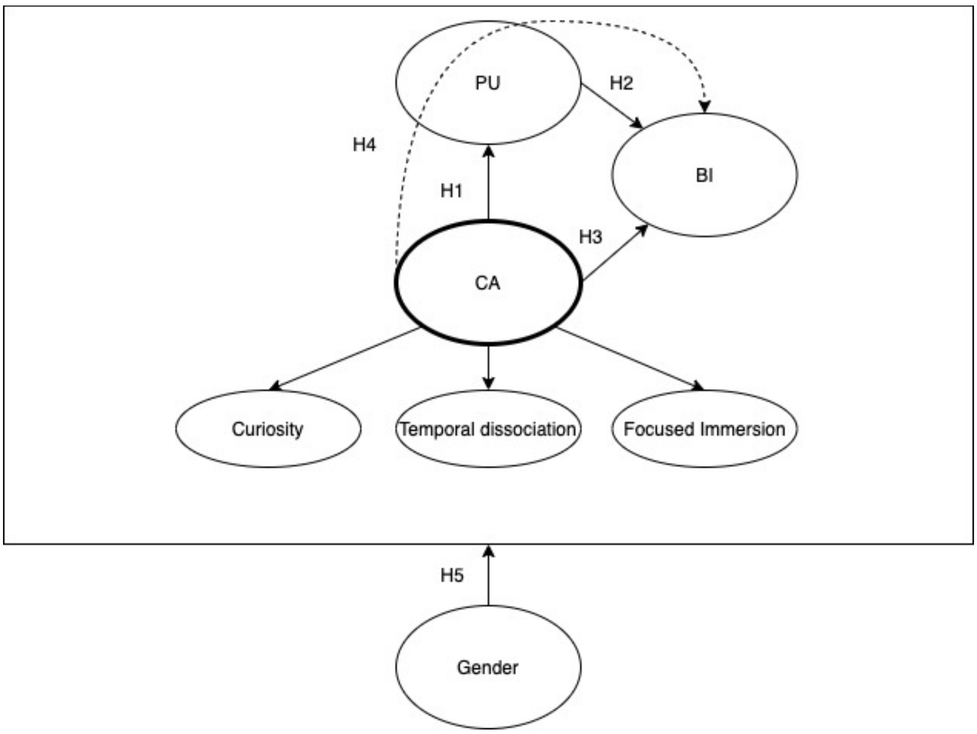


FIGURE 4.2 RESEARCH MODEL

Note: PU: Perceived usefulness, CA: Cognitive absorption, BI: Behavioural Intentions
CA a is second order construct. The dotted line indicates the path of indirect effect (CA -> PU -> BI).

4.5.1 The relation between cognitive absorption and perceived usefulness

The association between cognitive absorption and perceived usefulness is a consequence of the idea of self-perception (Bem, 1972), wherein people strive to rationalise their behaviour and therefore decrease cognitive dissonance (i.e., attitudes, conflict beliefs, or behaviour) (Shang et al., 2005). cognitive absorption establishes an individual's beliefs that technology is instrumental or useful for the accomplishment of tasks (Agarwal and Karahanna, 2000). Online purchasing depends on users experience of cognitive absorption, which positively relates to online shopping attitude and thus to actual behaviour (Shang et al., 2005). According to the theories discussed above, it is believed that whilst an individual experiences pleasure and gratification from engaging with technological activities in a cognitive absorption state, their conflicts are decreased in a pleasurable and enjoyable state, and they would perceive shopping with RSs as useful. Based on the above arguments, it is hypothesized that:

H1. Shoppers' cognitive absorption has a direct and positive effect on the perceived usefulness of RSs. (CA -> PU)

4.5.2 The relation between perceived usefulness and behavioural intentions to reuse RSs

Drawing from the TAM model, the perceived usefulness of RSs has a direct impact on shoppers' behavioural intentions to reuse RSs (Davis, 1989). The underlying assumption of the PU-BI relationship can be further explained based on the IS continuance model (Bhattacherjee, 2001), which argued that IS continuance usage intentions depend on the satisfaction of a user, the extent of users' expectation-confirmation and post-adoption expectations in the form of perceived usefulness (Bhattacherjee, 2001). The perceived usefulness of IS was central to the use of both pre- and post-adoption stages that significantly affected continued IS use by individuals (Bhattacherjee, 2001). Based on these models, it is hypothesized that:

H2. Shoppers' perceived usefulness of RSs has a positive effect on behavioural intentions to reuse RSs (PU -> BI)

4.5.3 The relation between cognitive absorption and behavioural intentions to reuse RSs

The association between cognitive absorption and behavioural intention to reuse RSs is based on the concept that flow can influence continuation intentions (Chang and Zhu, 2012). Consumers experiencing cognitive absorption while utilising a website to purchase online may intend to return to the website in the future (Wu and Huang, 2013, Shang et al., 2005, Hsu and Lu, 2004). Consumers who experience greater intrinsic enjoyment are frequently keener to return (Koufaris, 2002). The consumers' positive experience becomes a significant incentive for revisiting the site (Webster and Ahuja, 2006). Increased user engagement contributes to a positive perspective to use the website in the future (Webster et al., 1993, Luna et al., 2002). Chandra et al. (2012) and Ghasemaghaei (2020) detected that CA positively influenced the intentions to use the respective IS. Jumaan et al. (2020) found CA to be the most resilient indicator of continuance intentions. Balakrishnan and Dwivedi (2021) found that CA positively and significantly influenced technology continuation intentions. Based on these arguments, it is hypothesized that:

H3. Shoppers' cognitive absorption has a direct and positive effect on behavioural intentions to reuse RSs. (CA -> BI)

4.5.4 The relation between cognitive absorption, perceived usefulness and behavioural intentions to reuse RSs

In this study, the relationships proposed between cognitive absorption, perceived usefulness and behavioural intentions indicates that there could be a mediation effect. No reliable evidence was identified on the mediation effect of perceived usefulness of RSs on the relation between cognitive absorption and behavioural intentions to reuse RSs. Based on these arguments, the hypothesis is posited as:

H4. Shoppers' perceived usefulness of RSs mediates the influence of cognitive absorption on behavioural intentions to reuse (CA -> PU -> BI)

4.5.5 The moderating effect of gender

Task orientation can refer to the completion of shopping tasks in the online shopping environment. That is, males are more likely than females to follow RSs without taking their content into account in detail, since they prefer to use efficient tools in order to complete the purchasing task (Doong and Wang, 2011). Females, on the other hand, are more comprehensive processors while making judgments and show greater sensitivity to information (Cafferata and Tybout, 1989). Females are thus most likely to examine more carefully if the recommendation provided by RSs is helpful in comparison to men for the shopping task. It is vital to figure out the differential impact of gender on buying decisions and design gender-sensitive RSs. It is hypothesized that:

H5. The strength of the relationship between the constructs is significantly different in males and females.

4.6 METHODOLOGY

4.6.1 DATA COLLECTION AND DESCRIPTIVE STATISTICS

An online survey of Australian residents was conducted using the Zoho survey tool (survey.zoho.com). The research utilized the availability (or convenience sampling) method (Mitchell and Jolley, 2012), the participants were recruited by Zoho. The following are the grounds for the use of the convenience sampling method: data may be collected quickly and frequently in an economical way (Hair et al., 2019a) and was important to reach the participants during the COVID-19 pandemic. A quota was imposed to try to get an even split of male/female respondents. The recruitment decisions were designed to balance the goals of producing a broad, unadulterated sample and keeping the costs manageable (Boas et al., 2020). The participants were asked if they have used RSs to purchase products on Amazon. Only individuals who indicated that they had used RSs to purchase at least one item in the last six months of responding were allowed to take part. The usable sample consisted of 452 active Australian online shoppers of Amazon with different age groups. The collected data was subject to acquiescence response bias, univariant outlier and multivariant outlier assessment (Podsakoff et al., 2003). 86 responses were deleted out of 452 usable and valid responses. Accordingly, only 366 of the responses were used for subsequent analysis. Table 4.2 shows the demographics of the respondents. Amazon shoppers comprised 49.7% male (N = 182) and 50.3% female (N = 184). 33.6% of participants had a bachelor degree as the highest educational level, 23.5% of participants had a certificate course, 10.7% of participants had a diploma, 25.1% had a master's degree, and 6.6% had a PhD degree. The participants have used the Internet on average for more than six years, purchased online for approximately four to five years, and used RSs for more than one year.

TABLE 4.2 DEMOGRAPHICS

Items		Frequency	%
Gender			
	Male	182	49.7
	Female	184	50.3
Age Group			
	Less than 20 years	16	4.4
	20-25 years	102	27.9
	26-35 years	104	28.4
	36-45 years	99	27
	Over 45 years	45	12.3
Marital Status			
	Single	156	42.6
	Married	191	52.2
	Widowed	1	0.3
	Divorced	10	2.7
	Other	8	2.2
Education			
	Certificate	86	23.5
	Diploma	39	10.7
	Bachelor Degree	123	33.6
	Master Degree	92	25.1
	Doctorate/PhD	24	6.6
	Other	2	0.5
Geographic Location			
	VIC	114	31.1
	NSW	122	33.3
	QLD	65	17.8
	WA	32	8.7
	SA	15	4.1
	TAS	7	1.9
	ACT	10	2.7
	NT	1	0.3

4.6.2 MEASURES

The instrument and scales used in this research were adopted from previously validated studies. The measurements used a 5-point

Likert rating scale system with endpoints “strongly disagree” (value of 1) to “strongly agree” (value of 5). The literature indicated that the 5-point scale is less complicated and increases reaction rate (Babakus and Mangold, 1992, Devlin et al., 1993, Hayes, 1992). It is also the most widely used scale in marketing research (Zikmund and Babin, 2013). Measures of perceived usefulness construct included nine items and were adopted from (Wang and Benbasat, 2005), cognitive absorption construct comprised five items for focused immersion, three items of curiosity, and five items of temporal dissociation and was adopted from (Zhu and Morosan, 2014). Measures of behavioural intentions construct included three items and were adopted from (Benlian et al., 2012).

4.6.3 Normality and common method bias test

A test of normality was performed using Kolmogorov–Smirnov (KS) normality tests (Lilliefors, 1967). The outcome of Kolmogorov–Smirnov (KS) normality tests revealed a non-normal distribution of the data. Next, the common method bias (CMB) was assessed. The absence of CMB should be verified in social sciences research administering survey methods (Podsakoff et al., 2003). CMB was evaluated by the inclusion of the marker variable, marital status, which is theoretically not linked to the dependent variable, using steps designated for PLS-SEM (Lindell and Whitney, 2001). Each construct in the structural model was evaluated with and without a marker variable as an exogenous variable. The results reveal that there was low method variance in the proposed model between the marker variable and the hypothesized variables. The significance of the relation between the variables did not change. Secondly, as guided by (Kock, 2015), a more conservative approach for CMB assessment using a full collinearity test based on the variance inflation factor (VIF) was also conducted to test the CMB. The test revealed that the full collinearity VIFs of all latent variables 1.000 to 2.398 and were lower than the threshold of 3.3 (Kock, 2015). These results suggested that this research is unlikely to suffer from CMB.

4.7 Data analysis

Statistical significance was analysed using PLS-SEM (SmartPLS v3.3.3) (Ringle et al., 2015, Hair et al., 2016). due to the presence of a higher-order construct and non-normal distribution of data Current research is exploratory and aims to assess moderation across multiple relationships making PLS-SEM the preferred method for this research (Hair et al., 2019b, Matthews, 2017). Also, PLS-SEM is regarded as a better choice when the data has non-normality issues (Hair et al., 2019b). The current software and algorithmic framework were adopted as they are more flexible, practical, comprehensible and user-friendly (Kazancoglu and Demir, 2021). Several scholars within their respective fields (e.g., management information systems, marketing, accounting, strategic management, operations) have published studies summarising PLS-SEM use and the main reasons provided for application of PLS-SEM include the data distribution, exploratory nature, use of formative indicators, and sample size (Hair et al., 2012, Hair et al., 2017, Al-Emran et al., 2018, Chin et al., 2020).

The study involves a reflective-reflective type higher-order construct, i.e., cognitive absorption The repeated indicators approach was adopted to estimate the model proposed in this paper (Becker et al., 2012). The repeated indicator approach simultaneously estimated all constructs instead of individually estimating lower-order and higher-order dimensions (Becker et al., 2012). It also avoided interpretive confusion by considering the whole nomological network (i.e., both the lower and higher-order constructs), which the two-stage approach does not consider (Becker et al., 2012). As recommended in (Sarstedt et al., 2019), “mode A” was used to estimate cognitive absorption. As per the guidelines of the approach, all the indicators of curiosity, focused immersion and temporal dissociation were simultaneously assigned to the higher-order construct (cognitive absorption). Next, the assessment of the measurement model was conducted.

4.7.1 Assessment of the measurement model

First, the outer loadings of the items were assessed. All the indicators except FI4, loaded more than the recommended value of 0.7 (Campbell and Fiske, 1959). According to Campbell and Fiske (1959), items loading below 0.7 should be dropped from the structure of the construct. As a result, FI4 was dropped. Average variance extracted (AVE) was used to assess the convergent validity. All the constructs obtained an AVE above the cut-off criterion of 0.5 (Hair et al., 2019b). AVE for cognitive absorption was computed as advised in (Sarstedt et al., 2019). Second, for internal consistency reliability, Cronbach’s alpha and composite reliability (CR) was evaluated. All the values of Cronbach’s alpha and composite reliability (CR) was found to be above the cut-off criterion of 0.7 (Hair et al., 2016). Cronbach’s alpha and composite reliability (CR) for cognitive absorption was computed as guided in (Sarstedt et al., 2019). Convergent validity and reliability were established (see Table 4.3).

TABLE 4.3 MEASUREMENT MODEL PARAMETERS

Constructs	α	CR	AVE
BI	0.878	0.925	0.804
CU	0.856	0.913	0.777
FI	0.852	0.898	0.647
TD	0.903	0.928	0.721
PU	0.923	0.936	0.618
CA*	0.895	0.934	0.824

Note: BI: Behavioural Intentions, CU: Curiosity, FI: Focused immersion, PU: Perceived usefulness, CA: Cognitive absorption, TD: Temporal dissociation

* is used for higher-order construct

A new criterion called Heterotrait–monotrait (HTMT) ratios method was applied to estimate the discriminant validity, as it involves a stringent assessment (Henseler et al., 2015). HTMT values for cognitive absorption was computed as guided in (Sarstedt et al., 2019). HTMT values (see Table 4.4) were within the cut-off criterion of 0.90 suggesting no significant discriminant validity issue (Hair et al., 2019b).

TABLE 4.4 DISCRIMINANT VALIDITY (HTMT RATIOS)

	BI	**CU**	**FI**	**PU**	**CA***	**TD**
BI						
CU	0.810					
FI	0.803	0.878				
PU	0.885	0.795	0.845			
CA*	0.756	-	-	0.728		
TD	0.694	0.843	0.783	0.662	-	

Note: BI: Behavioural Intentions, CU: Curiosity, FI: Focused immersion, PU: Perceived usefulness, CA: Cognitive absorption, TD: Temporal dissociation

*is used for higher-order construct.

Cross-loadings were also used to assess discriminant validity (Urbach and Ahlemann, 2010). Table 4.5 illustrates that each item has been loaded higher onto its designated construct than its respective cross loadings. Discriminant validity was deemed satisfactory. The measurement model analysis for the study was concluded. Next, the assessment of the structural model was conducted.

TABLE 4.5 LOADINGS AND CROSS-LOADINGS

Constructs	**Items**	**Loadings and Cross-loadings**				
		BI	CU	FI	TD	PU
BI	BI1	**0.883**	0.642	0.627	0.545	0.711
	BI2	**0.899**	0.628	0.668	0.546	0.719
	BI3	**0.908**	0.620	0.625	0.577	0.715
CU	CU1	0.638	**0.900**	0.685	0.663	0.645
	CU2	0.621	**0.882**	0.652	0.622	0.632

	CU3	0.599	**0.862**	0.698	0.679	0.598
FI	FI1	0.655	0.695	**0.873**	0.605	0.703
	FI2	0.650	0.681	**0.900**	0.646	0.707
	FI3	0.627	0.685	**0.881**	0.619	0.695
	FI5	0.564	0.634	**0.846**	0.603	0.595
TD	TD1	0.594	0.657	0.693	**0.830**	0.631
	TD2	0.443	0.581	0.543	**0.844**	0.437
	TD3	0.547	0.620	0.610	**0.864**	0.510
	TD4	0.495	0.639	0.565	**0.843**	0.479
	TD5	0.545	0.654	0.582	**0.864**	0.523
PU	PU1	0.591	0.526	0.548	0.456	**0.764**
	PU2	0.618	0.504	0.583	0.446	**0.781**
	PU3	0.632	0.514	0.563	0.405	**0.780**
	PU4	0.628	0.528	0.564	0.443	**0.800**
	PU5	0.644	0.583	0.636	0.516	**0.789**
	PU6	0.615	0.577	0.678	0.563	**0.749**
	PU7	0.647	0.628	0.651	0.561	**0.804**
	PU8	0.633	0.605	0.660	0.495	**0.815**
	PU9	0.626	0.535	0.562	0.408	**0.789**

Note: BI: Behavioural Intentions, CU: Curiosity, FI: Focused immersion, TD: Temporal dissociation, PU: Perceived usefulness. The bold values are the indicator loading values corresponding to the constructs and others are cross-loading values.

4.7.2 Assessment of the structural model

The structural model aims at estimating the degree of significance of the path coefficient. To estimate this, a bootstrapping routine of 5000 sub-samples was performed (Hair et al., 2016). The path coefficients, t-values and significance of the paths are shown in Table 4.6. Figure 4.3 illustrates the output of the bootstrapping routine executed of the complete sample to establish a relationship between the latent constructs. The result revealed that all hypotheses were supported at a level $p < 0.001$ (see Table 4.6). There was a significant positive correlation between cognitive absorption and perceived usefulness, therefore supporting hypothesis *H1*. Perceived usefulness had a significant positive correlation with BI. The result confirmed the support for *H2*. Cognitive absorption also had a significant and positive relation with BI, empirically supporting *H3*.

4.7.3 Mediation analysis

The study used bootstrapping method to test the significance of the indirect effect. Bootstrapping allows the confidence interval to be estimated for factor stability. The bootstrapping method is superior to the Sobel test, especially regarding types I and II error rates (Zhao et al., 2010, Shrout and Bolger, 2002). The bootstrapping method showed that the indirect effect of cognitive absorption on behavioural intentions to reuse RSs through perceived usefulness is significant (see Table 4.6). Both direct and indirect effects of cognitive absorption on BI have significant values resulting in complementary mediation (Zhao et al., 2010). VAF method was also used to determine the magnitude of mediation (Hair et al., 2016). VAF = indirect effect/ total effect = (0.764*0.551)/0.743 = 0.56. Based on the criterion, $0.2 \leq VAF \leq 0.8$ is considered partial mediation (Hair et al., 2016). VAF method confirmed perceived usefulness partially mediates the relationship between cognitive absorption and behavioural intentions to reuse RSs in the complete sample. *H4* is supported based on the result of the mediation analysis.

TABLE 4.6 STRUCTURAL MODEL ASSESSMENT RESULTS

	β	**T Values**	**P Values**
CA -> PU*	0.764	30.911	0.000
PU -> BI*	0.551	9.183	0.000
CA -> BI*	0.743	27.195	0.000
Specific indirect effect			
CA -> PU -> BI*	0.421	8.695	0.000

Note: CA: Cognitive absorption, PU: Perceived usefulness, BI: Behavioural Intentions
* Sig. at $p < 0.001$

4.7.4 Coefficient of determinants (R^2) and predictive relevance (Q^2)

The coefficient of determinants (R^2) for two endogenous variables in this study, i.e., perceived usefulness was 0.583, and behavioural intentions to reuse RSs was 0.679. It indicated a moderate predictive accuracy for perceived usefulness (with 58.3% variations in perceived usefulness being explained by cognitive absorption) and behavioural intentions to reuse RSs (with 67.9% variations in perceived usefulness being explained by perceived usefulness and cognitive absorption) (Hair et al., 2019b). Predictive relevance (Q^2) was obtained in SmartPLS 3 by running a blindfolding procedure with an omission distance of seven. The Q^2 was 0.539 for behavioural intentions to reuse RSs, which is above the cut-off criterion of 0.35 indicating high out-of-sample predictive relevance (Hair et al., 2019b). The predictive power of the model is said to be acceptable and accurate according to the guidelines in Hair et al. (2019b).

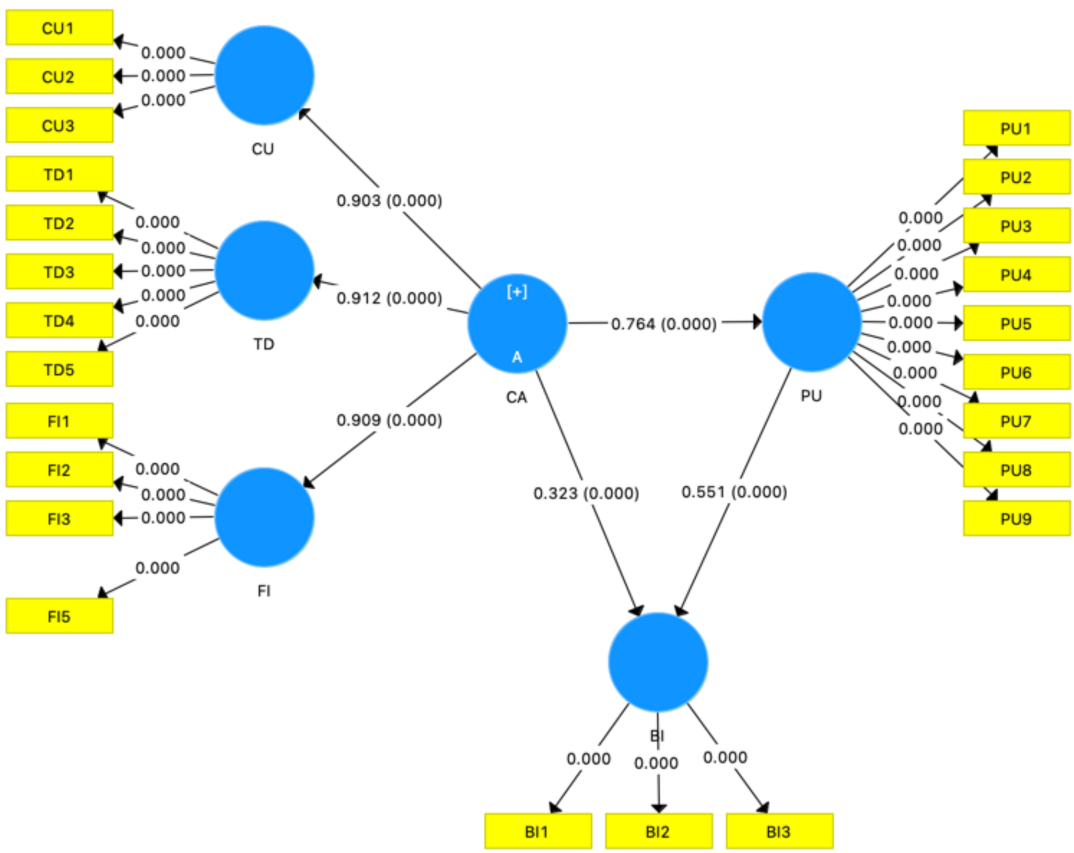


FIGURE 4.3 MEASUREMENT MODEL (COMPLETE SAMPLE)

Note: BI: Behavioural Intentions, CU: Curiosity, FI: Focused immersion, PU: Perceived usefulness, CA: Cognitive absorption, TD: Temporal dissociation
(0.000) indicates all factor weights, indicator loadings and direct paths are (Sig. at $p < 0.001$).

4.7.5 Multi-group analysis

The possible moderating effect of gender was examined using multi-group analysis (PLS-MGA) (Henseler, 2012). Prior to conducting the multi-group analysis, MICOM was estimated to check measurement invariance to ensure meaningful results (Henseler et al., 2016). MICOM is a 3-step process. These steps check the configural invariance, compositional invariance, and equal mean and equal variance (Henseler et al., 2016). According to the guidelines, the establishment of configural invariance and compositional invariance i.e., partial invariance is sufficient to qualify for PLS-MGA. The first Step of MICOM was attained by verifying that item, data treatment, and algorithm settings per model of measurement in male and female groups was identical. A permutation procedure was run to assess the results of the second and third steps of MICOM. The second step was to determine whether a composite correlates with male and female groups, which can be confirmed by assessing if the original correlation "C" was equal to 5% quantile of Cu. In this case, compositional invariance was established. Finally, the third step was to assess whether the difference in the permutation-based confidence interval for mean and variance values contained zero (Henseler et al., 2016). In this case, full invariance was attained (see Table 4.7).

TABLE 4.7 MICOM RESULTS

Step 1		**Step 2**			**Step 3(a)**			**Step 3(b)**			**Measurement Invariance**
	Configurational Invariance	C = 1	5% quantile of Cu	Compositional Invariance	Differences (= 0)	Confidence Interval (CIs) - Mean Value	Equal mean value	Difference (= 0)	Confidence Interval (CIs) - Variance Value	Equal variance value	
BI	Yes	1	1	Yes	0.312	[-0.199; 0.201]	No	0.194	[-0.322; 0.308]	Yes	Full
CA	Yes	1	1	Yes	0.417	[-0.206; 0.202]	No	0.268	[-0.278; 0.275]	Yes	Full
PU	Yes	1	1	Yes	0.311	[-0.207; 0.199]	No	0.217	[-0.337; 0.330]	Yes	Full

Note: CA: Cognitive absorption, PU: Perceived usefulness, BI: Behavioural Intentions

Following the establishment of full measurement invariance, PLS-MGA was performed using a 5000-bootstrapping resampling procedure to compare male and female samples. The PLS-MGA bootstrapping result revealed that that the effect of cognitive absorption is significantly different across gender. The direct effect of cognitive absorption on behavioural intentions to reuse RSs was significant in the case of females but was insignificant in the case of males. The rest of the paths were significant in both the samples (see Table 4.8). Figure 4.4 illustrates the output of the PLS-MGA of male and female samples executed to establish a relationship between the latent constructs.

TABLE 4.8 PLS-MGA BOOTSTRAPPING RESULT

	Male (n = 182)			Female (n = 184)		
Paths	**β**	**t-Values**	**p-Values**	**β**	**t-Values**	**p-Values**
CA -> PU	0.813	25.810	0.000	0.685	16.841	0.000
PU -> BI	0.731	9.676	0.000	0.429	5.891	0.000
CA -> BI	0.124	1.559	0.119	0.465	6.157	0.000
Specific indirect effect						
CA -> PU -> BI	0.594	9.509	0.000	0.294	5.333	0.000

Note: BI: Behavioural Intentions, PU: Perceived usefulness, CA: Cognitive absorption
(0.000) indicates (Sig. at $p < 0.001$)

Further VAF method was used to identify the difference in the indirect effect of cognitive absorption across gender. In case of female, VAF = indirect effect/ total effect = (0.685*0.429)/0.759 = 0.38. Based on the criterion, 0.2 ≤ VAF ≤ 0.8 is considered partial mediation (Hair et al., 2016). Using the VAF method, the study found perceived usefulness partially mediates the relationship between cognitive absorption and BI in the case of females. In the case of males, perceived usefulness also mediated the effect of cognitive absorption and behavioural intentions to reuse RSs (see Table 4.8). VAF method was used to determine the magnitude of mediation (Hair et al., 2016). VAF = indirect effect/ total effect = (0.813*0.731)/0.718 = 0.82. Based on the criterion, VAF ≥ 0.8 is considered full mediation (Hair et al., 2016). VAF method revealed perceived usefulness fully mediates the relationship between cognitive absorption and behavioural intentions to reuse RSs in the case of males.

TABLE 4.9 RESULTS OF THE WELCH-SATTERTHWAITE TEST

Paths	Path Coefficients-diff	t-Values	p-Values
CA -> PU*	0.128	2.49	0.014
PU -> BI*	0.302	2.889	0.004
CA -> BI*	-0.341	3.114	0.002
Specific indirect effect			
CA -> PU -> BI**	0.300	3.617	0.000

Note: BI: Behavioural Intentions PU: Perceived usefulness, CA: Cognitive absorption
* Sig at p < 0.05, ** Sig at p < 0.001

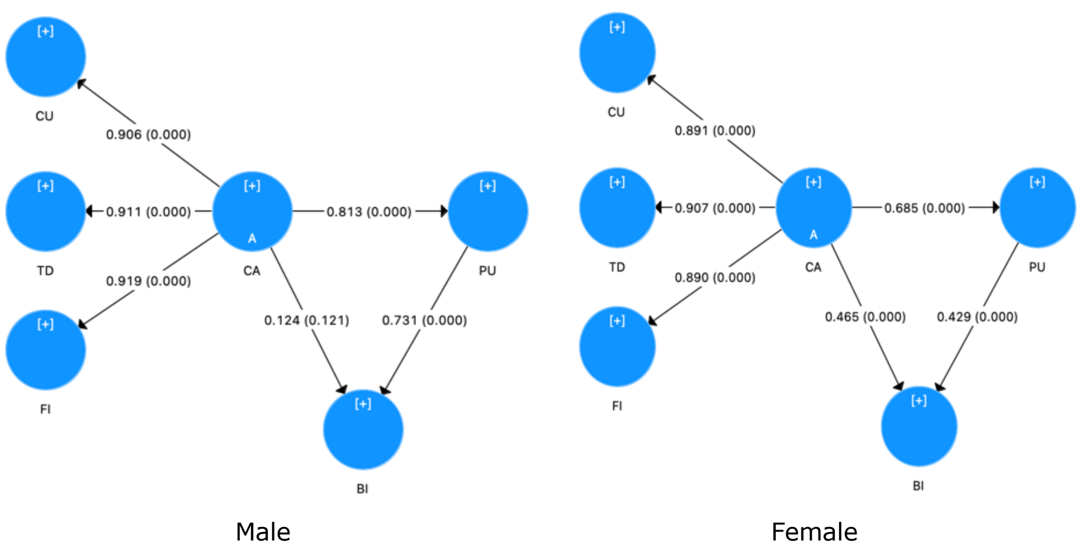


FIGURE 4.4 MEASUREMENT MODEL (MALE AND FEMALE SAMPLE)

Note: (0.000) indicates (Sig. at p < 0.001)

The difference between men and women was estimated by the Welch-Satterthwaite test (Hair et al., 2016). Table 4.9 illustrates the range in the path coefficients of both data sets (male and female). The result revealed a significant difference between two data sets across all paths in the proposed model, supporting *H5*. Welch-Satterthwaite test also provided support for the result of mediation analysis performed between two data sets (male and female) using the VAF method.

4.7.6 Importance-performance map analysis

The Importance-Performance Map Analysis (IPMA) provides an analysis dimension that takes into consideration the mean values of the latent variables' scores and extends to the reported PLS-SEM results of path coefficient estimates (Ringle and Sarstedt, 2016). The IPMA, in particular, checks the total impacts, which are important for constructing a construct with their performance indicated by their average latent variable scores. The aim is to recognize the elements that are most significant in the construct and thus have a high overall impact on the construct but low yield, i.e., the average latent variable scores are low (Ringle and Sarstedt, 2016).

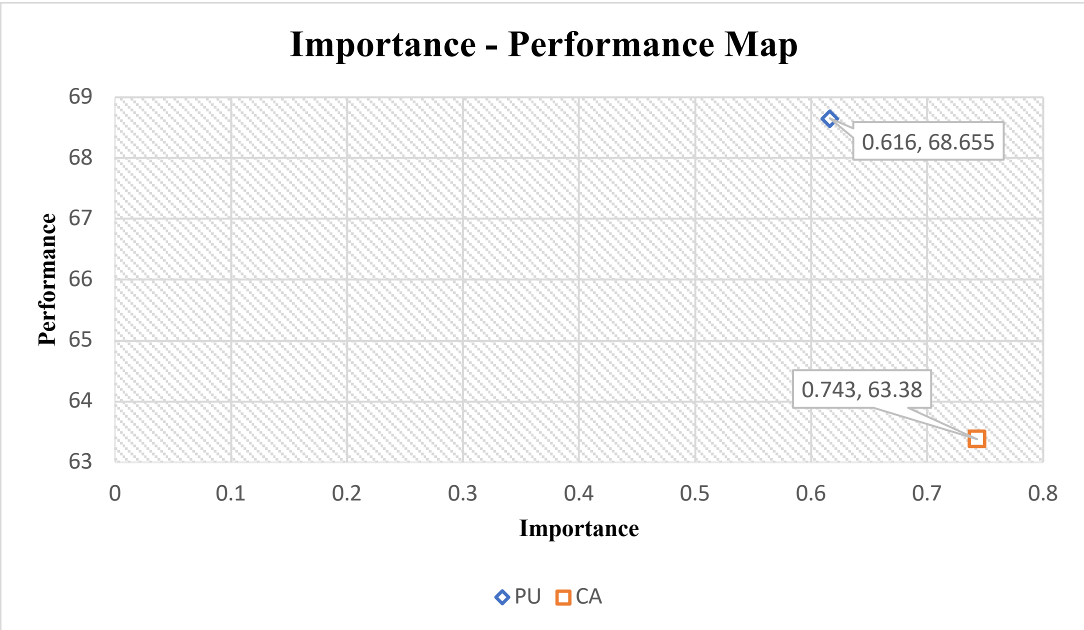


FIGURE 4.5 RESULT OF IMPORTANCE-PERFORMANCE MAP ANALYSIS

Note: PU: Perceived usefulness, CA: Cognitive absorption

The findings of the IPMA are based on two dimensions (i.e., importance and performance) (see Figure 4.5), which is essential to prioritize management activities (Hock et al., 2010). In this study, the IPMA shows that the importance of the elements cognitive absorption and perceived usefulness is high because it has a total effect of 0.743 and 0.616, respectively. In fact, the performance of cognitive absorption and perceived usefulness are 63.38 and 68.65, respectively. It is worth noting that aspects related to cognitive absorption should be given more priority to further increase the performance of behavioural intentions to reuse RSs because it was of the greatest importance, but it was low in performance in comparison to perceived usefulness.

4.8 Discussion

This study responds to the call for more empirical research by Xiao and Benbasat (2007), in line of RSs research. This study integrated TAM and flow theory to determine how cognitive absorption affects shoppers' behavioural intentions to reuse RSs. The study further examined the moderating effect of gender. PLS-IPMA was also performed to identify additional findings.

The findings on cognitive absorption indicated its significance not only in explaining the behavioural intentions but also the shoppers' perceived usefulness of recommender systems. Cognitive absorption increases the perceived usefulness of the recommender system and behavioural intentions to reuse RSs. It indicated that as the shoppers' level of cognitive absorption increases, the RSs usefulness belief is likely to be greatly positive. The finding is consistent with those of (Lee, 2018, Perumal et al., 2021, Shang et al., 2005). It was also found that cognitive absorption increases intentions to reuse RSs. The current study sustained the view of Balakrishnan and Dwivedi (2021) that cognitive absorption can enhance technology continuation intentions.

The present study found that the perceived usefulness of RSs is positively linked with shoppers' behavioural intentions to reuse RSs. Although the examination of this relationship is not novel, the effects of these two constructs are unknown when TAM is integrated with flow theory to examine shoppers' behavioural intentions to reuse RSs.

The result of moderation analysis using PLS-MGA bootstrapping results and Welch-Satterthwaite test revealed that the strength of the relationship between all the variables was significantly different in males and females. It was also identified that cognitive absorption did not have a significant direct effect on males' behavioural intentions to reuse RSs, which was consistent with (Ghasemaghaei, 2020). Another interesting finding was the result of mediation analysis that showed perceived usefulness could significantly induce an indirect effect between cognitive absorption and behavioural intentions to reuse RSs. The multi-group analysis revealed that perceived usefulness fully mediates the relation between cognitive absorption and behavioural intentions to reuse RSs in the case of males but only partially mediates in the case of females.

The results obtained from PLS-IPMA also indicated that cognitive absorption was more important than perceived usefulness. This was logical given the assumption that when interacting with RSs, shoppers' pleasure and enjoyment were more important than believe that using RSs would enhance the achievement of their shopping tasks. Cognitive absorption acting as a resilient predictor of behavioural intentions to reuse RSs was consistent with the existing literature in information systems (Jumaan et al., 2020, Balakrishnan and Dwivedi, 2021).

4.9 Limitation and future research

The findings of this research are limited by the use of a cross-sectional survey design. It is suggested that the association of these factors is explored with a longitudinal design in future studies. The current study was restricted to Amazon as the e-vendor. Further studies may be conducted using a less famous e-vendor that uses RSs, to analyse the causal relationships between factors presented in this study. This study used the method of availability (or convenience sampling) to locate respondents, and the research results may not be generalized to the entire population. The random sampling method could be used in future research to obtain representative data to verify that the results of this study could still be sustained. The data for this research was collected only in Australia and, consequently, to better understand and generalisation of the current research findings future research across different countries is encouraged.

4.10 Implications

This research adds significant contributions to the literature by empirically determining different influences of cognitive absorption and perceived usefulness on shoppers' intentions to reuse RSs. The research shows that a user's holistic experience, as measured by cognitive absorption, has a strong direct influence on behavioural intentions in the context of recommender systems. There has been little research on the impact of holistic consumer experience on behavioural intentions to reuse recommender systems, resulting in a lack of consensus, especially regarding the direct impact of holistic consumer experience on behavioural intentions to reuse RSs. This research emphasises the need of analysing intentions in relation to cognitive absorption in order to gain a more complete understanding of cognitive absorption's effect on behavioural intentions.

The investigation of moderation effects caused by shopper gender differences was also another important contribution of this research. Although some previous studies examined the role of gender, the effects of gender were not determined when the role of cognitive absorption and the reuse intentions was estimated. This study precisely estimated the moderation effect of gender across all paths proposed in the model, including indirect paths. The result of the moderation analysis demonstrated that the strength of correlation between the variables was significantly different in males and females. The finding of this study also indicated that cognitive absorption directly affected reuse intentions in females but not in males. The study complements RSs literature by providing a holistic understanding of how and why RSs reuse affects decision-making.

From a practical standpoint, the research suggests that e-vendors should pay attention to consumers' overall experience with RSs. E-vendor managers, in particular, must comprehend the key areas on which they must concentrate their efforts in order to improve the overall experience. The findings demonstrate that high levels of cognitive absorption in RSs are associated with an interaction dominated by curiosity, focused immersion, and temporal dissociation. The research suggests that e-vendors using RSs should also focus on improving RSs usefulness. RSs should provide particular attention to the quality of the information recommended and e-vendors should establish adequate quality control mechanisms to improve shoppers’ decision-making process. To enhance customer loyalty and ensure shoppers' needs are met, RSs should provide accurate, adequate and reliable information.

In terms of methodology, this research is among the first to utilize PLS-MGA to investigate the moderating effect of gender on the shoppers’ intentions to reuse RSs. The moderation analysis performed in this research recommends technology managers to incorporate gender-sensitive RSs. This is a novel study to employ latest techniques such as PLS-IPMA to identify the importance of elements in predicting shoppers' reuse intentions. More comprehensive knowledge of all factors importance and performance was demonstrated in additional findings provided by assessing PLS-IPMA results.

4.11 Conclusion

This research investigated the role of holistic experience on consumer behavioural intention to reuse recommender systems. The shopper's holistic experience with RSs in this research was denoted as cognitive absorption. The research used the technology acceptance model and flow theory to extend previous recommender systems research. The research demonstrated the need of improving the shopper's cognitive absorption to enhance their intentions to reuse RSs. This study contributes to the information system and consumer behaviour literature in the following perspectives. The present research fills an important gap in the RSs literature by placing special emphasis on explaining the effect of shopper's holistic experience with RSs on their intentions to reuse RSs. The findings enriched the literature about cognitive absorption and offered insights on the determinants of shoppers' intentions to reuse RSs and its effect on decision outcomes. The findings also revealed that cognitive absorption significantly influences behavioural intentions to reuse in females than males. These findings are timely and critical for the success of recommender systems.

4.12 References

ABUMALLOH, R. A., IBRAHIM, O. & NILASHI, M. 2020. Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce. *Technology in Society,* 61**,** 101253.

AGARWAL, R. & KARAHANNA, E. 2000. Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS quarterly***,** 665-694.

AGARWAL, R., SAMBAMURTHY, V. & STAIR, R. M. Cognitive Absorption and The Adoption Of New Information Technologies. Academy of Management Proceedings, 1997. Academy of Management Briarcliff Manor, NY 10510, 293-297.

AL-EMRAN, M., MEZHUYEV, V. & KAMALUDIN, A. PLS-SEM in information systems research: a comprehensive methodological reference. International Conference on Advanced Intelligent Systems and Informatics, 2018. Springer, 644-653.

ASHRAF, M., AHMAD, J., SHARIF, W., RAZA, A. A., SALMAN SHABBIR, M., ABBAS, M. & THURASAMY, R. 2020. The role of continuous trust in usage of online product recommendations. *Online Information Review,* 44**,** 745-766.

BABAKUS, E. & MANGOLD, W. G. 1992. Adapting the SERVQUAL scale to hospital services: an empirical investigation. *Health services research,* 26**,** 767.

BALAKRISHNAN, J. & DWIVEDI, Y. K. 2021. Role of cognitive absorption in building user trust and experience. *Psychology & Marketing,* 38**,** 643-668.

BECKER, J.-M., KLEIN, K. & WETZELS, M. 2012. Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models. *Long Range Planning,* 45**,** 359-394.

BEM, D. J. 1972. Self-perception theory. *Advances in experimental social psychology.* Elsevier.

BEM, S. L. 1981. Gender schema theory: A cognitive account of sex typing. *Psychological review,* 88**,** 354.

BENLIAN, A., TITAH, R. & HESS, T. 2012. Differential Effects of Provider Recommendations and Consumer Reviews in E-Commerce Transactions: An Experimental Study. *Journal of Management Information Systems,* 29**,** 237-272.

BHARATI, P. & CHAUDHURY, A. 2004. An empirical investigation of decision-making satisfaction in web-based decision support systems. *Decision support systems,* 37**,** 187-197.

BHATTACHERJEE, A. 2001. Understanding information systems continuance: An expectation-confirmation model. *MIS quarterly,* 25**,** 351-370.

BOAS, T. C., CHRISTENSON, D. P. & GLICK, D. M. 2020. Recruiting large online samples in the United States and India: Facebook, Mechanical Turk, and Qualtrics. *Political Science Research and Methods,* 8**,** 232-250.

CAFFERATA, P. & TYBOUT, A. M. 1989. Gender differences in information processing: a selectivity interpretation. *Cognitive and Affective Responses to Advertising.* Lexington Books.

CAMPBELL, D. T. & FISKE, D. W. 1959. Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological bulletin,* 56**,** 81-105.

CHANDRA, S., SRIVASTAVA, S. & THENG, Y.-L. 2009. Role of cognitive absorption and trust for collaboration in virtual world. *PACIS 2009 Proceedings***,** 82.

CHANDRA, S., SRIVASTAVA, S. C. & THENG, Y.-L. 2012. Cognitive absorption and trust for workplace collaboration in virtual worlds: An information processing decision making perspective. *Journal of the Association for Information Systems,* 13.

CHANG, H. H. & WANG, I. C. 2008. An investigation of user communication behavior in computer mediated environments. *Computers in Human Behavior,* 24**,** 2336-2356.

CHANG, Y. P. & ZHU, D. H. 2012. The role of perceived social capital and flow experience in building users' continuance intention to social networking sites in China. *Computers in Human Behavior,* 28**,** 995-1001.

CHIN, W., CHEAH, J.-H., LIU, Y., TING, H., LIM, X.-J. & CHAM, T. H. 2020. Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. *Industrial Management & Data Systems,* 120**,** 2161-2209.

CHOOPRAYOON, V., FUNG, C. C. & DEPICKERE, A. A. TECTAM, A modified technology acceptance model to assess E-commerce technologies adoption by Thai SME. TENCON 2007-2007 IEEE Region 10 Conference, 2007. IEEE, 1-4.

CLAISSE, G. & ROWE, F. 1987. The telephone in question: Questions on communication. *Computer Networks and ISDN Systems,* 14**,** 207-219.

CSIKSZENTMIHALYI, M. & CSIKZENTMIHALY, M. 1990. Flow: The psychology of optimal experience. *Journal of Leisure Research,* 24**,** 93-94.

CYR, D. & BONANNI, C. 2005. Gender and website design in e-business. *International Journal of Electronic Business,* 3**,** 565-582.

DA SILVA, E. Q., CAMILO-JUNIOR, C. G., PASCOAL, L. M. L. & ROSA, T. C. 2016. An evolutionary approach for combining results of recommender systems techniques based on collaborative filtering. *Expert Systems with Applications,* 53**,** 204-218.

DAVIS, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly,* 13**,** 319-340.

DEVLIN, S. J., DONG, H. & BROWN, M. 1993. Selecting a scale for measuring quality. *Marketing research,* 5.

DOONG, H. S. & WANG, H. C. 2011. Do males and females differ in how they perceive and elaborate on agent-based recommendations in Internet-based selling? *Electronic Commerce Research and Applications,* 10**,** 595-604.

EKSTRAND, M. D., TIAN, M., AZPIAZU, I. M., EKSTRAND, J. D., ANUYAH, O., MCNEILL, D. & PERA, M. S. All the cool kids, how do they fit in?: Popularity and demographic biases in recommender evaluation and effectiveness. Conference on Fairness, Accountability and Transparency, 2018. PMLR, 172-186.

GEFEN, D. & STRAUB, D. W. 1997. Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS quarterly***,** 389-400.

GHASEMAGHAEI, M. 2020. The impact of in-depth online recommendation agents on consumer disorientation and cognitive absorption perceptions. *Behaviour & Information Technology,* 39**,** 414-430.

GUO, Y. M. & RO, Y. K. 2008. Capturing flow in the business classroom. *Decision Sciences Journal of Innovative Education,* 6**,** 437-462.

HAIR, J., HOLLINGSWORTH, C. L., RANDOLPH, A. B. & CHONG, A. Y. L. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*.

HAIR, J. F., PAGE, M. & BRUNSVELD, N. 2019a. *Essentials of business research methods*, Routledge.

HAIR, J. F., RISHER, J. J., SARSTEDT, M. & RINGLE, C. M. 2019b. When to use and how to report the results of PLS-SEM. *European business review*.

HAIR, J. F., SARSTEDT, M., RINGLE, C. M. & MENA, J. A. 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science,* 40**,** 414-433.

HAIR, J. J. F., HULT, G. T. M., RINGLE, C. & SARSTEDT, M. 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage publications.

HAMPTON-SOSA, W. & KOUFARIS, M. 2005. The effect of web site perceptions on initial trust in the owner company. *International Journal of Electronic Commerce,* 10**,** 55-81.

HÄUBL, G. & TRIFTS, V. 2000. Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing science,* 19**,** 4-21.

HAYES, B. E. 1992. *Measuring Customer Satisfaction: Development and Use of Questionnaires,* Milwaukee, WI, ASQC Quality Press.

HENSELER, J. 2012. PLS-MGA: A non-parametric approach to partial least squares-based multi-group analysis. *Challenges at the interface of data analysis, computer science, and optimization.* Springer.

HENSELER, J., RINGLE, C. M. & SARSTEDT, M. 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science,* 43**,** 115-135.

HENSELER, J., RINGLE, C. M. & SARSTEDT, M. 2016. Testing measurement invariance of composites using partial least squares. *International Marketing Review,* 33**,** 405-431.

HOCK, C., RINGLE, C. M. & SARSTEDT, M. 2010. Management of multi-purpose stadiums: Importance and performance measurement of service interfaces. *International Journal of Services Technology and Management,* 14**,** 188-207.

HOFFMAN, D. L. & NOVAK, T. P. 1996. Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations. *Journal of Marketing,* 60**,** 50-68.

HSU, C.-L. & LU, H.-P. 2004. Why do people play on-line games? An extended TAM with social influences and flow experience. *Information & management,* 41**,** 853-868.

HUANG, Y.-C., CHANG, L. L., YU, C.-P. & CHEN, J. 2019. Examining an extended technology acceptance model with experience construct on hotel consumers' adoption of mobile applications. *Journal of Hospitality Marketing & Management,* 28**,** 957-980.

HWANG, Y. 2010. The moderating effects of gender on e-commerce systems adoption factors: An empirical investigation. *Computers in Human Behavior,* 26**,** 1753-1760.

JARVENPAA, S. L., TRACTINSKY, N. & VITALE, M. 2000. Consumer trust in an Internet store. *Information technology and management,* 1**,** 45-71.

JIA, R., HARTKE, H. & PEARSON, J. 2007. Can computer playfulness and cognitive absorption lead to problematic technology usage? *ICIS 2007 Proceedings***,** 22.

JUGOVAC, M. & JANNACH, D. 2017. Interacting with Recommenders—Overview and Research Directions. *ACM Trans. Interact. Intell. Syst.,* 7**,** Article 10.

JUMAAN, I. A., HASHIM, N. H. & AL-GHAZALI, B. M. 2020. The role of cognitive absorption in predicting mobile internet users' continuance intention: An extension of the expectation-confirmation model. *Technology in Society,* 63**,** 101355.

KAZANCOGLU, I. & DEMIR, B. 2021. Analysing flow experience on repurchase intention in e-retailing during COVID-19. *International Journal of Retail & Distribution Management,* ahead-of-print.

KIM, E. 2021. In-store shopping with location-based retail apps: perceived value, consumer response, and the moderating effect of flow. *Information Technology and Management,* 22**,** 83-97.

KOCK, N. 2015. Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec),* 11**,** 1-10.

KOMIAK, S. Y. X. & BENBASAT, I. 2006. The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly,* 30**,** 941.

KORZAAN, M. L. 2003. Going with the Flow: Predicting Online Purchase Intentions. *Journal of Computer Information Systems,* 43**,** 25-31.

KOUFARIS, M. 2002. Applying the technology acceptance model and flow theory to online consumer behavior. *Information systems research,* 13**,** 205-223.

KULVIWAT, S., BRUNER II, G. C., KUMAR, A., NASCO, S. A. & CLARK, T. 2007. Toward a unified theory of consumer acceptance technology. *Psychology & Marketing,* 24**,** 1059-1084.

KUMAR, N. & BENBASAT, I. 2006. The influence of recommendations and consumer reviews on evaluations of websites.(Research Note). *Information Systems Research,* 17**,** 425.

LEE, H. 2018. Intrinsic and extrinsic motivations affecting impulse-buying tendency in mobile shopping. *Social Behavior and Personality: an international journal,* 46**,** 683-694.

LI, C.-Y. 2015. The effects of source credibility and argument quality on employees' responses toward information system usage. *Asia Pacific Management Review,* 20**,** 56-64.

LI, N. & KIRKUP, G. 2007. Gender and cultural differences in Internet use: A study of China and the UK. *Computers & Education,* 48**,** 301-317.

LI, S. S. & KARAHANNA, E. 2015. Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the Association for Information Systems,* 16**,** 72.

LILLIEFORS, H. W. 1967. On the Kolmogorov-Smirnov test for normality with mean and variance unknown. *Journal of the American statistical Association,* 62**,** 399-402.

LIN, H.-F. 2009. Examination of cognitive absorption influencing the intention to use a virtual community. *Behaviour & Information Technology,* 28**,** 421-431.

LIN, X., FEATHERMAN, M., BROOKS, S. L. & HAJLI, N. 2019. Exploring gender differences in online consumer purchase decision making: An online product presentation perspective. *Information Systems Frontiers,* 21**,** 1187-1201.

LINDELL, M. K. & WHITNEY, D. J. 2001. Accounting for common method variance in cross-sectional research designs. *Journal of applied psychology,* 86**,** 114-121.

LU, Y., ZHOU, T. & WANG, B. 2009. Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory. *Computers in Human Behavior,* 25**,** 29-39.

LUNA, D., PERACCHIO, L. A. & DE JUAN, M. D. 2002. Cross-cultural and cognitive aspects of web site navigation. *Journal of the academy of marketing science,* 30**,** 397-410.

MAHNKE, R., BENLIAN, A. & HESS, T. 2015. A Grounded Theory of Online Shopping Flow. *International Journal of Electronic Commerce,* 19**,** 54-89.

MANSOURY, M., ABDOLLAHPOURI, H., SMITH, J., DEHPANAH, A., PECHENIZKIY, M. & MOBASHER, B. 2020. Investigating potential factors associated with gender discrimination in collaborative recommender systems. *arXiv preprint arXiv:2002.07786*.

MATTHEWS, L. 2017. Applying Multigroup Analysis in PLS-SEM: A Step-by-Step Process. *In:* LATAN, H. & NOONAN, R. (eds.) *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications.* Cham: Springer International Publishing.

MIDHA, V. 2012. Impact of consumer empowerment on online trust: An examination across genders. *Decision Support Systems,* 54**,** 198-205.

MITCHELL, M. L. & JOLLEY, J. M. 2012. *Research design explained*, Cengage Learning.

MPINGANJIRA, M. 2019. Cognitive absorption and behavioural intentions in virtual health communities. *Journal of Systems and Information Technology,* 21**,** 122-145.

NOVAK, T. P., HOFFMAN, D. L. & DUHACHEK, A. 2003. The influence of goal-directed and experiential activities on online flow experiences. *Journal of consumer psychology,* 13**,** 3-16.

PARBOTEEAH, D. V., VALACICH, J. S. & WELLS, J. D. 2009. The Influence of Website Characteristics on a Consumer's Urge to Buy Impulsively. *Information Systems Research,* 20**,** 60-78.

PERUMAL, S., YUSR, M. M., ALIYU, O. A., SALIMON, M. G. & SANURI, S. M. M. 2021. E-learning satisfaction and retention: a concurrent perspective of cognitive absorption, perceived social presence and technology acceptance model. *Journal of Systems and Information Technology,* ahead-of-print.

PODSAKOFF, P. M., MACKENZIE, S. B., LEE, J.-Y. & PODSAKOFF, N. P. 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology,* 88**,** 879-903.

RIEDL, R., HUBERT, M. & KENNING, P. 2010. Are There Neural Gender Differences in Online Trust? An fMRI Study on the Perceived Trustworthiness of eBay Offers. *MIS Quarterly,* 34**,** 397-428.

RINGLE, C. M. & SARSTEDT, M. 2016. Gain more insight from your PLS-SEM results. *Industrial management & data systems*.

RINGLE, C. M., WENDE, S. & BECKER, J.-M. 2015. SmartPLS 3. *Boenningstedt: SmartPLS GmbH*.

SALIMON, M. G., SANURI, S. M. M., ALIYU, O. A., PERUMAL, S. & YUSR, M. M. 2021. E-learning satisfaction and retention: a concurrent perspective of cognitive absorption, perceived social presence and technology acceptance model. *Journal of Systems and Information Technology*.

SARSTEDT, M., HAIR JR, J. F., CHEAH, J.-H., BECKER, J.-M. & RINGLE, C. M. 2019. How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ),* 27**,** 197-211.

SCHRAGE, M. 2021. The Transformational Power of Recommendation. *MIT Sloan Management Review,* 62**,** 17-21.

SENECAL, S., GHARBI, J.-E. & NANTEL, J. 2002. The influence of flow on hedonic and utilitarian shopping values. *ACR North American Advances,* 29**,** 483-484.

SHANG, R.-A., CHEN, Y.-C. & SHEN, L. 2005. Extrinsic versus intrinsic motivations for consumers to shop on-line. *Information & Management,* 42**,** 401-413.

SHEN, A. 2014. Recommendations as personalized marketing: insights from customer experiences. *Journal of Services Marketing,* 28**,** 414-427.

SHROUT, P. E. & BOLGER, N. 2002. Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods,* 7**,** 422-445.

SUKI, N. M., RAMAYAH, T. & SUKI, N. M. 2008. Internet shopping acceptance: Examining the influence of intrinsic versus extrinsic motivations. *Direct Marketing: An International Journal,* 2**,** 97-110.

URBACH, N. & AHLEMANN, F. 2010. Structural equation modeling in information systems research using partial least squares. *Journal of Information technology theory and application,* 11**,** 5-40.

VALINATAJBAHNAMIRI, M. & SIAHTIRI, V. 2021. Flow in computer-mediated environments: A systematic literature review. *International Journal of Consumer Studies*.

WANG, J., WANG, M. & WU, J. 2015. Empirical study on flow experience in China tourism e-commerce market. *Journal of Industrial Engineering and Management (JIEM),* 8**,** 349-364.

WANG, W. & BENBASAT, I. 2005. Trust in and Adoption of Online Recommendation Agents. *Journal of the Association of Information Systems,* 6**,** 72-101.

WANG, W., QIU, L., KIM, D. & BENBASAT, I. 2016. Effects of rational and social appeals of online recommendation agents on cognition-and affect-based trust. *Decision Support Systems,* 86**,** 48-60.

WEBSTER, J. & AHUJA, J. S. 2006. Enhancing the design of web navigation systems: The influence of user disorientation on engagement and performance. *Mis Quarterly***,** 661-678.

WEBSTER, J., TREVINO, L. K. & RYAN, L. 1993. The dimensionality and correlates of flow in human-computer interactions. *Computers in human behavior,* 9**,** 411-426.

WHANG, C. & IM, H. 2018. Does recommendation matter for trusting beliefs and trusting intentions? Focused on different types of recommender system and sponsored recommendation. *International Journal of Retail & Distribution Management,* 46**,** 944-958.

WU, I.-L. & HUANG, C.-Y. 2013. Analysing complaint intentions in online shopping: the antecedents of justice and technology use and the mediator of customer satisfaction. *Behaviour & Information Technology,* 34**,** 69-80.

XIAO, B. & BENBASAT, I. 2007. E-commerce product recommendation agents: use, characteristics, and impact. *MIS Q.,* 31**,** 137-209.

YANG, Z. & JUN, M. 2002. Consumer perception of e-service quality: from internet purchaser and non-purchaser perspectives. *Journal of Business strategies,* 19**,** 19-41.

ZHANG, F., GONG, T., LEE, V. E., ZHAO, G., RONG, C. & QU, G. 2016. Fast algorithms to evaluate collaborative filtering recommender systems. *Knowledge-Based Systems,* 96**,** 96-103.

ZHAO, X. A study on e-commerce recommender system based on big data. 2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), 2019. IEEE, 222-226.

ZHAO, X., LYNCH, J. G., JR. & CHEN, Q. 2010. Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research,* 37**,** 197-206.

ZHU, D. H., CHANG, Y. P., LUO, J. J. & LI, X. 2014. Understanding the adoption of location-based recommendation agents among active users of social networking sites. *Information Processing & Management,* 50**,** 675-682.

ZHU, W. W. & MOROSAN, C. 2014. An empirical examination of guests' adoption of interactive mobile technologies in hotels. *Journal of Hospitality and Tourism Technology*.

ZHU, Z., HU, X. & CAVERLEE, J. Fairness-aware tensor-based recommendation. Proceedings of the 27th ACM International Conference on Information and Knowledge Management, 2018. 1153-1162.

ZIKMUND, W. G. & BABIN, B. J. 2013. *Essentials of marketing research,* Australia ;, South-Western Cengage Learning.

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CHAPTER 5: PAPER 3 - Effects of curiosity, focused immersion, and temporal dissociation on continuous use intention of AI-driven recommender systems in e-commerce

5.1

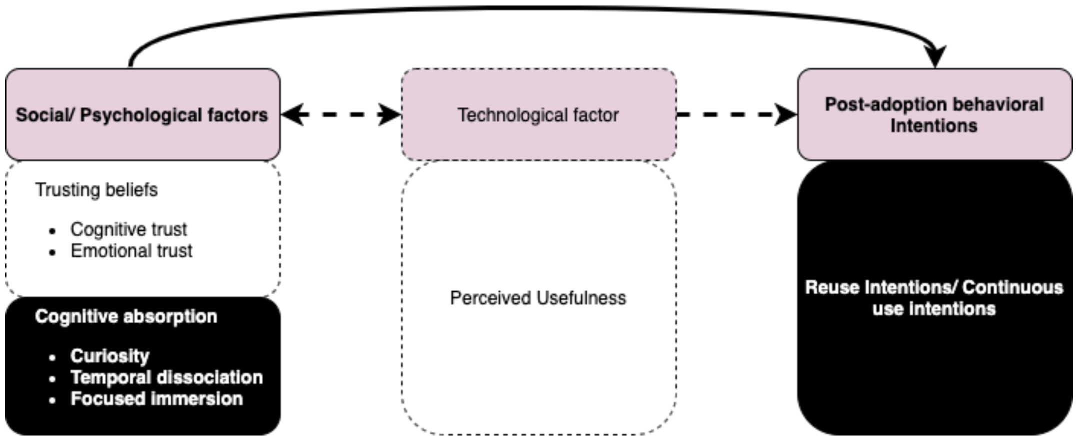

FIGURE 5.1 FRAMEWORK FOR CHAPTER 5

5.2 Preface

This chapter presents an empirical paper, a response to a call for papers on the application of AI and e-commerce, that at the time of submitting this thesis is published by Foresight, a Q2 journal. The paper is presented as it was last submitted to the journal. This chapter empirically explores the effects of the dimensions of cognitive absorption (curiosity, focused immersion, and temporal dissociation) separately on AI-driven RSs continuous use intention in e-commerce.

5.2.1 Highlights of this chapter

- Unique antecedents of continuous use intention were revealed by considering three dimensions of cognitive absorption: curiosity, focused immersion and temporal dissociation separately.

- Curiosity and focused immersion directly affect RSs continuous use intention.
- Temporal dissociation does not affect RSs continuous use intention

5.2.2 Citation detail

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EFFECTS OF CURIOSITY, FOCUSED IMMERSION, AND TEMPORAL DISSOCIATION ON CONTINUOUS USE INTENTION OF AI-DRIVEN RECOMMENDER SYSTEMS IN E-COMMERCE

ABSTRACT

Purpose – The applications of artificial intelligence (AI), natural language processing and machine learning in e-commerce are growing. Recommender systems (RSs) are interaction-based technologies based on AI that can offer recommendations for products for use or of interest to a potential consumer. Curiosity, focused immersion, and temporal dissociation are often treated as the dimensions of cognitive absorption, so exploring them separately can provide valuable insights into their dynamics. No prior empirical investigation has examined the effect of the dimensions of cognitive absorption independently on RSs continuous use intention.

Design/methodology/approach – A Quantitative research design was used to explore the effect of dimensions of cognitive absorption on AI-driven RSs continuous use intention in e-commerce. Data were gathered from 452 active users of Amazon through an online cross-sectional survey and were analysed using partial least squares structural equation modelling (PLS-SEM).

Findings – The findings indicated that curiosity and focused immersion directly affect RSs continuous use intention, but temporal dissociation does not affect RSs continuous use intention.

Originality/value – The current research focused on Amazon's RSs that use AI and machine learning techniques. The research aimed to empirically explore the effects of the dimensions of cognitive absorption separately on AI-driven RSs continuous use intention in e-commerce. This research may be of interest to executives working in both public and private industries to better harness the potential

of recommendations driven by AI to maximise RSs reuse and to enhance customer loyalty.

5.2.3 Keywords

Artificial intelligence, Recommender systems, Cognitive absorption, Curiosity, Focused immersion, Temporal dissociation, Continuous use intention

5.3 Introduction

Artificial intelligence (AI) driven recommendations are prevalent in today's marketplace. In 2019, the international AI market was estimated to be worth USD 39.9 billion; the compound annual growth rate (CAGR) is predicted to increase by 42.4 per cent from 2020 to 2027 (Chinchanachokchai et al., 2021). Recommender systems (RSs) aim to predict the interests of consumers and recommend to them products of interest to them (Ricci et al., 2011). More businesses are leveraging advances in AI, natural language processing, and machine learning capabilities to provide accurate and in-the-moment recommendations (Chinchanachokchai et al., 2021; Shen, 2014).

Past research reveals a number of factors that can influence the decision to continue using RSs such as perceived usefulness, perceived confirmation, trusting beliefs, satisfaction and perceived affective quality (Ashraf et al., 2020b, Benlian et al., 2012). The earlier research concentrated on technology acceptance theoretical frameworks with limited focus on the factors that capture the experience of consumers.

Consumers have their own ways to engage with technology, which typically lead to a holistic experience (Zhu and Morosan, 2014). In most technology acceptance theoretical frameworks, such experiences are not usually taken into account (Morosan, 2012). The shopping experience of users utilising AI-driven RSs cannot be limited to system beliefs and evaluation outcomes dimensions (e.g., attitudes, behaviours). As the technology is developed with the consumer's experience in mind (Nagasawa, 2008), specific dimensions related to experience need to be identified. The information gained from prior research is insufficient for practitioners using AI-driven RSs in e-commerce to identify specific dimensions that should be managed carefully to enhance continuous use intention.

Cognitive absorption has the ability to capture customers' experience with technology as it influences technology adoption intention (Ghasemaghaei, 2020) as well as continuous use intention (Balakrishnan and Dwivedi, 2021). However, the current research is the first to focus on the independent effects of cognitive absorption dimensions on continuous use intention in RSs.

In this paper, we address the following question: do focused immersion, temporal dissociation and curiosity have a significant direct effect on RSs continuous use intention? To answer this question, the research reported in this paper used PLS-SEM to empirically examine the proposed research model in the context of customers using an e-commerce website. This research may be of value for executives working in both the public and private industries to harness the potential of AI-driven RSs. According to the findings, customers' curiosity and focused immersion have a favourable impact on their continuous use intention of AI-driven RSs. Users are more likely to pay attention to features that e-vendors add, according to the findings, for e-commerce firms should implement elements that keep customers engaged in RSs to increase the continuous use intention.

5.4 Literature Review

Artificial intelligence (AI) is a computational system capable of performing human-oriented tasks such as decision making, problem-solving, and human-like reasoning behaviour (Russell, 2003). Artificial intelligence (AI) has become a popular method to prune a large amount of information so that users are guided towards those items that best meet their preferences and needs. An important class of AI is RSs, RSs that are commonly used for mining consumer's knowledge and further assisting in making marketing decisions (Balabanović and Shoham, 1997).

RSs are interaction-based technologies based on AI that offers recommendations for products of use or interest to a user (Mahmood and Ricci, 2009, Resnick and Varian, 1997). RSs have been developed in many areas such as music, films, news and products in general (Reddy et al., 2019). A large number of companies such as Amazon, LinkedIn, Spotify and Netflix implement RSs to assist customers in the decision-making process (Schrage, 2021). For more than two decades Amazon has been using collaborative filtering algorithm-based RSs (Smith and Linden, 2017). Amazon shows recommendations for new arrivals in previously preferential categories (Reddy et al., 2019). Amazon's recommendation mechanisms function in such a way that they identify users' interests based on their browsing history and recommend related products in a variety of forms, sizes, and brands (Smith and Linden, 2017).

5.4.1 Cognitive absorption

The concept of cognitive absorption (CA) (Agarwal and Karahanna, 2000), which has been developed based on multiple paradigms representing engagement, absorption and flow, was introduced for capturing holistic experiences. Cognitive absorption is a condition of intense engagement with a software (Agarwal and Karahanna, 2000). The theoretical foundation of CA is derived from work in individual psychology, and in particular, on studies related to the notion of cognitive engagement (Webster and Ho, 1997), the state of flow (Csikszentmihalyi and Csikzentmihaly, 1990) and a trait dimension called absorption (Tellegen and Atkinson, 1974). CA has been argued to include five dimensions: curiosity, control, focused immersion, temporal dissociation and heightened enjoyment (Agarwal and Karahanna, 2000). These dimensions can be categorised as cognitive and affective components. The cognitive component only includes heightened enjoyment, whereas affective components include curiosity, control, focused immersion, and temporal dissociation. Studies pertaining to CA does not always include all five of these dimensions. Some studies have argued that some dimensions of CA should be excluded as they believe that the context and tasks determine which components should be used. For instance, some studies have argued that three dimensions are suitable (Saadé and Bahli, 2005, Zhu and Morosan, 2014). Saadé and Bahli (2005) argued that cognitive absorption dimensions should include focused immersion, temporal dissociation and heightened enjoyment while Zhu and Morosan (2014) argued that CA dimensions should consist of curiosity, focused immersion, and temporal dissociation. In this research the conceptualisation of CA includes curiosity, focused immersion, and temporal dissociation and does not include two dimensions, namely heightened enjoyment and control due to its ambiguous role within the cognitive absorption dimensions (Zhu and Morosan, 2014).

Several notable researchers have studied and reported the significance of cognitive absorption in the context of IS (Jumaan et al., 2020, Zhu and Morosan, 2014, Balakrishnan and Dwivedi, 2021, Ghasemaghaei, 2020), yet, limited research has precisely estimated the influence of its dimensions independently. Ghasemaghaei (2020) argued that consumers' CA perception affects RSs effectiveness and intention to use RSs. Balakrishnan and Dwivedi (2021) emphasised that users' trust, experience, and CA have a significant effect on the intention to continue using technology. Jumaan et al. (2020) asserted that cognitive absorption was a significant predictor of the continued use of an interaction-based technology but had not specifically estimated the influence of its individual dimensions. Extending TAM with CA constructs in the setting of interactive mobile technologies (IMC) in hotels, Zhu and Morosan (2014) revealed that CA was the most significant predictor of IMC adoption attitudes and behaviour.

Recent studies argued that the dimensions of CA do not have an equal impact on behavioural intentions (Tan et al., 2015, Rutkowski et al., 2007, Visinescu et al., 2015), and their effects might be investigated independently. Variations in the degree of temporal dissociation influences a person's preference (Rutkowski et al. 2007). Tan et al. (2015) reported that focused immersion does not moderate the connection between satisfaction and continuous use intention, while temporal dissociation has a negative moderation effect. Increased curiosity, temporal dissociation and focused immersion all have an influence on behavioural intentions but increased heightened enjoyment has no effect (Visinescu et al. 2015). Based on the above arguments the present study investigated the dimensions of cognitive absorption individually on RSs continuous use intention.

To study the effect of cognitive absorption in the RSs context, curiosity, focused immersion, and temporal dissociation were chosen to structure a research model. Adopting the same approach as Webster and Ho (1997), this study treats these three dimensions separately. Curiosity, focused immersion, and temporal dissociation are defined as follows:

- Curiosity: the degree to which a person experiences sensory and cognitive curiosity (Agarwal and Karahanna, 2000);
- Focused immersion: the sensation of being completely absorbed, with all other demands on one's attention being neglected (Agarwal and Karahanna, 2000);
- Temporal dissociation: a lack of awareness of the passage of time while involved in an activity (Agarwal and Karahanna, 2000);

Finding the link between CA dimensions and a user's continuous use intention to use RSs may help to understand the ways in which attitudes and behaviours towards RSs are manifested and lead to continuous use of RSs.

5.4.2 Continuous use intention

The theoretical foundation of RSs continuous use intention is based on the concept of the IS continuance model (Bhattacherjee, 2001), IS continuous use intention being "an individual's intention to continue using an information system (in contrast to initial use or acceptance)" (Bhattacherjee, 2001). It is an essential element of the success of the service systems such as RSs (Ashraf *et al.*, 2020b, Benlian *et al.*, 2012, Bhattacherjee, 2001).

Table 5.1 shows the summary of existing studies relevant to RSs continuous use intention. It is evident from the synopsis that several factors that affect continuous use intention have been determined. Previous studies have neglected the effect of cognitive absorption, which is a key factor to understanding the continuous use intention of IS (Balakrishnan and Dwivedi, 2021, Jumaan et al., 2020). The state of the current literature on the continuous use intention of RSs provides inadequate information for e-vendor managers to understand which dimensions should be carefully controlled to promote the continuous use of RSs. The importance of exploring the concept of cognitive absorption for e-vendor managers that deploy AI-driven RSs must be acknowledge; recent studies have provided evidence of its influence continuous use intention of technology.

TABLE 5.1 SUMMARY OF PREVIOUS STUDIES ON RSS CONTINUOUS USE INTENTION.

Studies	Finding	Theoretical Framework
(Ashraf *et al.*, 2020a)	Users' perceived decision quality, usefulness, and satisfaction affect RSs continuous use intention, but not perceived decision effort.	IS continuance model
(Ashraf *et al.*, 2020b)	Users' continuous trust and perceived confirmation positively influence their satisfaction and perceived usefulness with the RSs, which makes them more likely to continue using RSs.	IS continuance model
(Benlian *et al.*, 2012)	Users' perceived usefulness, perceived ease of use, perceived affective quality and trust significantly affect RSs continuous use intention	Technology acceptance model
(Yang, 2021)	Satisfaction and trust in RSs positively and significantly affect RSs continuous use intention	The self-regulation process proposed

		by Bagozzi and IS success literature
(He *et al.*, 2021)	Users' perceived decision effort and perceived decision quality significantly affect RSs continuous use intention.	Effort-Accuracy Model and RSs acceptance literature

5.5 RESEARCH FRAMEWORK

Figure 5.2 shows the research model of users' RSs continuous use intention.

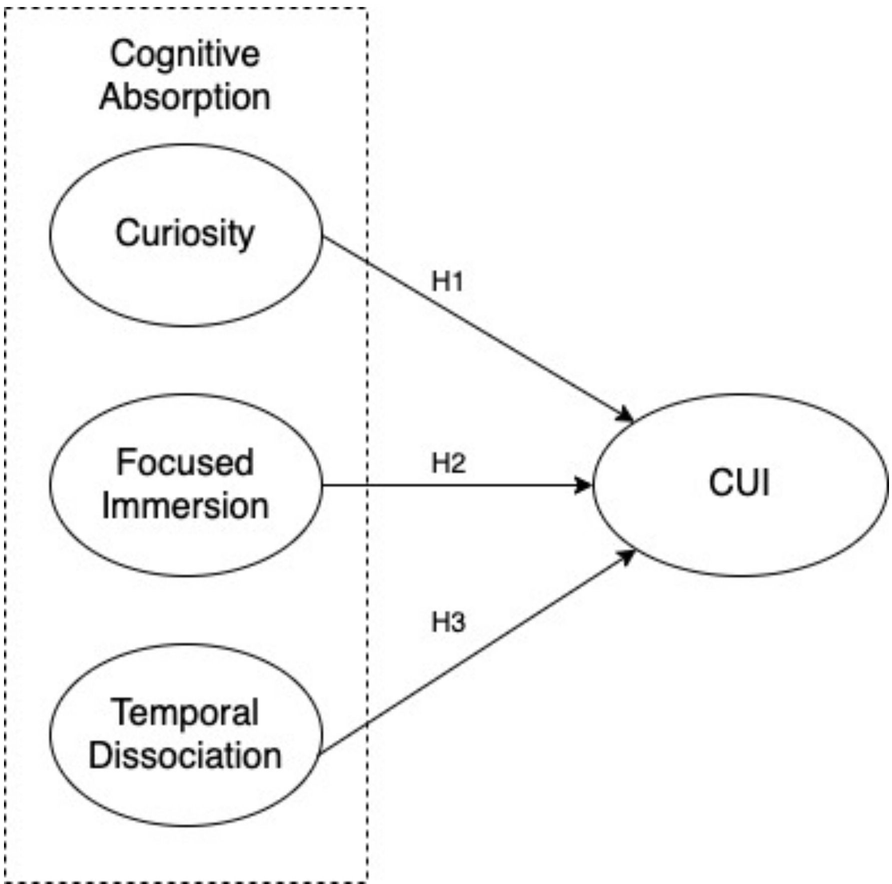

FIGURE 5.2 RESEARCH MODEL WITH HYPOTHESES

Note: CUI: Continuous use Intention

On the basis of the above literature review, the following hypotheses are proposed:

H1: *Increase in curiosity positively influences continuous use intention.*

H2: *Increase in focused immersion positively influences continuous use intention.*

H3: *Increase in temporal dissociation positively influences continuous use intention.*

5.6 Research Methodology

5.6.1 Sample and procedure

The examination of the research model was conducted using a survey research method. An online questionnaire was created using the Zoho survey tool (survey.zoho.com) to collect data from current users of Amazon’s RSs in Australia; 1361 responses were received. Based on the survey questionnaire's screening questions, 452 responses were considered usable and valid; the remaining responses were discarded because the respondent did not complete the survey due to the screening question restrictions. An additional 86 responses were discarded due to either being detected as acquiescence response bias (Podsakoff *et al.*, 2003), univariant outlier or multivariant outlier (Ho, 2013). Accordingly, only 366 responses were achieved and was used for subsequent analysis.

Table 5.2 shows the demographics of the respondents. Males accounted for about 49% of responses, while females accounted for around 50%. The age group of 26-35 years old had the most replies (over 28%), followed by 20-25 years old (almost 28%). Around 33% of respondents had bachelor's degrees, while 7% had PhDs. The majority of respondents had been using RSs for over a year and had purchased online for 4–5 years.

TABLE 5.2 RESPONDENTS' DEMOGRAPHIC PROFILE (N = 366)

Variable	Frequency	%	Variable	Frequency	%
Gender			**Education**		
Male	182	49.7	Certificate	86	23.5
Female	184	50.3	Diploma	39	10.7
Age Group			Bachelor Degree	123	33.6
Less than 20 years	16	4.4	Master Degree	92	25.1
20-25 years	102	27.9	Doctorate/PhD	24	6.6
26-35 years	104	28.4	Other	2	0.5
36-45 years	99	27	**Geographic Location**		
Over 45 years	45	12.3	VIC	114	31.1
Marital Status			NSW	122	33.3
Single	156	42.6	QLD	65	17.8
Married	191	52.2	WA	32	8.7
Widowed	1	0.3	SA	15	4.1
Divorced	10	2.7	TAS	7	1.9
Other	8	2.2	ACT	10	2.7
			NT	1	0.3

5.6.2 Measures

The study's questionnaire was designed using a number of 5-point Likert scale questions with responses ranging from "strongly disagree" (1) to "strongly agree" (5). The instrument and scales were adapted from previously validated research (see Appendix A). In particular, three items to measure continuous use intention were adopted from Benlian *et al.* (2012), and three items for curiosity, five items for focused immersion, and five items for temporal dissociation were adopted from Zhu and Morosan (2014).

5.6.3 Non-response bias

Non-response bias is a major problem in survey methodologies as it affects the generalizability of the findings (Michie and Marteau, 1999), and must be addressed in research studies (Lewis et al., 2013). Response bias occurs when an individual's response to a survey differs systematically from others invited participants (Menachemi, 2011). In this study, adequate precautions were taken to ensure that non-response was not a concern for this study. This was accomplished by doing a wave analysis on the data by splitting it into two data sets (early responders vs. late respondents) (Miller and Smith, 1983). The respondents were classified as early and late respondents considering the first 50 and last 50 questionaries received (Karahanna et al., 1999). The early and late wave responses for each construct were compared using a paired t-test to determine non-response bias. The paired t-test results for each construct indicated no statistically significant mean value for these two groups, i.e., the significance value of constructs in the study was above 0.05. The paired t-test results indicated that non-response bias is not of concern in this study.

5.6.4 Common method bias (CMB)

In social science studies using survey methodologies, the absence of CMB should be validated (Podsakoff et al., 2003). Both procedural and statistical techniques were used to control the CMB. In the research design, the participants remained anonymous and were reassured that there is no correct or incorrect answer, so were urged to reply to the questions asked as honestly as possible (Podsakoff et al., 2003).

Concerning statistical techniques, Lindell and Whitney's (2001) marker variable technique was performed to test the CMB. Marital status, which is a theoretically unrelated construct, was used as a marker variable. The variance of the dependent variable did not considerably increase with the addition of the marker variable. The correlation between the latent variable of the SEM and the marker variable was 0.044, and the significance was 0.213 which is substantially higher than the 0.05 criterion making it unnecessary to assume that the correlations are significant. A full collinearity test based on the variance inflation factor (VIF) was also performed (Kock, 2015). The examination revealed that the full collinearity VIFs of all latent variables ranged from 2.497 to 3.037 and were lower than the threshold of 3.3 (Kock, 2015). The use of procedural and statistical techniques (marker variable and full collinearity test) indicated that CMB is not of substantial concern in this study.

5.7 Data analysis

5.7.1 Hypothesis testing

This research utilized the PLS-SEM path modelling technique using SmartPLS 3.3 (Ringle et al., 2015). PLS-SEM offers greater statistical power compared to factor-based SEM and is more suitable for predictive testing than theory development (Hair et al., 2019). It is suitable for exploratory research, and where the goal is to predict and explain a target construct (Sarstedt et al., 2021). Prior studies did not fully investigate the research question of this study making PLS-SEM an appropriate choice. The analysis of the research model was conducted in two stages: (a) measurement model analysis and (b) structural model analysis.

5.7.2 Measurement model analysis

In this research, confirmatory factor analysis (CFA) was used to evaluate the measurement model in the SEM, with the goal of verifying and refining the items (components) and constructs (latent variables) in the model. Internal consistency reliability, convergent validity, and discriminant validity were the three criteria that should be investigated in this step (Hair Jr et al., 2021). Cronbach’s alpha value, composite reliability (CR) and rho_A were assessed to check the internal consistency among the components in each construct (see Table 5.3). Cronbach’s alpha value of all constructs ranged from 0.856 to 0.903, higher than the recommended value of 0.7 (Hair Jr et al., 2021). CR values of all constructs were higher than the benchmark of 0.70. rho_A, a newly recommended measure by Dijkstra and Henseler (2015), was also assessed and reliability estimates were above the benchmark of 0.70 (i.e., from 0.856 to 0.903). Values of Cronbach's alpha, composite reliability (CR) and rho_A indicated internal consistency reliability. Factor loadings and average variance extracted (AVE) were assessed to examine the convergent validity of the model. All the factor loading was higher than 0.7, representing high reliability levels. The AVE values of the constructs ranged from 0.721 to 0.804, higher than the recommended value of 0.5 (Hair Jr et al., 2021). These examinations indicated the internal consistency reliability and convergent validity of the model.

TABLE 5.3 ASSESSMENT OF SCALE RELIABILITY

Constructs	Items	Factor Loading	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
CUI			0.878	0.878	0.925	0.804
	CUI1	0.883				
	CUI2	0.900				
	CUI3	0.907				
Curiosity			0.856	0.858	0.913	0.777
	CU1	0.902				
	CU2	0.887				
	CU3	0.855				
Focused Immersion			0.898	0.901	0.929	0.766
	FI1	0.878				
	FI2	0.901				
	FI3	0.881				
	FI5	0.839				
Temporal Dissociation			0.903	0.908	0.928	0.721
	TD1	0.839				
	TD2	0.835				
	TD3	0.866				
	TD4	0.839				
	TD5	0.866				

Note: FI: Focused immersion, TD: Temporal dissociation, CU: Curiosity, CUI: Continuous use Intention

The discriminant validity was the next assessment criteria. The traditional technique of the Fornell-Larcker criterion and the HTMT ratios were used to assess discriminant validity. According to the Fornell-Larcker criterion (Fornell and Larcker, 1981), the square root of AVE should be higher than the inter-construct correlation values for all constructs. In this study, the square root of the AVE of each construct was higher than the inter-construct correlation values (see Table 5.4). The discriminant validity of the research model was further assessed using the HTMT ratio to estimate to what extent a construct within its components differs from other constructs (Henseler *et al.*, 2015). The HTMT ratios values (see Table 5.5) were less than the threshold value of 0.90 (Hair *et al.*, 2019). Discriminant validity among the constructs was attained.

TABLE 5.4 CORRELATION AND THE SQUARE ROOT OF AVE

	CUI	**Curiosity**	**Focused Immersion**	**Temporal Dissociation**
CUI	*0.897*			
Curiosity	0.703	*0.881*		
Focused Immersion	0.715	0.769	*0.875*	
Temporal Dissociation	0.624	0.744	0.710	*0.849*

Note: CUI: Continuous use Intention

TABLE 5.5 HTMT RATIOS

	CUI	**Curiosity**	**Focused Immersion**	**Temporal Dissociation**
CUI				
Curiosity	0.810			
Focused Immersion	0.803	0.878		
Temporal Dissociation	0.694	0.843	0.783	

Note: CUI: Continuous use Intention

The measurement model's internal consistency reliability, convergent validity, and discriminant validity all fulfilled their requirements, empirically verifying the measurement model's suitability in this research.

5.7.3 STRUCTURAL MODEL ANALYSIS

Hair *et al.* (2019) argued that structural model assessment entailed examining the collinearity among the exogenous constructs, significance and relevance of the path coefficients (β), examining the model's predictive accuracy and in particular determining the model's predictive accuracy through the coefficient of determination, R^2. The exogenous constructs' collinearity was measured by checking their VIF values. VIF values below 3.3 were regarded as ideal (Hair Jr *et al.*, 2021). An assessment of VIF values showed that all of them were less than 3.3, indicating that there is no reason to be concerned about collinearity issues. A bootstrapping procedure with a 5000-resampling was performed at a 5% significance level based on the direction of the hypotheses to determine the statistical significance of the path coefficients, β, and thus the significance of the hypotheses. Table 5.6 and Figure 5.3 shows the results of the structural model assessment.

TABLE 5.6 ASSESSMENT OF STRUCTURAL MODEL

Hypothesis	β	T Statistics	P Values	Result
H1: Curiosity -> CUI	0.323	4.328	0.000	Supported
H2: Focused Immersion -> CUI	0.392	5.327	0.000	Supported
H3: Temporal Dissociation -> CUI	0.105	1.430	0.153	Rejected

Note: CUI: Continuous use Intention

The explanatory power (R^2) of continuous use intention was 0.573, which means curiosity, focused immersion, and temporal dissociation explained 57% variance in continuous use intention. The R^2 value also exceeded the 0.10 cut-off criterion (Falk and Miller, 1992). The predictive accuracy of the PLS path model was assessed using the Stone-Geisser (Q^2) value based on the blindfolding procedure with omission distance of 7 (Hair Jr *et al.*, 2021). The Q^2 value for the exogenous variable was 0.452, indicating an acceptable level of predictive relevance of the proposed model (Hair *et al.*, 2019).

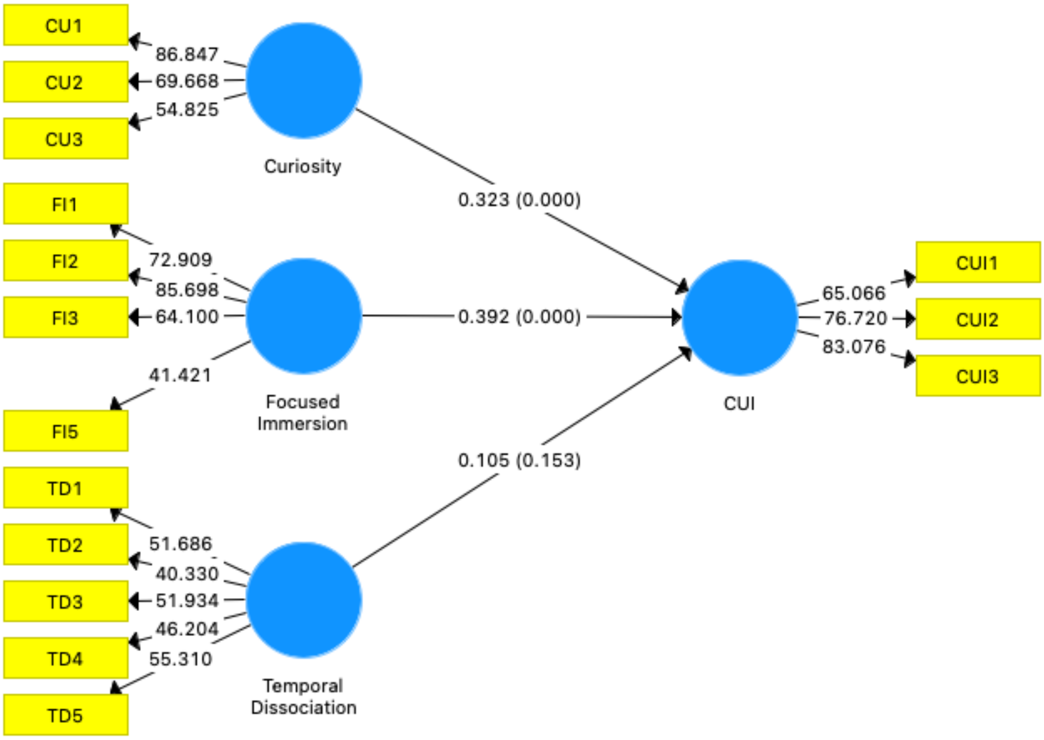

FIGURE 5.3 RESULTS OF THE RESEARCH MODEL ANALYSIS

Note: FI: Focused immersion, TD: Temporal dissociation, CU: Curiosity, CUI: Continuous use Intention

(0.000) direct paths are (Sig. at $p < 0.001$).

5.8 DISCUSSION

The study focused on active customers of Amazon in Australia. IS has investigated the impact of absorption on behavioural intentions, but limited research has examined the potential impact of each dimension in depth. This study is the first reported attempt to examine the connection between cognitive absorption dimensions and RSs continuous use intention. The current study focused on the consumer experience of RSs using the concept of cognitive absorption in contrast to prior studies focusing on technology acceptance theoretical frameworks (Yang, 2021, He et al., 2021, Ashraf et al., 2020b).

Out of three hypotheses, two hypotheses were supported (H1 and H2) (see table VI). The proposed model explained 57% variance in continuous use intention which reflects its strong predictive power

(Evans, 1996). The results show that curiosity and focused immersion were the strongest predictor of RSs' continuous use intention. The results align with the previous literature that suggests that a higher degree of curiosity and focused immersion correlates with stronger behavioural intention (Visinescu et al., 2015). The influence of curiosity on RSs continuous use intention can also be explained based on the information gap theory of curiosity (Loewenstein, 1994). According to the notion of the information gap, curiosity is sparked when people realise there is a gap between what they know and what they want to know (Loewenstein, 1994). Curiosity relating to bridging the gap acts as a motivating factor in inducing exploratory behaviour. Research on consumer behaviour also identified the role of information gap in evoking curiosity and consequently driving behavioural intentions (Dahabiyeh et al., 2021).

The results of focused immersion as a predictor of continued use intention can be explained based on the incentive-sensitization theory of addiction (Robinson and Berridge, 1993), which states that users who are in a more intense state of focused immersion are more likely to become hypersensitive, which increases the continuous use intention of RSs. Consumers are able to momentarily forget about their daily concerns and worries by immersing themselves in sensory sensations provided through focused immersion (Jennett et al., 2008). People lose awareness of their surroundings as they remain relatively immersed in IT-mediated tasks (Agarwal and Karahanna, 2000). This very pleasant state is typical of the pre-addiction phase of the incentive-sensitization process. Hypersensitization to RSs is likely to be centred on the perceived benefits of RSs constant usage, which provides a period free of tension, anxieties, and concerns when shopping online. The process of hypersensitization assures that RSs users will have even more enjoyment from every immersion session. Users will ultimately become fascinated by using RSs as the motivation to do so grows over time, leading to continuous use.

The study did not validate the effect of temporal dissociation on RSs continuous use intention. The result was similar to the prior results of Venter and Swart (2018) and Visinescu et al. (2015), where temporal dissociation had no effect on continuous use intention. A reasonable explanation for this result is that RSs are time-saving technologies that provide accurate and in-the-moment suggestions without taking up the users' time. The perception of temporal dissociation may not be noticeable in the case of RSs but it may differ in the case of other technologies such as virtual reality devices. The analysis answered the question of the role of focused immersion, temporal dissociation and curiosity in explaining RSs' continuous use intention. The results of this study are significant with both theoretical and managerial implications, as discussed below.

This study contributed to theory by highlighting the importance of the dimensions of cognitive absorption in understanding an individuals' experience with AI-driven RSs and continuous use intention of the AI-driven RSs. Unlike many previous studies, this study has made a unique contribution to the literature by considering the dimensions of cognitive absorption (curiosity, focused immersion, and temporal dissociation) separately. We responded to the call by Laurell et al. (2019) by revealing novel antecedents and investigating their impact on continuous use intention. The study provides a theoretical foundation for further investigation of the individual dimensions of cognitive absorption on behavioural intentions. The results showed that the approach of viewing cognitive absorption as a holistic construct should be avoided and should be instead looked at in terms of the individual dimensions. The study adds to the information gap theory by extending it to the context of online shopping involving consumers' RSs continuous use intention.

This study has contributed to management by indicating that the continuous use intention of the AI-driven RSs in e-commerce is positively influenced by a user's curiosity and focused immersion rather than temporal dissociation. In light of this finding, to increase focused immersion e-vendors who rely on AI-driven RSs should make a concentrated effort to include more features in their applications that compel users to pay attention whereas other attentional demands are, in essence, ignored. This finding also suggests that e-vendors might leverage curiosity to their advantage by restricting the amount of information AI-driven RSs shows (utilising the information gap strategy) and leaving some aspects to the imagination of the end user. For example, in order to encourage users to upgrade their accounts, social media platforms such as LinkedIn utilise an information gap approach that provides them with access to the number of profile views while concealing the identity of the viewers.

5.9 CONCLUSION

The experience of the consumer is critical to the success of any e-commerce activity because it affects their perceptions of value and the quality of the product or service, and hence affects customer loyalty and retention. This research empirically investigated the effects of the dimensions of cognitive absorption separately on AI-driven RSs continuous use intention in e-commerce.

5.9.1 LIMITATIONS AND FUTURE WORK

The findings of this study were subject to at least three limitations. First, the samples of this study comprised of active customers of Amazon. Future research could investigate samples comprising of active customers of different e-commerce platforms that use AI-driven RSs. Second, the research has taken a positivist approach and only focused on the customers' continuous use intention of the AI-driven RSs in e-commerce in Australia, and the findings may not be generalized to people in other nations or cultures. It is recommended that future studies include other countries. Third, this research only considered three dimensions of cognitive absorption: curiosity, focused immersion and temporal dissociation. Future research may consider other cognitive absorption dimensions such as control and heightened enjoyment.

5.10 References

Agarwal, R. and Karahanna, E. (2000), "Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage", *MIS Quarterly,* Vol. 24 No. 4, pp. 665-694.

Ashraf, M., Ahmad, J., Hamyon, A.A., Sheikh, M.R. and Sharif, W. (2020a), "Effects of post-adoption beliefs on customers' online product recommendation continuous usage: An extended expectation-confirmation model", *Cogent Business & Management,* Vol. 7 No. 1, 1735693.

Ashraf, M., Ahmad, J., Sharif, W., Raza, A.A., Salman Shabbir, M., Abbas, M. and Thurasamy, R. (2020b), "The role of continuous trust in usage of online product recommendations", *Online Information Review,* Vol. 44 No. 4, pp. 745-766.

Balabanović, M. and Shoham, Y. (1997), "Fab: content-based, collaborative recommendation", *Commun. ACM,* Vol. 40 No. 3, pp. 66–72.

Balakrishnan, J. and Dwivedi, Y.K. (2021), "Role of cognitive absorption in building user trust and experience", *Psychology & Marketing,* Vol. 38 No. 4, pp. 643-668.

Benlian, A., Titah, R. and Hess, T. (2012), "Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study", *Journal of Management Information Systems,* Vol. 29 No. 1, pp. 237-272.

Bhattacherjee, A. (2001), "Understanding information systems continuance: An expectation-confirmation model", *MIS Quarterly,* Vol. 25 No. 3, pp. 351-370.

Chinchanachokchai, S., Thontirawong, P. and Chinchanachokchai, P. (2021), "A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations", *Journal of Retailing and Consumer Services,* Vol. 61, 102528.

Csikszentmihalyi, M. and Csikzentmihaly, M. (1990), "Flow: The psychology of optimal experience", *Journal of Leisure Research,* Vol. 24 No. 1, pp. 93-94.

Dahabiyeh, L., Najjar, M.S. and Agrawal, D. (2021), "When ignorance is bliss: The role of curiosity in online games adoption", *Entertainment Computing*, Vol. 37 No. 100398, pp. 1-11.

Dijkstra, T.K. and Henseler, J. (2015), "Consistent partial least squares path modeling", *MIS Quarterly,* Vol. 39 No. 2, pp. 297-316.

Evans, J.D. (1996), Straightforward statistics for the behavioral sciences, Thomson Brooks/Cole Publishing Co, United States.

Falk, R.F. and Miller, N.B. (1992), *A primer for soft modeling,* University of Akron Press, Akron.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research,* Vol. 18 No. 1, pp. 39-50.

Ghasemaghaei, M. (2020), "The impact of in-depth online recommendation agents on consumer disorientation and cognitive absorption perceptions", *Behaviour & Information Technology,* Vol. 39 No. 4, pp. 414-430.

Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019), "When to use and how to report the results of PLS-SEM", *European Business Review,* Vol. 31 No. 1, pp. 2-24.

Hair Jr, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2021), *A primer on partial least squares structural equation modeling (PLS-SEM),* Sage publications, Thousand Oaks, CA.

He, Y., Ashraf, M., Sharif, W., Abbas, M., Raza, A., Jaafar, N.I., Sulaiman, A., Thurasamy, R. and Shabbir, M.S. (2021), "Impact of system- vs. consumer- generated recommendations on decision factors: A differential, moderating and mediating perspective", *Current Psychology*. https://doi.org/10.1007/s12144-021-02119-2

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the academy of marketing science,* Vol. 43 No. 1, pp. 115-135.

Ho, R. (2013), *Handbook of univariate and multivariate data analysis with IBM SPSS,* CRC press, New York.

Jennett, C., Cox, A.L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T. and Walton, A. (2008), "Measuring and defining the experience of immersion in games", *International Journal of Human-Computer Studies*, Vol. 66 No. 9, pp. 641-661.

Jumaan, I.A., Hashim, N.H. and Al-Ghazali, B.M. (2020), "The role of cognitive absorption in predicting mobile internet users' continuance intention: An extension of the expectation-confirmation model", *Technology in Society,* Vol. 63, 101355.

Karahanna, E., Straub, D.W. and Chervany, N.L. (1999), "Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs", *MIS Quarterly,* Vol. 23 No. 2, pp. 183-213.

Kock, N. (2015), "Common method bias in PLS-SEM: A full collinearity assessment approach", *International Journal of e-Collaboration (ijec),* Vol. 11 No. 4, pp. 1-10.

Laurell, C., Sandström, C., Berthold, A. and Larsson, D. (2019), "Exploring barriers to adoption of Virtual Reality through Social Media Analytics and Machine Learning–An assessment of technology, network, price and trialability", *Journal of Business Research*, Vol. 100 pp. 469-474

Lewis, E.F., Hardy, M. and Snaith, B. (2013), "An analysis of survey reporting in the imaging professions: is the issue of non-response bias being adequately addressed?", *Radiography,* Vol. 19 No. 3, pp. 240-245.

Lindell, M.K. and Whitney, D.J. (2001), "Accounting for common method variance in cross-sectional research designs", *Journal of applied psychology,* Vol. 86 No. 1, pp. 114-121.

Loewenstein, G. (1994), "The psychology of curiosity: A review and reinterpretation", *Psychological Bulletin*, Vol. 116 No. 1, pp. 75-98

Mahmood, T. and Ricci, F. (2009), "Improving recommender systems with adaptive conversational strategies", paper presented at the Proceedings of the 20th ACM conference on Hypertext and hypermedia, Torino, Italy, available at: https://doi.org/10.1145/1557914.1557930.

Menachemi, N. (2011), "Assessing response bias in a web survey at a university faculty", *Evaluation & Research in Education,* Vol. 24 No. 1, pp. 5-15.

Michie, S. and Marteau, T. (1999), "Non-response bias in prospective studies of patients and health care professionals", *International Journal of Social Research Methodology,* Vol. 2 No. 3, pp. 203-212.

Miller, L.E. and Smith, K.L. (1983), "Handling nonresponse issues", *Journal of Extension,* Vol. 21 No. 5, pp. 45-50.

Morosan, C. (2012), "Understanding the antecedents of perceived value of registered traveler biometric systems", *Journal of Hospitality Marketing & Management,* Vol. 21 No. 8, pp. 872-896.

Nagasawa, S. y. (2008), “Customer experience management”, *The TQM Journal*, Vol. 20 No 4, pp. 312-323.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of applied psychology,* Vol. 88 No. 5, p. 879-903.

Reddy, S.R.S., Nalluri, S., Kunisetti, S., Ashok, S. and Venkatesh, B. "Content-Based Movie Recommendation System Using Genre Correlation", Springer Singapore, Singapore, pp. 391-397.

Resnick, P. and Varian, H.R. (1997), "Recommender systems", *Commun. ACM,* Vol. 40 No. 3, pp. 56–58.

Ricci, F., Rokach, L. and Shapira, B. (2011), "Introduction to Recommender Systems Handbook", in Ricci, F., Rokach, L., Shapira, B. and Kantor, P.B. (Eds.), *Recommender Systems Handbook,* Springer US, Boston, MA, pp. 1-35.

Ringle, C.M., Wende, S. and Becker, J.-M. (2015), "SmartPLS 3", *Boenningstedt: SmartPLS GmbH*.

Robinson, T.E. and Berridge, K.C. (1993), "The neural basis of drug craving: an incentive-sensitization theory of addiction", *Brain research reviews*, Vol. 18 No. 3, pp. 247-291.

Russell, S.J. (2003), *Artificial intelligence : a modern approach,* Prentice Hall/Pearson Education, Upper Saddle River, N.J.

Rutkowski, A.-F., Saunders, C., Vogel, D. and Van Genuchten, M. (2007), "“Is it already 4 am in your time zone?” Focus immersion and temporal dissociation in virtual teams", *Small group research,* Vol. 38 No. 1, pp. 98-129.

Saadé, R. and Bahli, B. (2005), "The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: an extension of the technology acceptance model", *Information & Management,* Vol. 42 No. 2, pp. 317-327.

Sarstedt, M., Ringle, C.M. and Hair, J.F. (2021), "Partial Least Squares Structural Equation Modeling", in Homburg, C., Klarmann, M. and Vomberg, A.E. (Eds.), *Handbook of Market Research,* Springer International Publishing, Cham, pp. 1-47.

Schrage, M. (2021). The Transformational Power of Recommendation. *MIT Sloan Management Review*, 62(2), 17-21.

Shen, A. (2014), "Recommendations as personalized marketing: insights from customer experiences", *Journal of Services Marketing,* Vol. 28 No. 5, pp. 414-427.

Smith, B. and Linden, G. (2017), "Two Decades of Recommender Systems at Amazon.com", *IEEE Internet Computing,* Vol. 21 No. 3, pp. 12-18.

Tan, W.-K., Lee, P.-W. and Hsu, C.-W. (2015), "Investigation of temporal dissociation and focused immersion as moderators of satisfaction–continuance intention relationship: Smartphone as an example", *Telematics and Informatics,* Vol. 32 No. 4, pp. 745-754.

Tellegen, A. and Atkinson, G. (1974), "Openness to absorbing and self-altering experiences ("absorption"), a trait related to hypnotic susceptibility", *Journal of abnormal psychology (1965),* Vol. 83 No. 3, pp. 268-277.

Venter, M. and Swart, A.J. (2018), "An integrated model for the continuous use intention of Microsoft Office simulation software", in *2018 IEEE Global Engineering Education Conference (EDUCON)*, IEEE, Canary Islands, Spain, pp. 320-329.

Visinescu, L.L., Sidorova, A., Jones, M.C. and Prybutok, V.R. (2015), "The influence of website dimensionality on customer experiences, perceptions and behavioral intentions: An exploration of 2D vs. 3D web design", *Information & Management,* Vol. 52 No. 1, pp. 1-17.

Webster, J. and Ho, H. (1997), "Audience engagement in multimedia presentations", *The data base for advances in information systems,* Vol. 28 No. 2, pp. 63-77.

Yang, X. (2021), "Determinants of consumers' continuance intention to use social recommender systems: A self-regulation perspective", *Technology in Society,* Vol. 64, 101464.

Zhu, W.W. and Morosan, C. (2014), "An empirical examination of guests' adoption of interactive mobile technologies in hotels", *Journal of Hospitality and Tourism Technology,* Vol. 5 No. 1, pp. 78-94.

CHAPTER 6: DISCUSSION AND CONCLUSION OF THE RESEARCH PROJECT

6.1 Chapter introduction

This thesis reports on research that aimed to investigate salient factors influencing customers' intentions to reuse recommender systems. More specifically, this research answered the overarching research question: *"How do flow experience, trusting beliefs and perceived usefulness of RSs influence consumers' behavioural intentions to reuse RSs?"*

Essentially, this research sought to provide answers to the key research questions elicited as a consequence of gaps in the extant literature. In consonance with the research objectives and to answer the overarching research question, ten research questions of this research were posed:

- First, does consumers' trust propensity influence their trusting beliefs in an ongoing relationship with RSs?
- Second, do perceived usefulness act as an antecedent of trusting beliefs of RSs?
- Third, does a comprehensive framework of trusting beliefs play a significant positive role in the consumers' behavioural intentions to reuse RSs?
- Fourth, is the relation between perceived usefulness and behavioural intentions to reuse RSs mediated by trusting beliefs of RSs?
- Fifth, does product type serve as a moderator on consumers' behavioural intentions to reuse RSs?
- Sixth, does cognitive absorption have a direct effect on consumers' behavioural intentions to reuse RSs?

- Seventh, does cognitive absorption have a direct effect on consumers' perceived usefulness of RSs?
- Eighth, is the relation between cognitive absorption and behavioural intentions to reuse RSs mediated by perceived usefulness of RSs?
- Ninth, does gender serve as a moderator on consumers' behavioural intentions to reuse RSs?
- And lastly, do focused immersion, temporal dissociation and curiosity have a significant direct effect on RSs continuous use intention?

The research questions (RQs) posed were answered by employing a three-study quantitative research design. The introduction of this research, methodology and conceptual frameworks were presented in chapter one. This was followed by the relevant streams of literature in relation to the development of the conceptual frameworks were outlined in chapter two. The hypotheses were examined through three studies presented in chapter three, four and five.

The current chapter concludes and presents an in-depth discussion of the research findings. Section 6.2 presents the discussions and interpretations of the main findings of this research. Section 6.3 addresses significant implications to both theory and practice. Section 6.4 addresses the limitations of this research and advances suggestions for future research direction. Finally, the conclusion is presented in Section 6.5.

6.2 Discussion of the findings

In this research, an attempt was made to better capture human-technology interactions by incorporating post adoption factors such as cognitive absorption and trusting beliefs into the traditional TAM and ResQue Model. This research takes a new approach to RSs post-adoption research, focusing on trusting beliefs and the interactive experiences available to people who purchase online.

This section provides detailed discussion of the result of the three quantitative studies and hypotheses that address the research questions and fill the knowledge gap surrounding post adoption factors influencing intentions to reuse recommender systems from the user's perspective.

6.2.1 Trust propensity as an antecedent of trusting beliefs

The first research question aimed to investigate the role of trust propensity as antecedent of consumers' trusting beliefs in an ongoing relationship with recommender systems. The research question was addressed by analysing the research model proposed in the Study 1 (See Section 3.5). The correlation was tested and validated using a hypothesis previously articulated in Chapter 3: which reads as follows: *Consumers' trust propensity will have a direct effect on their trusting beliefs.*

The hypothesis test performed on the constructs revealed that trust propensity was a significant determinant of trusting beliefs ($\beta = 0.325$, $t = 8.035$, $p < 0.001$). Hence, the hypothesis was supported. The evidence of this outcome is depicted in Table 3.7. The result is in congruence with previous trust literature (Alarcon et al., 2018; Colquitt et al., 2007) that suggests trust propensity acts as an important predictor of trusting beliefs throughout the trust process. This finding implies that consumers' trust propensity plays an important role in increasing their trusting beliefs in an ongoing relationship with RSs.

6.2.2 Perceived usefulness as an antecedent of trusting beliefs

The second research question aimed to determine the role of perceived usefulness as an antecedent of trusting beliefs. Although the majority of the studies have argued that trusting beliefs increases perceived usefulness, the current research argues that trusting beliefs acts as an antecedent of perceived usefulness. The hypothesis, as previously outlined in Chapter 3: reads as follows: *Perceived usefulness of RSs will have a direct effect on consumers' trusting beliefs.*

The analysis of the structural model was performed to test and validate the hypothesis. The result of the analysis demonstrates that perceived usefulness of RSs has a direct effect on consumers' trusting beliefs ($\beta = 0.603$, $t = 3.483$, $p < 0.001$). The result of the outcome is presented in Table 3.7. Hence, the hypothesis was supported. The observed correlation between perceived usefulness and trusting beliefs can be explained based on the ResQue Model that argues user beliefs (i.e., perceived usefulness) affects user attitudes (i.e., trust and confidence) (Pu et al., 2011). Contrary to the studies in the field of RSs that argue that trust stimulates usefulness (Ashraf et al., 2020; Benlian et al., 2012; Wang & Benbasat, 2005), this research argued that the increase in perceived usefulness of RSs can positively influence trusting beliefs. The result advances the findings of the previous studies in information systems that assert perceived usefulness as an antecedent of trust (Harrigan et al., 2021; Pu et al., 2011). This finding implies that perceived usefulness of RSs is demonstrative of the potential of the RSs and therefore positively influences consumers' trusting beliefs.

6.2.3 TRUSTING BELIEFS ON BEHAVIOURAL INTENTIONS TO REUSE RSS

The third research question aimed to investigate whether the comprehensive framework of trusting beliefs that comprise cognitive and emotional trust positively affects consumers' behavioural intentions to reuse RSs. The hypothesis, as previously articulated in Chapter 3:, to answer this question, reads as follows: *Consumers'* *trusting beliefs will directly affect the behavioural intentions to reuse RSs.*

The result of the structural model analysis of the research model proposed in the study 1 demonstrate that trusting beliefs had a positive and direct effect on behavioural intentions to reuse RSs ($\beta = 0.282$, $t = 3.483$, $p < 0.001$) (See Table 3.7). This research extends the findings of the prior studies that argues that trusting beliefs affects behavioural intentions (Benlian et al., 2012; Wang & Benbasat, 2005) by incorporating cognitive and emotional trust to estimate trusting beliefs. Further, the PLSpredict analysis also indicated that incorporating emotional trust with cognitive trust to estimate trusting beliefs is more efficient in explaining consumers' behavioural intentions to reuse RSs (See Table 3.11). This finding implies that the effect of trusting beliefs in explaining consumers' behavioural intentions to reuse RSs can be more efficiently explained by considering trusting beliefs as a comprehensive framework that incorporates cognitive trust and emotional trust dimensions.

6.2.4 Trusting beliefs as a mediator

The fourth research question aimed to investigate the role of trusting belief as a mediator between perceived usefulness and behavioural intentions to reuse RSs. The hypothesis, as previously articulated in Chapter 3:, to answer this question, reads as follows: *Consumers' trusting beliefs mediate the direct effect of perceived usefulness of RSs on intentions to reuse RSs.*

The result of the mediation analysis showed that trusting beliefs partially mediated the relationship between perceived usefulness and behavioural intentions to reuse RSs (See Table 3.8). Hence, the hypothesis was supported. Contrary to the studies in the field of RSs that argue that trust stimulates usefulness which in turn will influence behavioural intentions (Ashraf et al., 2020; Benlian et al., 2012; Wang & Benbasat, 2005), this finding implies that if consumers perceive that RSs is useful in assisting in their decision-making process, they will develop trusting beliefs towards them, which will result in their intentions to reuse RSs.

6.2.5 Product type as a moderator

The fifth research question aimed at investigating whether product type serves as a moderator on consumers' behavioural intentions to reuse RSs. The research question was addressed by determining whether the strength of the association between the constructs presented in the research model in Study 1 differs between search and experience products. The hypothesis, as stated previously in Chapter 3:, to address this question is as follows: *The strength of the relationship between the constructs is significantly different in search and experience products.*

The result of the partial least squares multi-group analysis using the Welch-Satterthwait test revealed that the strength of relationship between search and experience products was found to be not significant (See Table 3.10). Hence, the hypothesis was not supported. This finding is at odds with previous research findings (Ashraf et al., 2019; Benlian et al., 2012). This discrepancy could be attributed to the context of the online shopping environment. Since the product attributes of experience products are more dependent on subjective experience, they cannot be evaluated directly prior to purchase (Liu et al., 2020). Consequently, the consumer may not notice any differences between the search and experience products.

6.2.6 Cognitive absorption on consumers' behavioural intentions to reuse RSs

The sixth research question is aimed at determining the effect of cognitive absorption on consumers' behavioural intentions to reuse recommender system. The hypothesis, as previously stated in

Chapter 4:, to address this research question reads as follows: *Shoppers' cognitive absorption has a direct and positive effect on behavioural intentions to reuse RSs.*

The result of the partial least squares structural equation modelling implies that there was a significant positive correlation between cognitive absorption and behavioural intentions ($\beta = 0.743$, $t = 27.195$, $p < 0.001$). Hence, the hypothesis was supported. The evidence of the outcome is clearly shown in (See Table 4.6). The finding assures the importance of cognitive absorption in the IT-mediated environment in e-commerce. The finding can be explained by the fact that flow is likely to occur during information-seeking activities associated with purchasing via recommender systems, and that flow experiences might attract customers and influence subsequent attitudes and usage intentions (Balakrishnan & Dwivedi, 2021; Mahnke et al., 2015). The results of the Importance-Performance Map Analysis show that consumers' behavioural intentions to reuse RSs should be given more attention because cognitive absorption is of the greatest importance, but its performance is poor in comparison to perceived usefulness (See Figure 4.5). Prior studies in the field of information system have conflicting findings regarding the influence of cognitive absorption on consumer behaviour. Shang et al. (2005) investigated the effect of cognitive absorption (measured as a first order variable), perceived usefulness and perceived ease of use with regards to online shopping behaviour among Taiwanese consumers and concluded that cognitive absorption does not have a positive direct effect on online shopping behaviour. Suki et al. (2008) reported that online shopping behaviour among Malaysian consumers was not directly affected by cognitive absorption (measured as a first order variable with limited measures). Inconsistencies in cognitive absorption outcomes in these studies could be attributed to a lack of consensus in the selection of measures of cognitive absorption. The finding of the current research implies that cognitive absorption is a vital determinant in the formation of consumers' behavioural intentions to reuse RSs. Consequently, this research suggests that an increase in cognitive absorption can in turn increase behavioural intentions to reuse RSs. Based on the discussion, it can also be inferred that the effect of cognitive absorption may vary depending on technology and measures of cognitive absorption.

6.2.7 Cognitive absorption on perceived usefulness of RSs

The seventh research question is aimed at investigating the effect of cognitive absorption on perceived usefulness of recommender systems. The research question was addressed by analysing the research model proposed in the Study 2. The hypothesis, as previously articulated in Chapter 4:, to answer this research question is as follows: *Shoppers' cognitive absorption has a direct and positive effect on the perceived usefulness of RSs.*

The result of the assessment of the structural model shows that there was a significant positive correlation between cognitive absorption and perceived usefulness ($\beta = 0.764$, $t = 30.911$, $p < 0.001$). The evidence of the outcome is clearly indicated in Table 4.6. The finding of this research echoes the findings of Saadé and Bahli (2005) and Salimon et al. (2021), thereby confirming cognitive absorption as a predictor of perceived usefulness. This finding indicates that the usefulness of recommender system increases, as they experience holistic engagement, derive fun, gratify and enjoy while interacting with them. This finding reinforces the notion that cognitive absorption works as an intrinsic factor in the cognitive entanglement of recommender system users for the sake of pleasure and enjoyment.

6.2.8 The mediating role of perceived usefulness

The aim research question eight is to determine whether the relation between cognitive absorption and behavioural intentions to reuse RSs is mediated by the perceived usefulness of RSs. The hypothesis, as stated previously in Chapter 4:, to address the research question is as follows: *Shoppers' perceived usefulness of RSs mediates the influence of cognitive absorption on behavioural intentions to reuse.*

The result of the bootstrapping method (See Table 4.6) and VAF method demonstrate that cognitive absorption indirectly affects behavioural intentions through perceived usefulness. The magnitude of mediation is complementary or partial (Hair et al., 2021; Zhao et al., 2010). Hence, the result provides strong support for the proposed hypothesis. The finding implies that as the shoppers' level of cognitive absorption increases the RSs usefulness beliefs which in turn positively influences behavioural intentions to reuse RSs. The multi-group analysis also shows that perceived usefulness fully mediates males' behavioural intentions to reuse RSs, whereas perceived usefulness partially mediates females' behavioural intentions to reuse RSs. The result advances the findings of the previous information system studies to the RS context that asserts the role of perceived usefulness as a mediating variable in affecting behavioural intentions (e.g., Chawla & Joshi, 2020; Hussein et al., 2019).

6.2.9 Gender as a moderator

The ninth research question is aimed at investigating the role of gender as a moderator on consumers' behavioural intentions to reuse RSs. The research question was addressed by determining whether the strength of the association between the constructs presented in the research model in Study 2 differs between males and females. The hypothesis, as previously articulated in Chapter 4:

to answer the research question is as follows: *The strength of the relationship between the constructs is significantly different in males and females.*

The result of the partial least squares multi-group analysis using the bootstrapping method and the Welch-Satterthwait test revealed that the strength of the relationship between male and female sample was found to be significantly different (See Table 4.8 and

Table 4.9). This finding confirms that males and females search for information differently when shopping online, and that shoppers' interactions with RSs are significantly moderated by gender.

6.2.10 FOCUSED IMMERSION, TEMPORAL DISSOCIATION AND CURIOSITY ON RSS CONTINUOUS USE INTENTION

The final research question was aimed to determine the effect of focused immersion, temporal dissociation and curiosity on RSs continuous use intention. The hypothesis, as stated previously in Chapter 5: to address this question is as follows:

H1: *Increase in curiosity positively influences continuous use intention.*

H2: *Increase in focused immersion positively influences continuous use intention.*

H3: *Increase in temporal dissociation positively influences continuous use intention.*

The result of the SEM (See Table 5.6) demonstrates an increase in curiosity ($\beta = 0.323$, $t = 4.328$, $p < 0.001$). An increase in focused immersion positively influences continuous use intention ($\beta = 0.329$, $t = 5.327$, $p < 0.001$). However, temporal dissociation has an insignificant relationship with continuous use intention ($\beta = 0.105$, $t = 1.430$, $p = 0.153$). The findings observed in this study mirror those of the previous studies that have examined the effects of focused immersion, temporal dissociation and curiosity with respect to continuous use intention (Venter & Swart, 2018; Visinescu et al., 2015). This finding indicates that the continuous use intention of the AI-driven RSs in e-commerce is positively influenced by a user's curiosity and focused immersion more than temporal dissociation.

6.3 Implications of this thesis

The findings of this research have both academic and practical contributions. The following section presents these contributions to the extant literature.

6.3.1 Academic contributions

This research has made several important academic contributions as follows: This thesis contributes to the body of knowledge on customer behaviour by determining the influence of trusting beliefs, cognitive absorption, perceived usefulness, focused immersion, temporal dissociation and curiosity on customer behavioural intentions to reuse recommender systems. This also work contributes to the existing knowledge on user-centric evaluation of recommender system by development and validation of three proposed research model. The result showed that all the proposed models had useful explanatory power in predicting consumers' behavioural intentions to reuse recommender systems.

Study 1 extends the ResQue Model by integrating trusting beliefs as an antecedent of behavioural intentions to reuse recommender system. In contrast to several previous research studies that ignored the emotional trust dimension of trusting beliefs, the Study 1 contributes to the knowledge by extending the work of Ashraf et al. (2019) by empirically investigating the effect of a comprehensive framework of trusting beliefs that integrates cognitive and emotional dimension on consumers' behavioural intentions to reuse recommender systems. The PLSpredict method was also employed in this work to examine the predictive model's out-of-sample predictive power or predictive validity (Shmueli et al., 2016). The result confirmed that the consumers' behavioural intentions to reuse RSs can be better explained by incorporating emotional trust into the model. Study 1 also contributes to the trust-centred studies based on RSs by demonstrating the role of trust propensity as an antecedent of trusting beliefs in an ongoing relationship. Study 1 used a multidisciplinary approach and made a typical combination novelty by developing and validating a research model by integrating concepts from IS literature (recommender systems, perceived usefulness), trust literature (trust propensity, trusting beliefs) and the use of up-to-date as well as the most efficient statistical approach (PLS-MGA) to test the moderation effect of product type and the PLSpredict technique for predictive model assessment. Despite the insignificant results of the moderation analysis performed in Study 1, it may contribute to our understanding of Australian consumers who, when purchasing products using recommender systems, may not notice the difference between the search product and the experience product due to the influence of the online shopping context.

Study 2 responds to the call for more empirical research in line of RSs research by Xiao and Benbasat (2007). In recommender systems literature there is a dearth of study on the influence of cognitive absorption, and little is known about how cognitive absorption affects consumers' behavioural intentions to reuse RSs or their decision outcomes. Study 2 adds to a growing body of literature on factors influencing consumers' behavioural intentions to reuse recommender systems by highlighting the role of cognitive absorption. Study 2 proposed a research model that combined robust theoretical models such as the technology acceptance model and flow theory to provide more comprehensive understanding of factors determining behavioural intentions to reuse recommender systems. This approach is likely to ensure a stable theory development. The empirical findings of Study 2 show that cognitive absorption directly and indirectly affects consumers' behavioural intentions to reuse recommender systems. Further, Study 3 responds to the call for investigating novel antecedents of information system continuous use intention by Laurell et al. (2019) and makes a unique contribution to the literature by considering the dimensions of cognitive absorption (curiosity, focused immersion, and temporal dissociation) separately. Study 3 extends the information gap theory to the context of online shopping involving consumers' RSs continuous use intention.

Most previous studies have employed a laboratory experimental method; there have been fewer studies focusing on the real consumer environment and therefore unable to study how decision makers actually get information and use it in the decision-making process (Zha et al., 2013). As a result, this research offered empirical evidence on the link between study variables by gathering primary data from current and active users of RSs in the context of Amazon in Australia. The result of three quantitative studies explained how consumers' perceptions of RSs performance are influenced by several evaluation variables, which in turn determines whether or not they intend to reuse RSs in the future. The purpose of this study was to add to the body of knowledge about how real Amazon customers view and use online recommendations while making online purchases.

The current research employs a positivist paradigm and a quantitative deductive methodology to examine consumers' behavioural intentions to reuse RSs as a human behavioural response and a social reality that can be objectively evaluated via the application of standard scientific methods. The research employed up-to-date statistical method such as MICOM and PLS-MGA, which are considered to be more robust methods to determine the moderating effect of product type and gender. Study 1 used the PLSpredict technique to determine the appropriate causal-predictive model. Study 2 used the Partial Least Square Importance-Performance Map Analysis (PLS-IPMA) to provide additional evidence that cognitive absorption is an important determinant of consumer behavioural intention to reuse RSs.

The three research models proposed in this research will serve as a foundation for future research and can be used by researchers investigating different types of decision support systems. This research avenue holds great promise for helping information systems academics to better understand why users continue to use or avoid using a recommender system.

6.3.2 Practical contributions

The findings of this research have wide range of practical implications, in addition to theoretical contributions. This research gives practitioners interested in designing effective recommender systems principles for developing recommender systems that include instrumental effects, cognitive absorption, trust, and emotions to provide customers with a holistic purchase experience.

Optimizing machine-learning algorithms alone for reliable suggestions and RSs reuse may not be enough. The significance and dominant impacts of trusting beliefs, perceived usefulness and cognitive absorption, in this research, present e-vendors such as

Amazon with potential fruitful areas to affect consumers' behavioural intentions to reuse RSs. An e-vendor should attempt to change potential key performance indicators (KPIs) from being solely a sales-based approach to an engagement-based approach by designing useful, convenient, and trustworthy recommender systems. The use of textual and explanatory components in recommender systems by e-vendors can mimic the way information flows between humans, increasing customer trust and lowering their anxiety about making use of the recommendation system (Kunkel et al., 2019; Pu & Chen, 2007). Based on the findings of the research, e-vendors should also focus on improving the emotional trust of consumers. RSs that provide rapid feedback (e.g., those that combine components of the telephonic conversation) and mechanism for understanding communication cues (such as sound, video, and text) might help to establish emotional trust more successfully (Gallié & Guichard, 2005; Rocco et al., 2001). Having a high level of trust propensity is a significant factor in a consumer's view that the recommender system is trustworthy. It is impossible for an e-vendor to influence a customer' trust propensity, even if certain customer groups are singled out for special attention.

Further, consistent with the prior information systems literature, this research emphasises that e-vendors who employ RSs should concentrate on making them more useful. RSs should pay special attention to the quality of the information they offer to customers in order to help them make better purchasing decisions. RSs should provide accurate, appropriate, and reliable information to improve customer loyalty and meet shoppers' needs.

E-vendors who employ recommender systems should focus on improving their customers' overall recommender systems experience, i.e., cognitive absorption, because it is a critical component of the person's intentions to reuse RSs. According to the findings, this may be accomplished through stimulating shoppers' focused immersion and curiosity. It is imperative that e-vendors who utilise RSs make a concerted effort to incorporate attention-grabbing elements, gripping users such that other attentional demands are largely ignored promoting focused immersion. On the other hand, limiting the amount of information RS displays, e-vendors can exploit curiosity to their favour by employing the approach of the information gap and leaving some things up to the imagination of their customers. For example, social media companies like LinkedIn use an information gap technique to persuade users to upgrade their accounts, providing them with access to the number of profile views while obscuring the identities of the viewers. When compared to men's cognitive absorption perception, women's cognitive absorption perception has a considerable favourable impact on behaviour intention to reuse recommender systems. In general, the research established the importance of increasing shoppers' cognitive absorption to increase their intentions to reuse RSs.

Practical implications for e-vendors can be drawn from this research in the form of product recommendation marketing techniques and sales-efficient e-commerce websites that increase overall customer trustworthiness and shopping experience. Depending on their strategic orientation in terms of channels (e.g., internet versus mobile), product categories (e.g., experience versus search goods), and customer groups (e.g., males versus females), online retailers should assess which types of consumer reactions or variations of these are most advantageous to accelerate sales. As a result, e-vendors could alter the presence of recommender systems on their e-commerce platform. Furthermore, the findings from this research could be used to test different e-commerce website designs and evaluate how much emphasis should be placed on recommender systems at each step of the purchasing funnel, which breaks down the consumer–product interaction process into four steps: awareness, interest, purchase, and loyalty.

In accordance with the above discussion, paying attention to customers' recommender system evaluation beliefs may have a favourable impact on recommender system reuse intentions and would result in long success and sustainability of recommender systems.

6.4 Research limitations and future research

The findings presented in this research are subject to various limitations. To begin, the study employed a cross-sectional survey approach. Future research should examine the relationship between these variables using a longitudinal survey approach. Second, considering respondents were selected using a non-probability sampling method, the research findings cannot be generalised to the entire population. It is recommended that future research should employ a random sampling technique to gather representative data in order to confirm that the findings of this study can still be upheld. Third, the research is conducted in the context of e-commerce in Australia, which may differ from other nations and industries. Consumer behaviour can be influenced by culture, and this could be investigated further in future research. Fourth, this study focused exclusively on Amazon's recommender systems that employ collaborative filtering. Further study should be conducted on the proposed model utilising a lesser-known e-commerce platform that employs recommender systems with a different underlying algorithmic strategy, such as content-based filtering or hybrid filtering. Fifth, because the study employed self-reported intentions to reuse as a proxy for behavioural intentions to reuse recommender systems, the results may not be as accurate as actual reuse. Sixth, this study examined only three aspects of cognitive absorption:

curiosity, focused immersion, and temporal dissociation. Future research may examine additional dimensions of cognitive absorption, such as control and heightened enjoyment. Seventh, although the current study found no evidence of a moderating effect of product type on consumers' behavioural intentions to reuse RSs, future research may evaluate different variables and situations that may have a strong moderating effect on consumers' behavioural intentions in the product type.

6.5 Chapter summary

In conclusion, this research examines factors that determine consumers’ behavioural intentions to reuse RSs. In doing so, this proposes three conceptual models based on robust underlying theoretical models such as the ResQue Model, TAM, theory of trust formation, flow theory and cognitive absorption. In order to test the hypotheses posed in this research to answer the research questions, this research uses a quantitative approach which is consistent with the positivist paradigm. A questionnaire that reflects the proposed research constructs was developed to collect the primary data for the study. The data was collected from current active Amazon customers, who have used RSs for making purchase decisions. Since, this thesis is quantitative with a deductive approach, it employs rigorous statistical analysis tools such as partial least squares structural equation modelling (PLS-SEM) and partial least squares multi-group analysis (PLS-MGA) to validate and confirm the proposed conceptual models by testing the relationships being hypothesized. The thesis provides novel perspectives, approaches and models to examine factors that determines consumers’ behavioural intentions to reuse RSs.

The findings of this research provide empirical evidence for the significant impact of perceived usefulness, flow, trusting beliefs, curiosity and focused immersion on consumers’ behavioural intentions to reuse RSs. The findings also show the prominence of the moderating effect of male and female consumers' behavioural intentions to reuse RSs. It indicates that these factors are most crucial for e-vendors wishing to enhance the consumers' behavioural intentions to reuse recommender systems. Finally, research contributions, limitations, and future research are highlighted.

REFERENCES

Abrams, K. v. (2021). *Global Ecommerce Forecast 2021*. eMarketer. https://www.emarketer.com/content/global-ecommerce-forecast-2021

Abumalloh, R. A., Ibrahim, O., & Nilashi, M. (2020). Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce. *Technology in Society, 61*, 101253.

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*(4), 665-694.

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences, 28*(3), 557-582.

Aghion, P., Jones, B. F., & Jones, C. I. (2019). 9. Artificial Intelligence and Economic Growth. In A. A. J. G. A. Goldfarb (Ed.), *The Economics of Artificial Intelligence: An Agenda* (pp. 237-290). University of Chicago Press. https://doi.org/10.7208/9780226613475-011

Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A., & Darwesh, A. (2020). A systematic study on the recommender systems in the E-commerce. *IEEE Access, 8*, 115694-115716.

Alarcon, G. M., Lyons, J. B., Christensen, J. C., Bowers, M. A., Klosterman, S. L., & Capiola, A. (2018). The role of propensity to trust and the five factor model across the trust process. *Journal of Research in Personality, 75*, 69-82.

Alharbi, H., & Sandhu, K. (2018). Explaining and predicting continuance usage intention of e-learning recommender systems: an empirical evidence from Saudi Arabia. *International Journal of Business Information Systems, 29*(3), 297-323. https://doi.org/10.1504/IJBIS.2018.095565

Aljukhadar, M., & Senecal, S. (2021). The Effect of Consumer-Activated Mind-Set and Product Involvement on the Compliance With Recommender System Advice. *SAGE Open, 11*(3), 21582440211031550. https://doi.org/10.1177/21582440211031550

Allport, G. W., & Lindzey, G. (1954). *Handbook of social psychology*. Addison-Wesley.

Amin, M., Rezaei, S., & Tavana, F. S. (2015). Gender differences and consumer’s repurchase intention: the impact of trust propensity, usefulness and ease of use for implication of innovative online retail. *International Journal of Innovation and Learning, 17*(2), 217-233.

Andreini, D., Pedeliento, G., Zarantonello, L., & Solerio, C. (2018). A renaissance of brand experience: Advancing the concept through a multi-perspective analysis. *Journal of Business Research, 91*, 123-133. https://doi.org/10.1016/j.jbusres.2018.05.046

Argilés-Bosch, J. M., Garcia-Blandón, J., & Ravenda, D. (2022). Cost behavior in e-commerce firms. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-021-09528-2

Ashraf, M., Ahmad, J., Hamyon, A. A., Sheikh, M. R., & Sharif, W. (2020). Effects of post-adoption beliefs on customers’ online product recommendation continuous usage: An extended expectation-confirmation model. *Cogent Business & Management, 7*(1), 1735693. https://doi.org/10.1080/23311975.2020.1735693

Ashraf, M., Ahmad, J., Sharif, W., Raza, A. A., Salman Shabbir, M., Abbas, M., & Thurasamy, R. (2020). The role of continuous trust in usage of online product recommendations [Article]. *Online Information Review, 44*(4), 745-766. https://doi.org/10.1108/OIR-05-2018-0156

Ashraf, M., Ismawati Jaafar, N., & Sulaiman, A. (2019). System- vs. consumer-generated recommendations: affective and social-psychological effects on purchase intention [Article]. *Behaviour and Information Technology, 38*(12), 1259-1272. https://doi.org/10.1080/0144929X.2019.1583285

Ayanso, A., Herath, T. C., & O'Brien, N. (2015). Understanding continuance intentions of physicians with electronic medical records (EMR): An expectancy-confirmation perspective. *Decision Support Systems, 77*, 112-122.

Babbie, E. R. (2015). *The Practice of Social Research*. Cengage Learning.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing, 38*(4), 643-668. https://doi.org/10.1002/mar.21462

Barari, N., RezaeiZadeh, M., Khorasani, A., & Alami, F. (2020). Designing and validating educational standards for E-teaching in virtual learning environments (VLEs), based on revised Bloom's taxonomy. *Interactive Learning Environments*, 1-13. https://doi.org/10.1080/10494820.2020.1739078

Barragáns-Martínez, A. B., Costa-Montenegro, E., Burguillo, J. C., Rey-López, M., Mikic-Fonte, F. A., & Peleteiro, A. (2010). A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition. *Information Sciences, 180*(22), 4290-4311.

Barta, S., Flavián, C., & Gurrea, R. (2021). Managing consumer experience and online flow: Differences in handheld devices vs PCs. *Technology in Society, 64*, 101525. https://doi.org/10.1016/j.techsoc.2020.101525

Becker, L., & Jaakkola, E. (2020). Customer experience: fundamental premises and implications for research. *Journal of the Academy of Marketing Science, 48*(4), 630-648. https://doi.org/10.1007/s11747-019-00718-x

Behera, R. K., Gunasekaran, A., Gupta, S., Kamboj, S., & Bala, P. K. (2020). Personalized digital marketing recommender engine. *Journal of Retailing and Consumer Services, 53*, 101799. https://doi.org/10.1016/j.jretconser.2019.03.026

Benlian, A., Titah, R., & Hess, T. (2012). Differential Effects of Provider Recommendations and Consumer Reviews in E-Commerce Transactions: An Experimental Study. *Journal of Management Information Systems, 29*(1), 237-272. https://doi.org/10.2753/MIS0742-1222290107

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS quarterly, 25*(3), 351-370. https://doi.org/10.2307/3250921

Bigras, É., Léger, P. M., & Sénécal, S. (2019). Recommendation agent adoption: How recommendation presentation influences employees' perceptions, behaviors, and decision quality [Article]. *Applied Sciences (Switzerland), 9*(20), Article 4244. https://doi.org/10.3390/app9204244

Bilgihan, A., Okumus, F., Nusair, K., & Bujisic, M. (2014). Online experiences: flow theory, measuring online customer experience in e-commerce and managerial implications for the lodging industry. *Information Technology & Tourism, 14*(1), 49-71.

Blau, P. (1964). Power and exchange in social life. In: New York: J Wiley & Sons.

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2018). Creating Effective Online Customer Experiences. *Journal of Marketing, 83*(2), 98-119. https://doi.org/10.1177/0022242918809930

Blomberg, B., Cooper, D., & Schindler, P. (2008). Business research methods.(2nd European ed.). In: New York: McGraw-Hill Education.

Bock, G.-W., Lee, J., Kuan, H.-H., & Kim, J.-H. (2012). The progression of online trust in the multi-channel retailer context and the role of product uncertainty. *Decision Support Systems, 53*(1), 97-107. https://doi.org/10.1016/j.dss.2011.12.007

Brömmelstroet, M. t. (2017). PSS are more user-friendly, but are they also increasingly useful? *Transportation Research Part A: Policy and Practice, 104*, 96-107.

Bryman, A. (2012). *Social Research Methods*. OUP Oxford.

Bustamante, J. C., & Rubio, N. (2017). Measuring customer experience in physical retail environments. *Journal of Service Management*. 28(5), 884- 913. https://doi.org/10.1108/JOSM-06-2016-0142

Butler Jr, J. K. (1991). Toward understanding and measuring conditions of trust: Evolution of a conditions of trust inventory. *Journal of management, 17*(3), 643-663.

Cassell, J., & Bickmore, T. (2000). External manifestations of trustworthiness in the interface. *Communications of the ACM, 43*(12), 50-56.

Chang, I. C., Chou, P.-C., Yeh, R. K.-J., & Tseng, H.-T. (2016) Factors influencing Chinese tourists' intentions to use the Taiwan Medical Travel App. *Telematics and Informatics, 33*(2), 401-409. https://doi.org/10.1016/j.tele.2015.09.007

Chang, Y.-S., & Fang, S.-R. (2013). Antecedents and distinctions between online trust and distrust: Predicting high-and low-risk internet behaviors. *Journal of Electronic Commerce Research, 14*(2), 149.

Chau, P. Y., Ho, S. Y., Ho, K. K., & Yao, Y. (2013). Examining the effects of malfunctioning personalized services on online users' distrust and behaviors. *Decision Support Systems, 56*, 180-191.

Chawla, D., & Joshi, H. (2020). Role of mediator in examining the influence of antecedents of mobile wallet adoption on attitude and intention. *Global Business Review*, 1-17. https://doi.org/10.1177/0972150920924506

Chen, L., Yang, Y., Wang, N., Yang, K., & Yuan, Q. (2019). How serendipity improves user satisfaction with recommendations? a large-scale user evaluation. The World Wide Web Conference, San Francisco, CA, USA.

Cheng, P., OuYang, Z., & Liu, Y. (2019). Understanding bike sharing use over time by employing extended technology continuance theory. *Transportation Research Part A: Policy and Practice, 124*, 433-443. https://doi.org/10.1016/j.tra.2019.04.013

Cheng, S.-I., Chen, S.-C., & Yen, D. C. (2015). Continuance intention of E-portfolio system: A confirmatory and multigroup invariance analysis of technology acceptance model. *Computer Standards & Interfaces, 42*, 17-23.

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services, 61*, 102528. https://doi.org/10.1016/j.jretconser.2021.102528

Chiu, C.-K., Lin, C.-P., Chen, K.-J., Liu, C.-M., & Ma, H.-C. (2019). Modeling continuance intention towards Mobile Travel Service System (MTSS): a theoretical perspective of motivation and dependency. *Review of Managerial Science, 13*(4), 749-769. https://doi.org/10.1007/s11846-017-0257-9

Choi, J., Lee, H. J., & Kim, Y. (2011). The influence of social presence on customer intention to reuse online recommender systems: The roles of personalization and product type [Article]. *International journal of electronic commerce, 16*(1), 129-153. https://doi.org/10.2753/JEC1086-4415160105

Chooprayoon, V., Fung, C. C., & Depickere, A. A. (2007). TECTAM, A modified technology acceptance model to assess E-commerce technologies adoption by Thai SME. TENCON 2007-2007 IEEE Region 10 Conference

Cloutman, N. (2021). *Online Shopping in Australia* (X0004). IBISWorld. https://www.ibisworld.com/au/industry/online-shopping/1837/

Cohen, L., Manion, L., & Morrison, K. (2017). *Research Methods in Education* (8th ed.). Routledge.

Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of applied psychology, 92*(4), 909.

Cook, T. D., Campbell, D. T., & Shadish, W. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin Boston, MA.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Creswell, J. W., & Plano Clark, V. L. (2011). *Designing and conducting mixed methods research*. SAGE Publications.

Csikszentmihalyi, M. (2000). *Beyond boredom and anxiety: experiencing flow in work and play*. Jossey-Bass Publishers.

Csikszentmihalyi, M., & Csikzentmihaly, M. (1990). Flow: The psychology of optimal experience. *Journal of Leisure Research, 24*(1), 93-94. https://doi.org/10.1080/00222216.1992.11969876

Csikszentmihalyi, M., Larson, R., & Prescott, S. (2014). The ecology of adolescent activity and experience. In *Applications of Flow in Human Development and Education* (pp. 241-254). Springer.

Dadoun, A., Defoin-Platel, M., Fiig, T., Landra, C., & Troncy, R. (2021). How recommender systems can transform airline offer construction and retailing. *Journal of Revenue and Pricing Management, 20*(3), 301-315. https://doi.org/10.1057/s41272-021-00313-2

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review, 14*(1), 57-74.

Fang, H., Guo, G., & Zhang, J. (2015). Multi-faceted trust and distrust prediction for recommender systems. *Decision Support Systems, 71*, 37-47.

Fishbein, M., & Ajzen, I. (1975). Intention and Behavior: An introduction to theory and research. Addison-Wesley.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric, 10*(2).

Fleischmann, M., Amirpur, M., Grupp, T., Benlian, A., & Hess, T. (2016). The role of software updates in information systems continuance—An experimental study from a user perspective. *Decision Support Systems, 83*, 83-96.

Fraedrich, J., Thorne, D. M., & Ferrell, O. (1994). Assessing the application of cognitive moral development theory to business ethics. *Journal of business Ethics, 13*(10), 829-838.

Galeano, D., & Paccanaro, A. (2018). A recommender system approach for predicting drug side effects. 2018 International Joint Conference on Neural Networks (IJCNN),

Gallié, E.-P., & Guichard, R. (2005). Do collaboratories mean the end of face-to-face interactions? An evidence from the ISEE project. *Economics of Innovation and New Technology, 14*(6), 517-532. https://doi.org/10.1080/1043859042000304052

Gan, C., & Li, H. (2018). Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications. *Computers in Human Behavior, 78*, 306-315. https://doi.org/10.1016/j.chb.2017.10.003

Gao, W., Li, W., Fan, H., & Jia, X. (2021). How customer experience incongruence affects omnichannel customer retention: The moderating role of channel characteristics. *Journal of Retailing and Consumer Services, 60*, 102487. https://doi.org/10.1016/j.jretconser.2021.102487

Garcin, F., Faltings, B., Donatsch, O., Alazzawi, A., Bruttin, C., & Huber, A. (2014). *Offline and online evaluation of news recommender systems at swissinfo.ch* Proceedings of the 8th ACM Conference on Recommender systems, Foster City, Silicon Valley, California, USA. https://doi.org/10.1145/2645710.2645745

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51-90.

Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information Systems, 1*(1), 8.

Gemmis, M. D., Lops, P., Musto, C., Narducci, F., & Semeraro, G. (2015). Semantics-aware content-based recommender systems. In *Recommender systems handbook* (pp. 119-159). Springer.

Ghani, J. A., & Deshpande, S. P. (1994). Task characteristics and the experience of optimal flow in human—computer interaction. *The Journal of psychology, 128*(4), 381-391.

Ghasemaghaei, M. (2020). The impact of in-depth online recommendation agents on consumer disorientation and cognitive absorption perceptions [Article]. *Behaviour and Information Technology, 39*(4), 414-430. https://doi.org/10.1080/0144929X.2019.1598496

Giffin, K. (1967). The contribution of studies of source credibility to a theory of interpersonal trust in the communication process. *Psychological bulletin, 68*(2), 104-120.

Gomez-Uribe, C. A., & Hunt, N. (2015). The netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems (TMIS), 6*(4), 1-19.

Gopalani, A., & Shick, K. (2011). The service-enabled customer experience: a jump-start to competitive advantage. *Journal of Business Strategy, 32*(3), 4-12. https://doi.org/10.1108/02756661111121947

Grant, B. M., & Giddings, L. S. (2002). Making sense of methodologies: A paradigm framework for the novice researcher. *Contemporary Nurse, 13*(1), 10-28. https://doi.org/10.5172/conu.13.1.10

Grix, J. (2002). Introducing Students to the Generic Terminology of Social Research. *Politics, 22*(3), 175-186. https://doi.org/10.1111/1467-9256.00173

Guo, Y., Wang, M., & Li, X. (2017). Application of an improved Apriori algorithm in a mobile e-commerce recommendation system. *Industrial Management & Data Systems*.

Haddaway, N. R. A. U. P. C. C., & McGuinness, L. A. (2021). *PRISMA2020: R package and ShinyApp for producing PRISMA 2020 compliant flow diagrams (Version 0.0.2).* In Zenodo. http://doi.org/10.5281/zenodo.5082518

Hair, J. J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Harman, J. L., O'Donovan, J., Abdelzaher, T., & Gonzalez, C. (2014). Dynamics of human trust in recommender systems. Proceedings of the 8th ACM Conference on Recommender systems, Silicon Valley, CA.

Harrigan, M., Feddema, K., Wang, S., Harrigan, P., & Diot, E. (2021). How trust leads to online purchase intention founded in perceived usefulness and peer communication. *Journal of Consumer Behaviour*, 1-16. https://doi.org/10.1002/cb.1936

He, Y., Ashraf, M., Sharif, W., Abbas, M., Raza, A., Jaafar, N. I., Sulaiman, A., Thurasamy, R., & Shabbir, M. S. (2021). Impact of system- vs. consumer- generated recommendations on decision factors: A differential, moderating and mediating perspective. *Current Psychology*. https://doi.org/10.1007/s12144-021-02119-2

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Trans. Inf. Syst., 22*(1), 5–53. https://doi.org/10.1145/963770.963772

Ho, G., Wheatley, D., & Scialfa, C. T. (2005). Age differences in trust and reliance of a medication management system. *Interacting with computers, 17*(6), 690-710.

Ho, R. (2013). *Handbook of univariate and multivariate data analysis with IBM SPSS*. CRC press.

Hoffman, D. L., & Novak, T. P. (1996). Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations. *Journal of Marketing, 60*(3), 50-68. https://doi.org/10.1177/002224299606000304

Hoffman, D. L., & Novak, T. P. (2009). Flow online: lessons learned and future prospects. *Journal of interactive marketing, 23*(1), 23-34.

Homburg, C., Jozić, D., & Kuehnl, C. (2017). Customer experience management: toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science,* *45*(3), 377-401. https://doi.org/10.1007/s11747-015-0460-7

Hu, R., & Pu, P. (2009). Acceptance issues of personality-based recommender systems. Proceedings of the third ACM conference on Recommender systems,

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. *European Journal of Marketing, 53*(6), 1073-1098. https://doi.org/10.1108/EJM-12-2016-0794

Hudson, L. A., & Ozanne, J. L. (1988). Alternative Ways of Seeking Knowledge in Consumer Research. *Journal of Consumer Research, 14*(4), 508-521. https://doi.org/10.1086/209132

Hunt, S. D. (1991). *Modern Marketing Theory: Critical Issues in the Philosophy of Marketing Science.* South Western Publishing.

Hussein, L. A., Baharudin, A. S., Jayaraman, K., & Kiumarsi, S. (2019). B2B e-commerce technology factors with mediating effect perceived usefulness in Jordanian manufacturing SMES. *Journal of Engineering Science and Technology, 14*(1), 411-429.

Hyun, H., Thavisay, T., & Lee, S. H. (2021). Enhancing the role of flow experience in social media usage and its impact on shopping. *Journal of Retailing and Consumer Services*, 102492. https://doi.org/10.1016/j.jretconser.2021.102492

Ifinedo, P. (2017). Examining students' intention to continue using blogs for learning: Perspectives from technology acceptance, motivational, and social-cognitive frameworks. *Computers in Human Behavior, 72*, 189-199. https://doi.org/10.1016/j.chb.2016.12.049

Iovine, A., Narducci, F., & Semeraro, G. (2020). Conversational Recommender Systems and natural language:: A study through the ConveRSE framework. *Decision Support Systems, 131*, 113250. https://doi.org/10.1016/j.dss.2020.113250

Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal, 16*(3), 261-273. https://doi.org/10.1016/j.eij.2015.06.005

Jannach, D., & Jugovac, M. (2019). Measuring the Business Value of Recommender Systems. *ACM Trans. Manage. Inf. Syst., 10*(4), Article 16. https://doi.org/10.1145/3370082

Jessup, S. A., Schneider, T. R., Alarcon, G. M., Ryan, T. J., & Capiola, A. (2019). The measurement of the propensity to trust automation. International Conference on Human-Computer Interaction. Springer, Cham.

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International journal of cognitive ergonomics, 4*(1), 53-71.

Jiang, Z., & Benbasat, I. (2004). Virtual Product Experience: Effects of Visual and Functional Control of Products on Perceived Diagnosticity and Flow in Electronic Shopping. *Journal of Management Information Systems, 21*(3), 111-147. https://doi.org/10.1080/07421222.2004.11045817

Jin, X.-L., Lee, M. K., & Cheung, C. M. (2010). Predicting continuance in online communities: model development and empirical test. *Behaviour & Information Technology, 29*(4), 383-394.

Johnson, P., & Duberley, J. (2000). Understanding Management Research. In P. Johnson & J. Duberley (Eds.), *Understanding management research* (pp. 39-61). SAGE Publications Ltd. https://doi.org/10.4135/9780857020185

Joo, Y. J., Kim, N., & Kim, N. H. (2016). Factors predicting online university students' use of a mobile learning management system (m-LMS). *Educational Technology Research and Development, 64*(4), 611-630. https://doi.org/10.1007/s11423-016-9436-7

JothiLakshmi, S., & Thangaraj, M. (2018). Design and development of recommender system for target marketing of higher education institution using EDM. *International Journal of Applied Engineering Research, 13*(19), 14431-14437.

Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society, 60*, 101212. https://doi.org/10.1016/j.techsoc.2019.101212

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly, 23*(2), 183-213. https://doi.org/10.2307/249751

Karga, S., & Satratzemi, M. (2019). Using explanations for recommender systems in learning design settings to enhance teachers' acceptance and perceived experience. *Education and Information Technologies, 24*(5), 2953-2974. https://doi.org/10.1007/s10639-019-09909-z

Katarya, R., & Verma, O. P. (2018). Efficient music recommender system using context graph and particle swarm. *Multimedia Tools and Applications, 77*(2), 2673-2687.

Kelley, K., Clark, B., Brown, V., & Sitzia, J. (2003). Good practice in the conduct and reporting of survey research. *International Journal for Quality in health care, 15*(3), 261-266.

Kim, D. J. (2005). Cognition-based versus affect-based trust determinants in e-commerce: A crosscultural comparison study. Association for Information Systems - 26th International Conference on Information Systems, ICIS 2005: Forever New Frontiers,

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems, 44*(2), 544-564. https://doi.org/10.1016/j.dss.2007.07.001

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and Satisfaction, Two Stepping Stones for Successful E-Commerce Relationships: A Longitudinal Exploration. *Information Systems Research, 20*(2), 237-257. https://doi.org/10.1287/isre.1080.0188

Klaus, P. (2013). The case of Amazon. com: towards a conceptual framework of online customer service experience (OCSE) using the emerging consensus technique (ECT). *Journal of Services Marketing*. *27*(6), 443-457. https://doi.org/10.1108/JSM-02-2012-0030

Knijnenburg, B., Willemsen, M., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems [Article]. *User Modeling & User-Adapted Interaction, 22*(4), 441-504. https://doi.org/10.1007/s11257-011-9118-4

Knijnenburg, B. P., & Willemsen, M. C. (2015). Evaluating recommender systems with user experiments. In *Recommender systems handbook* (pp. 309-352). Springer.

Komiak, S. X., & Benbasat, I. (2004). Understanding customer trust in agent-mediated electronic commerce, web-mediated electronic commerce, and traditional commerce. *Information technology and management, 5*(1), 181-207.

Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS quarterly, 30*(4), 941. https://doi.org/10.2307/25148760

Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. *User Modeling and User-Adapted Interaction, 22*(1), 101-123. https://doi.org/10.1007/s11257-011-9112-x

Kuechler, M. (1998). The Survey Method:An Indispensable Tool for Social Science Research Everywhere? *American Behavioral Scientist, 42*(2), 178-200. https://doi.org/10.1177/0002764298042002005

Kunkel, J., Donkers, T., Michael, L., Barbu, C.-M., & Ziegler, J. (2019). Let me explain: Impact of personal and impersonal explanations on trust in recommender systems. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, New York, NY, USA.

Kuo, E. W., & Thompson, L. F. (2014). The influence of disposition and social ties on trust in new virtual teammates. *Computers in Human Behavior, 37*, 41-48.

Laurell, C., Sandström, C., Berthold, A., & Larsson, D. (2019). Exploring barriers to adoption of Virtual Reality through Social Media Analytics and Machine Learning–An assessment of technology, network, price and trialability. *Journal of Business Research, 100*, 469-474.

Lee, J. D., & Katrina, S. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors, 46*(1), 50-80. https://doi.org/10.1518/hfes.46.1.50_30392

Lee, J. D., & See, K. (2004). Trust in technology: Designing for appropriate reliance. *Human Factors, 46*(1), 50-80.

Lee, M.-C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education, 54*(2), 506-516.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal of*

Marketing, 80(6), 69-96. https://doi.org/10.1509/jm.15.0420

Leong, L.-Y., Hew, T.-S., Tan, G. W.-H., & Ooi, K.-B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications, 40*(14), 5604-5620. https://doi.org/10.1016/j.eswa.2013.04.018

Li, L., Chen, J., & Raghunathan, S. (2020). Informative Role of Recommender Systems in Electronic Marketplaces: A Boon or a Bane for Competing Sellers. *MIS Quarterly, 44*(4).

Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the Association for Information Systems, 16*(2), 72-107. https://doi.org/10.17705/1jais.00389

Li, Y., Liu, J., & Ren, J. (2019). A novel learning model based on trust diffusion and global item for recommender systems. *IEEE Access, 7*, 170270-170281.

Lin, Z. (2014). An empirical investigation of user and system recommendations in e-commerce. *Decision Support Systems, 68*, 111-124.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of applied psychology, 86*(1), 114-121. https://doi.org/10.1037/0021-9010.86.1.114

Linden, G., Smith, B., & York, J. (2003). Amazon. com recommendations: Item-to-item collaborative filtering. *IEEE internet computing, 7*(1), 76-80.

Liu, L., Yu, S., Wei, X., & Ning, Z. (2018). An improved Apriori–based algorithm for friends recommendation in microblog. *International Journal of Communication Systems, 31*(2), e3453.

Liu, Z., Lei, S.-h., Guo, Y.-l., & Zhou, Z.-a. (2020). The interaction effect of online review language style and product type on consumers' purchase intentions. *Palgrave Communications, 6*(1), 1-8.

Loehlin, J. C., & Beaujean, A. A. (2016). *Latent variable models: An introduction to factor, path, and structural equation analysis*. Psychology Press.

Logesh, R., Subramaniyaswamy, V., Malathi, D., Sivaramakrishnan, N., & Vijayakumar, V. (2020). Enhancing recommendation stability of collaborative filtering recommender system through bio-inspired clustering ensemble method. *Neural Computing and Applications, 32*(7), 2141-2164. https://doi.org/10.1007/s00521-018-3891-5

Looney, C. A., Akbulut, A. Y., & Poston, R. S. (2008). Understanding the determinants of service channel preference in the early stages of adoption: A social cognitive perspective on online brokerage services. *Decision Sciences, 39*(4), 821-857.

Lu, Y., Zhao, L., & Wang, B. (2010). From virtual community members to C2C e-commerce buyers: Trust in virtual communities and its effect on consumers' purchase intention. *Electronic Commerce Research and Applications, 9*(4), 346-360.

Mahfouz, A. Y., Joonas, K., & Opara, E. U. (2020). An overview of and factor analytic approach to flow theory in online contexts. *Technology in Society, 61*, 101228. https://doi.org/10.1016/j.techsoc.2020.101228

Mahnke, R., Benlian, A., & Hess, T. (2015). A Grounded Theory of Online Shopping Flow. *International Journal of Electronic Commerce, 19*(3), 54-89. https://doi.org/10.1080/10864415.2015.1000222

Mark, W. (1969, 12/31). Ethics in Research. *Australasian Journal of Information Systems, 8*(2). https://doi.org/10.3127/ajis.v8i2.244

Martínez-López, F. J., Esteban-Millat, I., Cabal, C. C., & Gengler, C. (2015). Psychological factors explaining consumer adoption of an e-vendor's recommender [Article]. *Industrial Management and Data Systems, 115*(2), 284-310. https://doi.org/10.1108/IMDS-10-2014-0306

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management, 34*(1), 1-13. https://doi.org/10.1016/j.ijinfomgt.2013.06.002

Massey, A. P., Khatri, V., & Montoya-Weiss, M. M. (2007). Usability of online services: The role of technology readiness and context. *Decision Sciences, 38*(2), 277-308.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model Of Organizational Trust. *Academy of Management Review, 20*(3), 709-734. https://doi.org/10.5465/amr.1995.9508080335

McInnes, M. D., Moher, D., Thombs, B. D., McGrath, T. A., Bossuyt, P. M., Clifford, T., Cohen, J. F., Deeks, J. J., Gatsonis, C., & Hooft, L. (2018). Preferred reporting items for a systematic review and meta-analysis of diagnostic test accuracy studies: the PRISMA-DTA statement. *Jama, 319*(4), 388-396.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002a). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334-359.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002b). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The Journal of Strategic Information Systems, 11*(3-4), 297-323.

Meuter, M. L., Bitner, M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. *Journal of Marketing, 69*(2), 61-83.

Miles, D. A. (2017). A taxonomy of research gaps: Identifying and defining the seven research gaps. Doctoral Student Workshop: Finding Research Gaps-Research Methods and Strategies, Dallas, Texas,

Millecamp, M., Htun, N. N., Jin, Y., & Verbert, K. (2018). Controlling Spotify recommendations: effects of personal characteristics on music recommender user Interfaces. Proceedings of the 26th Conference on user modeling, adaptation and personalization (pp. 101-109).

Montazemi, A. R., & Saremi, H. Q. (2014). The Effectiveness of Electronic Word of Mouth on Consumers' Perceptions of Adopting Products/Services.

Mooney, R. J., & Roy, L. (2000). Content-based book recommending using learning for text categorization. Proceedings of the fifth ACM conference on Digital libraries,

Moorman, C., Deshpandé, R., & Zaltman, G. (1993). Factors Affecting Trust in Market Research Relationships. *Journal of Marketing, 57*(1), 81-101. https://doi.org/10.1177/002224299305700106

Mouakket, S. (2018). The role of personality traits in motivating users' continuance intention towards Facebook: Gender differences. *The Journal of High Technology Management Research, 29*(1), 124-140. https://doi.org/10.1016/j.hitech.2016.10.003

Mpinganjira, M. (2019). Cognitive absorption and behavioural intentions in virtual health communities. *Journal of Systems and Information Technology, 21*(1), 122-145. https://doi.org/10.1108/JSIT-06-2017-0044

Murphy, G. B. (2003). Propensity to trust, purchase experience, and trusting beliefs of unfamiliar e-commerce ventures. *New England Journal of Entrepreneurship, 6*(2), 10.

Nah, F. F.-H., Eschenbrenner, B., DeWester, D., & Park, S. R. (2012). Impact of flow and brand equity in 3D virtual worlds. In *Cross-Disciplinary Models and Applications of Database Management: Advancing Approaches* (pp. 277-297). IGI Global.

Ng, Y. M. M. (2020). Re-examining the innovation post-adoption process: The case of Twitter discontinuance. *Computers in Human Behavior, 103*, 48-56. https://doi.org/10.1016/j.chb.2019.09.019

Nguyen, T. T., Dang, M. T., Luong, A. V., Liew, A. W.-C., Liang, T., & McCall, J. (2019). Multi-label classification via incremental clustering on an evolving data stream. *Pattern Recognition, 95*, 96-113. https://doi.org/10.1016/j.patcog.2019.06.001

Nilashi, M., Ibrahim, O., & Bagherifard, K. (2018). A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. *Expert Systems with Applications, 92*, 507-520. https://doi.org/10.1016/j.eswa.2017.09.058

Nilashi, M., Jannach, D., Ibrahim, O. b., Esfahani, M. D., & Ahmadi, H. (2016). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. *Electronic Commerce Research and Applications, 19*, 70-84. https://doi.org/10.1016/j.elerap.2016.09.003

Novak, T. P., Hoffman, D. L., & Yung, Y.-F. (2000). Measuring the Customer Experience in Online Environments: A Structural Modeling Approach. *Marketing Science, 19*(1), 22-42. https://doi.org/10.1287/mksc.19.1.22.15184

Osatuyi, B., & Qin, H. (2018). How vital is the role of affect on post-adoption behaviors? An examination of social commerce users. *International Journal of Information Management, 40*, 175-185. https://doi.org/10.1016/j.ijinfomgt.2018.02.005

Ozkara, B. Y., Ozmen, M., & Kim, J. W. (2017). Examining the effect of flow experience on online purchase: A novel approach to the flow theory based on hedonic and utilitarian value. *Journal of Retailing and Consumer Services, 37*, 119-131.

Pal, S., & Pal, S. (2018). Recommender system in e-commerce: Bringing revolution in marine product industry. *Indian Journal of Computer Science, 3*(5), 7-13.

Pan, C., & Li, W. (2010). Research paper recommendation with topic analysis. 2010 International Conference On Computer Design and Applications (Vol. 4, pp. V4-264). IEEE.

Panniello, U., Gorgoglione, M., & Tuzhilin, A. (2016). Research note—In CARSs we trust: How context-aware recommendations affect customers' trust and other business performance measures of recommender systems. *Information Systems Research, 27*(1), 182-196.

Park, J.-H. (2019). Resource recommender system based on psychological user type indicator. *Journal of Ambient Intelligence and Humanized Computing, 10*(1), 27-39.

Park, Y. S., Konge, L., & Artino, A. R. J. (2019). The Positivism Paradigm of Research. *Academic Medicine, Publish Ahead of Print*. https://doi.org/10.1097/acm.0000000000003093

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems, 27*(2), 159-188.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International journal of electronic commerce, 7*(3), 101-134.

Pine, B. J., & Gilmore, J. H. (2011). *The experience economy*. Harvard Business Press.

Pinsonneault, A., & Kraemer, K. (1993). Survey Research Methodology in Management Information Systems: An Assessment. *Journal of Management Information Systems, 10*(2), 75-105. https://doi.org/10.1080/07421222.1993.11518001

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology, 88*(5), 879.

Pu, P., & Chen, L. (2007). Trust-inspiring explanation interfaces for recommender systems. *Knowledge-Based Systems, 20*(6), 542-556. https://doi.org/10.1016/j.knosys.2007.04.004

Pu, P., Chen, L., & Hu, R. (2011). A user-centric evaluation framework for recommender systems. Proceedings of the fifth ACM conference on Recommender systems,

Pu, P., Chen, L., & Hu, R. (2012). Evaluating recommender systems from the user's perspective: survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*(4), 317-355. https://doi.org/10.1007/s11257-011-9115-7

Punyatoya, P. (2019). Effects of cognitive and affective trust on online customer behavior. *Marketing Intelligence & Planning, 37*(1), 80-96. https://doi.org/10.1108/MIP-02-2018-0058

Qahri Saremi, H. (2014). *An Elaboration Likelihood Model Perspective on the Effectiveness of Electronic Word of Mouth Recommendations* McMaster University]. Canada. http://hdl.handle.net/11375/16138

Qazi, M., Tollas, K., Kanchinadam, T., Bockhorst, J., & Fung, G. (2020). Designing and deploying insurance recommender systems using machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(4), e1363.

Qin, Y., & Liu, H. (2022). Application of Value Stream Mapping in E-Commerce: A Case Study on an Amazon Retailer. *Sustainability, 14*(2). https://doi.org/10.3390/su14020713

Ratnasingham, P. (1998). The importance of trust in electronic commerce. *Internet research*.

Recker, J. (2010). Continued use of process modeling grammars: the impact of individual difference factors. *European Journal of Information Systems, 19*(1), 76-92.

Reeves, B., & Nass, C. (1997). The media equation: How people treat computers, television, & new media like real people & places: By Byron Reeves and Clifford Nass. CSLI Publications/Cambridge University Press, Stanford, CA/Cambridge, U.K. (1996). *Computers & mathematics with applications, 33*(5), 128-128. https://doi.org/10.1016/S0898-1221(97)82929-X

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Commun. ACM, 40*(3), 56–58. https://doi.org/10.1145/245108.245121

Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to Recommender Systems Handbook. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender Systems Handbook* (pp. 1-35). Springer US. https://doi.org/10.1007/978-0-387-85820-3_1

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: introduction and challenges. In *Recommender systems handbook* (pp. 1-34). Springer.

Ridings, C. M., Gefen, D., & Arinze, B. (2002, 2002/12/01/). Some antecedents and effects of trust in virtual communities. *The Journal of Strategic Information Systems, 11*(3), 271-295. https://doi.org/10.1016/S0963-8687(02)00021-5

Riesenbeck, H., & Perrey, J. (2009). *Power brands: Measuring, making, and managing brand success*. John Wiley & Sons.

Rissler, R., Nadj, M., & Adam, M. (2017). Flow in information systems research: review, integrative theoretical framework, and future directions. Proceedings of the Wirtschaftsinformatik 2017, St.Gallen, Switzerland.

Robertson, T. S., & Kassarjian, H. H. (1991). *Handbook of consumer behavior*. Prentice Hall.

Rocco, E., Finholt, T. A., Hofer, E. C., & Herbsleb, J. (2001). Out of sight, short of trust. Presentation at the Founding Conference of the European Academy of Management. Barcelona, Spain,

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online Customer Experience in e-Retailing: An empirical model of Antecedents and Outcomes. *Journal of Retailing, 88*(2), 308-322. https://doi.org/10.1016/j.jretai.2012.03.001

Rotter, J. B. (1971). Generalized expectancies for interpersonal trust. *The American psychologist, 26*(5), 443-452. https://doi.org/10.1037/h0031464

Roztocki, N. (2001). Using internet-based surveys for academic research: opportunities and problems. Proceedings of the 2001 American Society for Engineering Management (ASEM) National Conference (pp. 290-295).

Rust, R. T., & Lemon, K. N. (2001). E-service and the consumer. *International journal of electronic commerce, 5*(3), 85-101.

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: an extension of the technology acceptance model. *Information & Management, 42*(2), 317-327. https://doi.org/10.1016/j.im.2003.12.013

Salam, A. F., Iyer, L., Palvia, P., & Singh, R. (2005). Trust in e-commerce. *Commun. ACM, 48*(2), 72–77. https://doi.org/10.1145/1042091.1042093

Salimon, M. G., Sanuri, S. M. M., Aliyu, O. A., Perumal, S., & Yusr, M. M. (2021). E-learning satisfaction and retention: a concurrent perspective of cognitive absorption, perceived social presence and technology acceptance model. *Journal of Systems and Information Technology, 23*(1), 106-129. https://doi.org/10.1108/JSIT-02-2020-0029

Saunders, M., Lewis, P., & Thornhill, A. (2012). *Research methods for business students* (Sixth edition. ed.). Pearson.

Schaefer, K. E., Chen, J. Y., Szalma, J. L., & Hancock, P. A. (2016). A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human Factors, 58*(3), 377-400.

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web* (pp. 291-324). Springer.

Schmitt, B. (1999, 1999/04/01). Experiential Marketing. *Journal of Marketing Management, 15*(1-3), 53-67. https://doi.org/10.1362/026725799784870496

Schrage, M. (2021). The Transformational Power of Recommendation. *MIT Sloan Management Review, 62*(2), 17-21.

Scotland, J. (2012). Exploring the Philosophical Underpinnings of Research: Relating Ontology and Epistemology to the Methodology and Methods of the Scientific, Interpretive, and Critical Research Paradigms. *English Language Teaching, 5*(9), 9-16. https://doi.org/10.5539/elt.v5n9p9

Shambour, Q. (2021). A deep learning based algorithm for multi-criteria recommender systems. *Knowledge-Based Systems, 211*, 106545. https://doi.org/10.1016/j.knosys.2020.106545

Shang, D., & Wu, W. (2017). Understanding mobile shopping consumers’ continuance intention. *Industrial Management & Data Systems, 117*(1), 213-227. https://doi.org/10.1108/IMDS-02-2016-0052

Shang, R.-A., Chen, Y.-C., & Shen, L. (2005). Extrinsic versus intrinsic motivations for consumers to shop on-line. *Information & Management, 42*(3), 401-413. https://doi.org/10.1016/j.im.2004.01.009

Shankar, A., & Patterson, M. (2001). Interpreting the Past, Writing the Future. *Journal of Marketing Management, 17*(5-6), 481-501. https://doi.org/10.1362/026725701323366890

Sheng, X., Li, J., & Zolfagharian, M. A. (2014). Consumer initial acceptance and continued use of recommendation agents: Literature review and proposed conceptual framework. *International Journal of Electronic Marketing and Retailing, 6*(2), 112-127.

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior, 98*, 277-284.

Shin, D.-H. (2010). The effects of trust, security and privacy in social networking: A security-based approach to understand the pattern of adoption. *Interacting with computers, 22*(5), 428-438.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552-4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Shobeiri, S., Mazaheri, E., & Laroche, M. (2015). Shopping online for goods vs. services: Where do experiential features help more? *International Journal of Consumer Studies, 39*(2), 172-179. https://doi.org/10.1111/ijcs.12165

Shoja, B. M., & Tabrizi, N. (2019). Customer reviews analysis with deep neural networks for e-commerce recommender systems. *IEEE Access, 7*, 119121-119130.

Smith, B., & Linden, G. (2017). Two Decades of Recommender Systems at Amazon.com. *IEEE internet computing, 21*(3), 12-18. https://doi.org/10.1109/MIC.2017.72

Spector, P. E. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology, 34*(2), 125-137.

Srivastava, A., Bala, P. K., & Kumar, B. (2020). New perspectives on gray sheep behavior in E-commerce recommendations. *Journal of Retailing and Consumer Services, 53*, 101764. https://doi.org/10.1016/j.jretconser.2019.02.018

Stafford, T. F., Stafford, M. R., & Schkade, L. L. (2004). Determining uses and gratifications for the Internet. *Decision Sciences, 35*(2), 259-288.

Su, H.-J., Comer, L. B., & Lee, S. (2008). The effect of expertise on consumers' satisfaction with the use of interactive recommendation agents [Article]. *Psychology & Marketing, 25*(9), 859-880. https://doi.org/10.1002/mar.20244

Suki, N. M., Ramayah, T., & Suki, N. M. (2008). Internet shopping acceptance: Examining the influence of intrinsic versus extrinsic motivations. *Direct Marketing: An International Journal, 2*(2), 97-110. https://doi.org/10.1108/17505930810881752

Sun, H. (2010). Sellers' trust and continued use of online marketplaces. *Journal of the Association for Information Systems, 11*(4), 182-211.

Sun, Y., Liu, L., Peng, X., Dong, Y., & Barnes, S. J. (2014). Understanding Chinese users' continuance intention toward online social networks: an integrative theoretical model. *Electronic Markets, 24*(1), 57-66.

Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services. *Industrial Management & Data Systems, 116*(3), 508-525. https://doi.org/10.1108/IMDS-05-2015-0195

Sztompka, P. (1999). *Trust: A sociological theory*. Cambridge university press.

Tan, W.-K., Lee, P.-W., & Hsu, C.-W. (2015). Investigation of temporal dissociation and focused immersion as moderators of satisfaction–continuance intention relationship: Smartphone as an example. *Telematics and Informatics, 32*(4), 745-754. https://doi.org/10.1016/j.tele.2015.03.007

Tarus, J. K., Niu, Z., & Kalui, D. (2018). A hybrid recommender system for e-learning based on context awareness and sequential pattern mining. *Soft Computing, 22*(8), 2449-2461.

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information*

Systems Research, 6(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Tekin, A. K., & Kotaman, H. (2013). The Epistemological Perspectives on Action Research1. *Journal of Educational and Social Research, 3*, 1.

Tellegen, A., & Atkinson, G. (1974). Openness to absorbing and self-altering experiences ("absorption"), a trait related to hypnotic susceptibility. *Journal of abnormal psychology (1965), 83*(3), 268-277. https://doi.org/10.1037/h0036681

Thompson, L., & Fine, G. A. (1999). Socially shared cognition, affect, and behavior: A review and integration. *Personality and Social Psychology Review, 3*(4), 278-302.

Todd, P., & Benbasat, I. (2000). Inducing compensatory information processing through decision aids that facilitate effort reduction: An experimental assessment. *Journal of Behavioral Decision Making, 13*(1), 91-106.

Toledo, R. Y., Alzahrani, A. A., & Martinez, L. (2019). A food recommender system considering nutritional information and user preferences. *IEEE Access, 7*, 96695-96711.

Trevino, L. K., & Webster, J. (1992). Flow in computer-mediated communication: Electronic mail and voice mail evaluation and impacts. *Communication research, 19*(5), 539-573.

Tsalikis, J., & Fritzsche, D. J. (2013). Business Ethics: A Literature Review with a Focus on Marketing Ethics. In A. C. Michalos & D. C. Poff (Eds.), *Citation Classics from the Journal of Business Ethics: Celebrating the First Thirty Years of Publication* (pp. 337-404). Springer Netherlands. https://doi.org/10.1007/978-94-007-4126-3_17

Tuli, F. (2010). The Basis of Distinction Between Qualitative and Quantitative Research in Social Science: Reflection on Ontological, Epistemological and Methodological Perspectives. *Ethiopian Journal of Education and Sciences, 6*(1), 97-108. http://dx.doi.org/10.4314/ejesc.v6i1.65384

Turban, E., Lee, J., King, D., & Chung, H. M. (2002). Electronic commerce: A managerial perspective (International Edition). *Prentice Hall USA, 4*(9), 523-527.

Tussyadiah, I. P., Zach, F. J., & Wang, J. (2020). Do travelers trust intelligent service robots? *Annals of Tourism Research, 81*, 102886. https://doi.org/10.1016/j.annals.2020.102886 van Ackere, A. (1993). The principal/agent paradigm: Its relevance to various functional fields. *European Journal of Operational Research, 70*(1), 83-103. https://doi.org/10.1016/0377-2217(93)90234-E

Van Lange, P. A. (2015). Generalized trust: Four lessons from genetics and culture. *Current Directions in Psychological Science, 24*(1), 71-76.

Vandecasteele, A., & Devillers, R. (2015). Improving Volunteered Geographic Information Quality Using a Tag Recommender System: The Case of OpenStreetMap. In J. Jokar Arsanjani, A. Zipf, P. Mooney, & M. Helbich (Eds.), *OpenStreetMap in GIScience: Experiences, Research, and Applications* (pp. 59-80). Springer International Publishing. https://doi.org/10.1007/978-3-319-14280-7_4

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science, 46*(2), 186-204.

Venter, M., & Swart, A. J. (2018). An integrated model for the continuous use intention of Microsoft Office simulation software. Canary Islands, Spain.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. *Journal of Retailing, 85*(1), 31-41. https://doi.org/10.1016/j.jretai.2008.11.001

Verhulst, N., Vermeir, I., Slabbinck, H., Larivière, B., Mauri, M., & Russo, V. (2020). A neurophysiological exploration of the dynamic nature of emotions during the customer experience. *Journal of Retailing and Consumer Services, 57*, 102217. https://doi.org/10.1016/j.jretconser.2020.102217

Visinescu, L. L., Sidorova, A., Jones, M. C., & Prybutok, V. R. (2015). The influence of website dimensionality on customer experiences, perceptions and behavioral intentions: An exploration of 2D vs. 3D web design. *Information & Management, 52*(1), 1-17. https://doi.org/10.1016/j.im.2014.10.005

Wang, J., Wang, M., & Wu, J. (2015). Empirical study on flow experience in China tourism e-commerce market. *Journal of Industrial Engineering and Management (JIEM), 8*(2), 349-364. https://doi.org/10.3926/jiem.1393

Wang, W., & Benbasat, I. (2005). Trust in and Adoption of Online Recommendation Agents. *Journal of the Association of Information Systems, 6*(3), 72-101. https://doi.org/10.17705/1jais.00065

Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems, 23*(4), 217-246.

Wang, W., & Benbasat, I. (2008). Attributions of trust in decision support technologies: A study of recommendation agents for e-commerce. *Journal of Management Information Systems, 24*(4), 249-273.

Wang, W., & Benbasat, I. (2009). Interactive decision aids for consumer decision making in E-commerce: The influence of perceived strategy restrictiveness [Article]. *MIS Quarterly: Management Information Systems, 33*(2), 293-320. https://doi.org/10.2307/20650293

Wang, W., Xu, J., & Wang, M. (2018). Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust vs. Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations [Article]. *Management Science, 64*(11), 5198-5219. https://doi.org/10.1287/mnsc.2017.2906

Webster, J., & Ho, H. (1997). Audience engagement in multimedia presentations. *The data base for advances in information systems, 28*(2), 63-77. https://doi.org/10.1145/264701.264706

Wigand, R. T. (1997). Electronic commerce: Definition, theory, and context. *The information society, 13*(1), 1-16.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior, 67*, 221-232. https://doi.org/10.1016/j.chb.2016.10.028

Xia, W., & Lee, G. (2000). The influence of persuasion, training, and experience on user perceptions and acceptance of IT innovation. ICIS 2000 Proceedings, Brisbane, Australia.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. *MIS Quarterly, 31*(1), 137-209. https://doi.org/10.2307/25148784

Xiao, B., & Benbasat, I. (2011). Product-related deception in e-commerce: A theoretical perspective. *MIS Quarterly*, *35*(1), 169–195. https://doi.org/10.2307/23043494

Xiao, B., & Benbasat, I. (2015). Designing Warning Messages for Detecting Biased Online Product Recommendations: An Empirical Investigation. *Information Systems Research, 26*(4), 793-811. https://doi.org/10.1287/isre.2015.0592

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. *Decision Support Systems, 110*, 46-57. https://doi.org/10.1016/j.dss.2018.03.005

Xu, J., Benbasat, I., & Cenfetelli, R. T. (2014). The nature and consequences of trade-off transparency in the context of recommendation agents. *MIS Quarterly, 38*(2), 379-406.

Yakovleva, M., Reilly, R. R., & Werko, R. (2010). Why do we trust? Moving beyond individual to dyadic perceptions. *Journal of applied psychology, 95*(1), 79.

Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management, 58*(102315), 1-13. https://doi.org/10.1016/j.ijinfomgt.2021.102315

Yang, X. (2021). Determinants of consumers' continuance intention to use social recommender systems: A self-regulation perspective. *Technology in Society, 64*, 101464. https://doi.org/10.1016/j.techsoc.2020.101464

Yaobin, L., & Tao, Z. (2007). A research of consumers' initial trust in online stores in China. *Journal of research and practice in information technology, 39*(3), 167-180.

Yi, M. Y., Jackson, J. D., Park, J. S., & Probst, J. C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management, 43*(3), 350-363. https://doi.org/10.1016/j.im.2005.08.006

Zha, X., Li, J., & Yan, Y. (2013). Information self-efficacy and information channels: Decision quality and online shopping satisfaction. *Online Information Review, 37*(6), 872-890. https://doi.org/10.1108/OIR-09-2012-0156

Zhang, B., Wang, N., & Jin, H. (2014). Privacy concerns in online recommender systems: influences of control and user data input. 10th Symposium On Usable Privacy and Security ({SOUPS} 2014), Menlo Park, CA.

Zhang, H., Lu, Y., Gupta, S., & Gao, P. (2015). Understanding group-buying websites continuance. *Internet research, 25*(5), 767-793. https://doi.org/10.1108/IntR-05-2014-0127

Zhang, J., & Curley, S. P. (2018). Exploring Explanation Effects on Consumers' Trust in Online Recommender Agents. *International Journal of Human–Computer Interaction, 34*(5), 421-432. https://doi.org/10.1080/10447318.2017.1357904

Zhang, K. Z. K., Cheung, C. M. K., & Lee, M. K. O. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision. *International Journal of Information Management, 34*(2), 89-98. https://doi.org/10.1016/j.ijinfomgt.2013.12.001

Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research, 37*(2), 197-206. https://doi.org/10.1086/651257

Zhou, Z., Jin, X.-L., & Fang, Y. (2014). Moderating role of gender in the relationships between perceived benefits and satisfaction in social virtual world continuance. *Decision Support Systems, 65*, 69-79.

Zhu, W. W., & Morosan, C. (2014). An empirical examination of guests' adoption of interactive mobile technologies in hotels. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/JHTT-09-2013-0029

Ziegler, C.-N., McNee, S. M., Konstan, J. A., & Lausen, G. (2005). Improving recommendation lists through topic diversification. In *Proceedings of the 14th international conference on World Wide Web* (pp. 22-32), New York, NY, USA.

Zikmund, W. G., Carr, J. C., & Griffin, M. (2013). *Business Research Methods* (9th ed.). Cengage Learning.

Zou, P. X. W., & Sunindijo, R. Y. (2015). Research Methodology and Research – Practice Nexus. In *Strategic Safety Management in Construction and Engineering* (pp. 180-213). John Wiley & Sons, Ltd.

APPENDICES

APPENDIX A: PARTICIPANT INFORMATION FOR USQ RESEARCH PROJECT QUESTIONNAIRE

University of Southern Queensland

UNIVERSITY OF SOUTHERN QUEENSLAND AUSTRALIA

Participant Information for USQ Research Project Questionnaire

Project Details	
Title of Project:	The multi-dimensional effects of consumers' trust and cognitive absorption on behavioural intentions to reuse recommender systems in e-commerce
Human Research Ethics Approval Number:	H20REA201

Research Team Contact Details

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Description

This project is being undertaken as part of a PhD.

The purpose of this project is to understand your opinion about the use of online recommendation.

The research team requests your assistance because you meet the study criteria and can provide valuable data, which is significant for this research. The holistic experience of online recommendation is a sparse research area, and little is known on how it contributes towards consumer buying intention based on online recommendations. In addition, it has been evident form past research that trust play a crucial role in the consumer buying intention based online recommendations. Therefore, this project will pay a special attention to investigate the role of sub-dimensions of Trust in the consumer buying intention based online recommendations in Australian e-commerce.

Participation

Your participation will involve completion of an online questionnaire that will take approximately 20 of your time.

Questions will include your opinion regarding the use of online recommendation. The questionnaire would be structured closed ended and would be based on a Likert scale with ratings ranging from Strongly Disagree to Strongly Agree.

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. You will be unable to withdraw data collected about yourself after you have participated in this questionnaire.

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 not directly benefit you. However, it may be useful for designing, improving and managing the continuous usage of online recommendation.

Risks

There are minimal risks associated with your participation in this project. The only risk is imposition of time.

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.

The research output will be intended for an anticipated publication or reporting of research findings, including anticipated student output (thesis, Journal Article etc).

If you would like to have access to a summary of the research results please contact the research team. Details can be found in the **"Research Team Contact Details"** section at the top of Page No. 1 of this document.

Any data collected as a part of this project will be stored securely as per University of Southern Queensland's Research Data Management policy.

Consent to Participate

Clicking on "I agree to participate" button 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 Manager of Research Integrity and Ethics on +61 7 4631 1839 or email researchintegrity@usq.edu.au. The Manager of Research Integrity and Ethics 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 INSTRUMENT

Opinion on the use of online recommendations

Your participation in this study involves answering a set of questions which will take approximately 20 minutes.

Directions: Please read each question carefully and respond by choosing an appropriate response. Please ensure you answer all questions. Failing to respond to all questions could make the questionnaire invalid. There are no right or wrong answers. The first response that comes to your mind is usually the best answer.

SECTION 1: Please answer the following questions related to your personal experience with internet usage and online buying.

1. How many years have you been using the internet?

☐ Less than 1 year	☐ 3-4 years	☐ 6-7 years
☐ 1-2 years	☐ 4-5 years	☐ More than 7 years
☐ 2-3 years	☐ 5-6 years	

2. Approximately, how long have you been purchasing online?

☐ Less than 1 year	☐ 2-3 years	☐ 4-5 years
☐ 1-2 years	☐ 3-4 years	☐ More than 5 years

SECTION 2: We would like to seek your knowledge about **Recommender System** (hereafter it is called RS). This study stated that Recommender system (RS) is a web-based technology that recommends tailored products or services to

customers based on their past buying behaviour or their specified preferences or the preference of other like-minded customers.

Please note: Amazon typically uses recommender systems to offer recommendations under the labels "Frequently bought together" or “Compare to similar items” or "Customers who bought... also bought".

3. Have you used RS for buying product(s) online over last six months?

☐ Yes

☐ No

4. Please specify the product(s) that you have purchased from Amazon.com.au over last 6 months.

☐ Eyeglass	☐ Cell phone	☐ Laptop
☐ Home Electronics	☐ Digital Camera	☐ Kitchen Utensils
☐ DVD Player	☐ Motorcycle Parts	☐ Photographic Equipment
☐ Printer	☐ Network Equipment	☐ Electronic Accessories
☐ Movies/Music CDs	☐ Books/Magazine	☐ Cleaning Products
☐ Clothing	☐ Leather Purse	☐ Shoes
☐ Perfume	☐ Cosmetics	☐ Software
☐ Watch	☐ Pet Supplies	☐ None of these

(If your response to the above question is None of these, you are not eligible for this survey)

5. How many product(s) have you brought from Amazon.com.au over the last 6 months.

☐ 1-5	☐ 11-15	☐ More than 20
☐ 6-10	☐ 15-20	

6. Approximately, how long have you been using the RS for online purchases?

☐ Less than 6 Months	☐ 2-3 years	☐ More than 5 years
☐ 6 Months - 1 Year	☐ 3-4 years	
☐ 1-2 years	☐ 4-5 years	

<u>**Directions:**</u> **Please circle the response applicable to the most appropriate box of each statement which correspond most closely to your desired response.**

SECTION 3: Please share your experience about using the RS in the online purchase decision process.

		Strongly Disagree		Neutral		Strongly Agree
7						
a	It is easy for me to trust a person/thing.	1	2	3	4	5
b	My tendency to trust a person/thing is high.	1	2	3	4	5
c	I tend to trust a person/thing, even	1	2	3	4	5

	though I have little knowledge of it.					
d	Trusting someone or something is not difficult.	1	2	3	4	5
8	The RS was					
a	competent in recommending the required product	1	2	3	4	5
b	an expert to recommend the product according to my preference	1	2	3	4	5
c	effective in recommending the required product	1	2	3	4	5
		1	2	3	4	5
9	I believe that the RS dealing with me					
a	was in my best interest	1	2	3	4	5
b	felt like it would do its best to help me	1	2	3	4	5
c	to find the best product	1	2	3	4	5
10	I believe the RS was					
a	truthful	1	2	3	4	5
b	unbiased	1	2	3	4	5
c	honest	1	2	3	4	5
d	sincere and genuine	1	2	3	4	5
11	While relying on the RS for my buying decision, I felt					
a	assured	1	2	3	4	5
b	comfortable	1	2	3	4	5

c	contend.	1	2	3	4	5
12						
a	Using RS enabled me to find suitable <product type> more quickly.	1	2	3	4	5
b	Using RS improved the quality of analysis and searching I performed to find suitable <product type>.	1	2	3	4	5
c	Using RS made the search task for <product type> easier to complete.	1	2	3	4	5
d	Using RS enhanced my effectiveness in finding suitable <product type>.	1	2	3	4	5
e	Using RS gave me more control over the <product type> search task.	1	2	3	4	5
f	Using RS allowed me to accomplish more analysis than would otherwise have been possible.	1	2	3	4	5
g	Using RS greatly enhanced the quality of my judgments.	1	2	3	4	5

h	Using RS conveniently supported all the various types of analysis needed to find suitable <product type>.	1	2	3	4	5
i	Overall, I found RS useful in finding suitable <product type>.	1	2	3	4	5
13						
a	Amazon's RS makes it easy for me to build a relationship with this company.	1	2	3	4	5
b	I would like to use this RS again in the future.	1	2	3	4	5
c	I am satisfied with the service provided by Amazon's RS.	1	2	3	4	5
d	I feel that using Amazon's RS is a good way to spend my time.	1	2	3	4	5
14						
a	While using the RS, I am able to block out most other distractions.	1	2	3	4	5
b	While using the RS, I am absorbed in what I am doing.	1	2	3	4	5

c	While on the RS, I am immersed in the task I am performing.	1	2	3	4	5
d	When on the RS, I get distracted by other attentions very easily.	1	2	3	4	5
e	While on the RS, my attention does not get diverted very easily.	1	2	3	4	5
f	Time appears to go by very quickly when I am using the RS.	1	2	3	4	5
g	Sometimes I lose track of time when I am using the RS.	1	2	3	4	5
h	Time flies when I am using the RS.	1	2	3	4	5
i	Most times when I get on to the RS, I end up spending more time that I had planned.	1	2	3	4	5
j	I often spend more time on the RS than I had intended.	1	2	3	4	5
k	Using the RS excites my curiosity.	1	2	3	4	5
l	Interacting with the RS makes me curious.	1	2	3	4	5
m	Using the RS arouses my imagination.	1	2	3	4	5

15	If you needed to purchase a similar product in the future, how likely is it that					
a	you would intend to continue using RS in the future?	1	2	3	4	5
b	you would predict your use of this RS to continue in the future?	1	2	3	4	5
c	you plan to continue using this RS in the future?	1	2	3	4	5

SECTION 3: In this section, please answer the following questions related to your personal information.

16. What is your gender?

☐ Male ☐ Female ☐ Prefer not to say

Other (Specify) ________________

17. What is your age group?

☐ Less than 20 years ☐ 26-35 years ☐ Over 45 years

☐ 20-25 years ☐ 36-45 years

18. What is your marital status?

☐ Single ☐ Widowed Other (Specify) *(e.g., separated)* __________

☐ Married ☐ Divorced

19. What is your highest level of education?

☐ Certificate ☐ Bachelor Degree ☐ Doctorate/PhD

☐ Diploma ☐ Master Degree Other (Specify)_______

20. What is your Occupation?

☐ Private Employed ☐ Unemployed Other (Specify) ________
☐ Self-Employed ☐ Student
☐ Government Employed ☐ Retiree

21. Which state are you from?

☐ VIC ☐ NSW ☐ TAS
☐ QLD ☐ WA ☐ SA
☐ NT ☐ ACT

APPENDIX C: THE MEASURES

Perceived Usefulness (PU) Wang & Benbasat, (2005)

PU1 Using RS enabled me to find suitable <product> more quickly.

PU2 Using RS improved the quality of analysis and searching I performed to find suitable <product>.

PU3 Using RS made the search task for <product> easier to complete.

PU4 Using RS enhanced my effectiveness in finding suitable <product>.

PU5 Using RS gave me more control over the <product> search task.

PU6 Using RS allowed me to accomplish more analysis than would otherwise have been possible.

PU7 Using RS greatly enhanced the quality of my judgments.

PU8 Using RS conveniently supported all the various types of analysis needed to find suitable <product>.

PU9 Overall, I found RS useful in finding suitable <product>.

Trust Propensity (TP) Wang & Benbasat, (2007)

TP1 It is easy for me to trust a person/thing.

TP2 My tendency to trust a person/thing is high.

TP3 I tend to trust a person/thing, even though I have little knowledge of it.

TP4 Trusting someone or something is not difficult.

Trusting Beliefs (TB) Ashraf et.al., (2019)

BT1 The RS was competent in recommending the required product.

BT2 The RS was an expert to recommend the product according to my preference.

BT3 The RS was effective in recommending the required product.

CT1 I believe that the RS dealing with me was in my best interest.

CT2 I believe that the RS dealings with me felt like it would do its best to help me.

CT3 I believe that the RS dealings with me to find the best product.
IT1 I believe the RS was truthful.
IT2 I believe the RS was unbiased.
IT3 I believe the RS was honest.
IT4 I believe the RS was sincere and genuine.
ET1 While relying on the RS for my buying decision, I felt assured.
ET2 While relying on the RS for my buying decision, I felt comfortable.
ET3 While relying on the RS for my buying decision, I felt contend.

Cognitive Absorption (CA) Zhu and Morosan (2014)
FI1 While using the RS, I am able to block out most other distractions.
FI2 While using the RS, I am absorbed in what I am doing.
FI3 While on the RS, I am immersed in the task I am performing.
FI4 When on the RS, I get distracted by other attentions very easily.
FI5 While on the RS, my attention does not get diverted very easily.
TD1 Time appears to go by very quickly when I am using the RS.
TD1 Sometimes I lose track of time when I am using the RS.
TD3 Time flies when I am using the RS.
TD4 Most times when I get on to the RS, I end up spending more time that I had planned.
TD5 I often spend more time on the RS than I had intended.
CU1 Using the RS excites my curiosity.
CU2 Interacting with the RS makes me curious.
CU3 Using the RS arouses my imagination.

Reuse Intentions/ Continuous use intention Benlian et. al., (2012)
If you needed to purchase a similar product in the future, how
BI1 likely is it that . . .
BI2 . . . you would intend to continue using RS in the future?

BI3 . . . you would predict your use of this RS to continue in the future?

. . . you plan to continue using this RS in the future?