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# A Configurational Approach to CSP Selection and Rejection

Mohammad Alamgir Hossain[a], Alvedi Sabani[a], Sachithra Lokuge[b], Yee Ling Boo[a], Shahriar Kaisar[a], and Preetha Menon[c]

[a]RMIT University, Melbourne, Australia; [b]University of Southern Queensland, Springfield, Australia; [c]FLAME University, Pune, India

**ABSTRACT**
Selecting the appropriate cloud service provider (CSP) is crucial for organizations, significantly impacting business performance and growth. However, the multitude of available providers can make this decision daunting. Existing studies focus on technical and operational CSP attributes but often overlook how these attributes should be configured, especially their interdependencies. To address this gap, we explore parsimonious configurations for CSP acceptance and rejection. Using a configurational approach and fuzzy-set qualitative comparative analysis (fsQCA), we uncover complex nonlinear relationships among key attributes. The fsQCA provides the combinations of causal recipes associated with the acceptance and rejection of a CSP, supporting the conjunction, equifinality, and asymmetry perspectives. Our results reveal that no single attribute is pivotal; instead, four configurations predict CSP selection, while five foresee rejection. Notably, we identified configurations tailored for small vs. medium-sized enterprises. This study enriches both theory and practical approaches in CSP selection, offering new insights for choosing CSPs.

**KEYWORDS**
Cloud service provider; configuration; fsQCA; SME

## Introduction

Cloud computing, which provides on-demand access to computing resources via the Internet from any device at any time, has become essential for businesses of all sizes, particularly small and medium enterprises (SMEs).[1,2] Accordingly, several studies e.g., Chen, Wang, Liang and Zhang[3] Zhang, Wang and Liang[4] have developed a general understanding why SMEs adopt cloud computing services. Meanwhile, numerous cloud service providers (CSPs), including major players like Amazon (AWS), IBM, Google (GCP), Microsoft (Azure), and Oracle (OCI), as well as smaller niche providers, have entered the marketplace to meet the growing demand for cloud computing services.[5] Given the abundance of competing CSPs, selecting the right provider has become a complex yet crucial task for SMEs, as it can significantly impact business performance and growth.[6,7,8]

As the market increasingly shifts toward the externalization of business information technology (IT) systems, SMEs carefully evaluate their specific needs vis-à-vis the attributes of the CSPs to select the most suitable one. They value technical attributes such as security, accessibility, customizability, and scalability.[9] Additionally, they assess non-technical operational attributes, including performance, quality of support, and reputation.[10] When selecting a CSP, SMEs consider multiple attributes simultaneously, which collectively support their various business objectives. Yet, glaringly, "*most of the existing work assumes that the service attributes are independent of one another, while in reality, there are interdependencies between attributes. Consideration of the interdependent relationship between selection criteria is critical for rational decision-making*".[9(148)] Empirical research on CSP selection has often relied on conventional regression methods, which imply independent effects of individual attributes on selection outcomes.[10] While some studies have employed multi-criteria decision-making (MCDM) methods like the analytical hierarchy process (AHP) e.g., Godse and Mulik,[11] they still struggle to fully elucidate the combined effects of these attributes. Therefore, studies, for example Sun, Dong, Hussain, Hussain and Chang[9] suggest that "*more advanced techniques need to be explored to model the relationships between multiple attributes and enable service selection based on mutually interdependent criteria.*"

Against this backdrop, this study employs the fuzzy-set qualitative analysis (fsQCA), a more advanced data analysis method, to explore the intricate interdependencies and configurational relationships among CSP attributes that SMEs consider during CSP selection. Specifically, this study investigates the following research question:

**CONTACT** Mohammad Alamgir Hossain mohammad.hossain@rmit.edu.au Business and Human Rights (BHRIGHT) Centre and School of Accounting, Information Systems, and Supply Chain, RMIT University, Melbourne, VIC 3000, Australia

> Which combinations of technical and operational attributes of CSPs predict their selection or rejection by SMEs?

To address the research question, this study employs the fsQCA technique, which combines elements of fuzzy logic and set theory. FsQCA examines how different combinations of conditions (i.e., attributes of CSPs) can lead to a specific outcome (e.g., CSP selection).[12] The decision to use fsQCA over other conventional methods like structural equation modeling (SEM) is based on its ability to handle complex, non-linear relationships and small to medium sample sizes. Unlike SEM, fsQCA captures the interplay between attributes, providing a nuanced understanding of the research question. Additionally, it effectively deals with asymmetric relationships among attributes and identifies unique configurations that explain the negation of the outcome variable (e.g., rejection of a CSP). By leveraging fsQCA, this study offers comprehensive insights into CSP selection beyond what traditional methods like SEM can provide.

Based on data collected from 213 SMEs, our analysis reveals four distinct configurations that represent various combinations of CSP attributes, effectively explaining CSP selection. Additionally, five configurations shed light on the criteria for rejecting a CSP. To enhance our understanding, we conduct further analysis, tailoring unique configurations specifically to SMEs, distinguishing between small and medium-sized enterprises.

This study holds significant implications for both researchers and practitioners. Firstly, it addresses the research call made by Sun, Dong, Hussain, Hussain and Chang,[9] who recognize CSP selection as a complex problem and advocate for newer research methods. By utilizing fsQCA, our study provides a superior alternative to past methods that relied on regression analysis. Furthermore, we have formulated and substantiated three propositions aligned with complexity theory, specifically applied in the SME sector.[13] From a practical standpoint, the identified configurations assist SMEs in their CSP selection process, while also offering guidelines to CSPs on how to package technical and operational attributes to appeal to SMEs. Additionally, this robust tool not only helps find the right CSP but also facilitates the rejection of misfit options.

The paper is structured into six sections. First, it delves into the intricacies of CSP selection and its significance for the configurational model. It then outlines the conceptual framework and justifies the propositions. A synopsis of the fsQCA research design and methodology follows. The findings are then presented, leading to a discussion that connects these results with the initial propositions, enriching the understanding of the central research query. The paper concludes by discussing the study's impact, acknowledging its constraints, and proposing avenues for subsequent inquiry.

## The attributes of CSP selection

Selecting a CSP, especially for SMEs, is a complex process involving multiple criteria and challenges.[10] Customers need to consider factors such as environmental conditions, organizational requirements, and other relevant aspects that determine the suitability of a CSP.[14] The literature distinguishes technical/functional (hard) and non-technical/non-functional/operational (soft) attributes of CSPs e.g., Kumar, Mishra and Kumar.[15] For instance, Godse and Mulik[11] highlight technical attributes like functionality, architecture, and usability, along with operational attributes such as vendor reputation and cost. Table 1 summarizes these attributes and their roles in cloud computing, supported by a selection of references.

### *Technical attributes*

The technical attributes refer to the technical aspects of CSPs, such as performance, reliability, portability, and customizability.[16,23] From a literature review, Sun, Dong, Hussain, Hussain and Chang[9] identified five functional attributes: security, performance, accessibility, usability, scalability, and functionality. Among these, *performance* is a key technical attribute evaluated based on quality of service (QoS) parameters such as throughput, response time, availability, and system capacity.[19,24] Next, security—encompassing confidentiality, privacy, and data integrity—is crucial for CSP selection. CSPs must provide a secure environment for firms to store and access their data.[19] Although some studies consider accessibility and usability as separate attributes,[9] others view accessibility, deployability, learnability, and operability as different dimensions of usability. *Usability* refers to the ease of learning and using a system; the easier it is to understand and operate a system, the faster an organization can migrate to the cloud environment.

Users often have varying requirements that may change dynamically. Therefore, cloud systems must possess *scalability* to scale up or down when the demand for resources grows or shrinks.[9] *Customizability* is equally crucial as it allows CSPs to offer tailor-made services with a range of infrastructures, platforms, and

**Table 1.** The factors important for the selection of CSP.

| Variable | Definition | The role in cloud computing | Source |
|---|---|---|---|
| Performance | It measures how efficiently a cloud service provider delivers computing resources like processing power, storage, and network connectivity to meet user needs | Evaluate the provider's performance metrics, such as processing speed, latency, and network bandwidth, to ensure optimal performance and seamless user experiences | Sun, Dong, Hussain, Hussain and Chang[9] |
| Security | Refers to the measures and practices implemented to protect systems, data, and networks from unauthorized access, damage, or disruption, ensuring confidentiality, integrity, and availability | Cloud security involves practices, technologies, and policies to protect data, applications, and infrastructure, focusing on confidentiality, integrity, availability, privacy, and compliance. | Xu and Mahenthiran[16] |
| Accessibility | The degree to which a system and the information it contains can be accessed with relatively low effort. | Reflects on how easy it is to access a CSP's services. | Sun, Dong, Hussain, Hussain and Chang[9] |
| Scalability | Refers to the ability of a system/software to handle increased demand without compromising performance. It allows for seamless expansion or contraction of resources as needed. | It enables CSPs to dynamically adjust resources based on demand, accommodating growth, and ensuring efficient performance. | Lehrig, Eikerling and Becker[17] |
| Reliability | The ability of a cloud service to perform its intended function continuously and consistently over a period, without failure or interruption. | It ensures consistent performance, minimizes downtime, and enables seamless operation of a CSP withstanding any system failure. | Xu and Mahenthiran[16] |
| Usability | The ease with which users can interact with and use cloud-based services, applications, and resources. | Assesses the platform's layout and design, organization, and user friendliness. | Nadeem[18] |
| Portability | The ability of software and data to be moved or used across different cloud platforms or environments without requiring significant modifications or reconfiguration. | It enables seamless migration of data and applications between different cloud environments, enhancing flexibility and reducing dependency on a single provider. | Garg, Versteeg and Buyya[19] |
| Customizability | The degree to which users can configure and tailor cloud services to meet specific user requirements and preferences. | It allows CSPs to tailor services and solutions to meet the diverse needs of a wide range of users. | Jagli, Purohit and Chandra[20] |
| Reputation | The perceived trustworthiness, reliability, and quality of a cloud service provider. | Reflects the overall evaluation of a CSP's quality, shaped by client experiences and recommendations. | Schneider and Sunyaev[2] |
| Pricing | The cost structure of cloud services, which typically include usage-based fees, subscription fees, or a combination of both. | Understand the provider's pricing structure and how it aligns with your budget. Consider both upfront costs and ongoing operational expenses. | Rahimi, Jafari Navimipour, Hosseinzadeh, Moattar and Darwesh[21] |
| Level of Support | It refers to the level of customer service and technical support provided by a cloud service provider to its users. | The different levels of customer service and technical support are associated with the severity of the support cases and pricing. | Lang, Wiesche and Krcmar[10] |
| Service Variety | The variety of cloud services, including IaaS, PaaS, SaaS, and specialized solutions, that a CSP offers to meet diverse user needs. | Accommodating different cohorts of clients' objectives and needs with the different range of services to create diversity in cloud services provided. | Schneider and Sunyaev[2] |
| Resource Distribution | The management of computing resources, including processing power, memory, storage, and bandwidth, across cloud servers and data centers | The capacity to provide efficient allocation of resources is key to improve the performance of cloud computing, reduce the costs and most importantly meeting the clients' needs. | Sun, Dong, Hussain, Hussain and Chang[9] |
| Subscription Flexibility | The ability to adjust subscription plans by changing service levels, altering resource amounts, or modifying features. | Clients are given the flexibility to adjust and recalibrate their needs and objectives when circumstance changes and cloud service providers can adhere to that. | Lang, Wiesche and Krcmar[10] |
| Rapport | The creation of a positive, productive relationship between a CSP and its customers through knowledgeable, attentive, and courteous support. | The engagement with a CSP and its client is a continuous partnership that builds upon the trust, reliability as well as the support system developed around this relationship. | Benlian, Koufaris and Hess[22] |
| Geolocation | The physical location of the data centers or servers that provide a cloud service. | As cloud computing evolves, data geolocation becomes crucial for ensuring privacy and security due to regulatory requirements. | Lang, Wiesche and Krcmar[10] |
| Legal Compliance | The compliance of CSPs with relevant laws, regulations, and standards governing the storage, processing, and transmission of data. | Legal compliance is vital for clients with specific regulatory requirements, necessitating CSP adherence to standards like GDPR or HIPAA. | Lehrig, Eikerling and Becker[17] |
| Monitoring | The ability to observe, collect, and analyze performance metrics and other relevant data related to cloud-based resources and services. | A CSP's monitoring capability ensures data security, privacy, and compliance, while actively detecting and addressing potential breaches. | Lang, Wiesche and Krcmar[10] |
| Service Capability | The vendor's ability to manage and deploy both tangible (e.g., physical infrastructure, human resources) and intangible (e.g., knowledge, customer orientation) IT resources. | Service capabilities are shaped by the vendor's expertise, technical and managerial IT skills, and client-perceived reputation. | Wulf, Westner and Strahringer[1] |

software.[9,25,26] *Reliability* is another key element, ensuring cloud services are available from any location at any time and are resilient to failure.[16] Finally, *portability* is vital as it enables the quick and seamless migration of data, applications, or software without requiring significant modifications.[27]

### Operational attributes

The operational attributes, which refer to the operational aspects of the providers, are "considered the most significant" for CSP selection.[15(7015)] Sun, Dong, Hussain, Hussain and Chang[9] identified three operational attributes: payment, reputation, and resource distribution. The *cost* of CSP subscription, including payment and pricing, is often considered one of the most important factors in CSP selection.[21] CSPs need to provide subscription flexibility, particularly for SMEs, to accommodate varied user needs and match pricing accordingly.[28] SMEs also evaluate CSPs' *reputation* to understand the community's view and assessment of the quality, trustworthiness, and reliability of the services provided.[2] Furthermore, the *allocation of virtualized IT resources* is complex but critical, as it determines execution time, response time, and resource utilization.[29] The *geolocation* of the CSP is also important for data privacy, security, and legal compliance.[30] Additionally, the level of support, service variety, and rapport are significant factors.[31,32] The *level of support* may include customer service and technical support. Similarly, *service capability*, which depends on the number of servers, networks, and the size of the CSP, is crucial for SMEs as they may lack the necessary expertise.[33] SMEs also value the *monitoring capabilities* of a CSP, which ensure security, privacy[34] and *legal compliance*.[35]

### The extant methodology for CSP selection

In the context of selecting CSPs, researchers have explored various methodologies. Benlian, Koufaris and Hess[22] conducted a comprehensive study combining literature review, focus groups, and surveys to develop a framework for assessing SaaS provider service quality. They identified security and responsiveness as pivotal factors influencing service quality. In contrast, Lang, Wiesche and Krcmar[14] utilized the Delphi method and expert interviews to rank functionality, legal compliance, contract terms, server geolocation, and flexibility as the most critical factors in CSP selection. He, Han, Yang, Grundy and Jin[36] discussed a novel approach for selecting services in multi-tenant SaaS environments, emphasizing the importance of Quality of Service (QoS).

Notably, different multi-criteria decision-making (MCDM) techniques have been employed. For further insights, see Kumar, Singh and Garg.[8] For instance, using AHP, Garg, Versteeg and Buyya[37] ranked CSPs by assigning weights to attributes (e.g., such as security, cost, performance, and usability) based on their interdependencies. Similarly, Tanoumand, Ozdemir, Kilic and Ahmed[38] employed a fuzzy AHP, emphasizing factors like security and performance. Other studies e.g., Sun, Dong, Hussain, Hussain and Liu[39] Sun, Ma, Zhang, Dong and Hussain[40] Youssef[41] explored different variations of MCDM methods to evaluate CSPs based on diverse criteria. For instance, to evaluate and rank cloud service providers, Al-Faifi, Song, Hassan, Alamri and Gumaei[42] introduced a robust method for CSP selection, combining clustering and MCDM techniques. While these approaches help in selecting CSPs based on predefined criteria, they offer limited insights into the complex interrelationships among different attributes and may not fully support service providers in customizing services to meet diverse user demands.

Given the limitations of existing techniques in explaining the complexity of CSP selection, there is a need for advanced research methods. The fsQCA technique offers a promising solution to address these gaps. It can comprehensively examine and elucidate how various combinations of CSP attributes lead to their selection.

### Identifying the conditions for configurational model

Theoretically, the 19 attributes identified from literature review in section 2.1 can be included in a configurational model. However, fsQCA computes $2^k$ possible configurations (i.e., combinations) that may occur to predict an outcome variable, where $k$ represents the number of conditions (i.e., attributes). Hence, for 19 variables, there will be 524,288 possible configurations to evaluate, which is not practical. Therefore, this study adopts the scholarly approach used by Tam and Tummala[43] for vendor selection in a telecommunication system. They found that the presence of too many vendor-specific criteria makes pairwise comparisons in AHP impractical for evaluating vendors. Following their methodology, we conducted a short survey to identify the most important conditions (i.e., CSP attributes) for formulating the configurational model.

A questionnaire with these attributes and their definitions was sent to 40 SMEs. Each respondent rated each attribute on a three-point scale: "not important" (3), "somewhat important" (2), and "very important" (1) for CSP selection. We employed a multi-faceted approach, including professional networks, social media, and industry associations, to recruit participants, resulting in 29 valid responses. The attributes are arranged in descending order of their mean values in Figure 1. The mean of the mean values is 2.1, and the average of the highest (2.7) and lowest (1.6) mean values is 2.2. Attributes with mean values greater than 2.2 were considered for our configurational model. We identified four technical conditions (reliability, performance, security, usability) and three operational

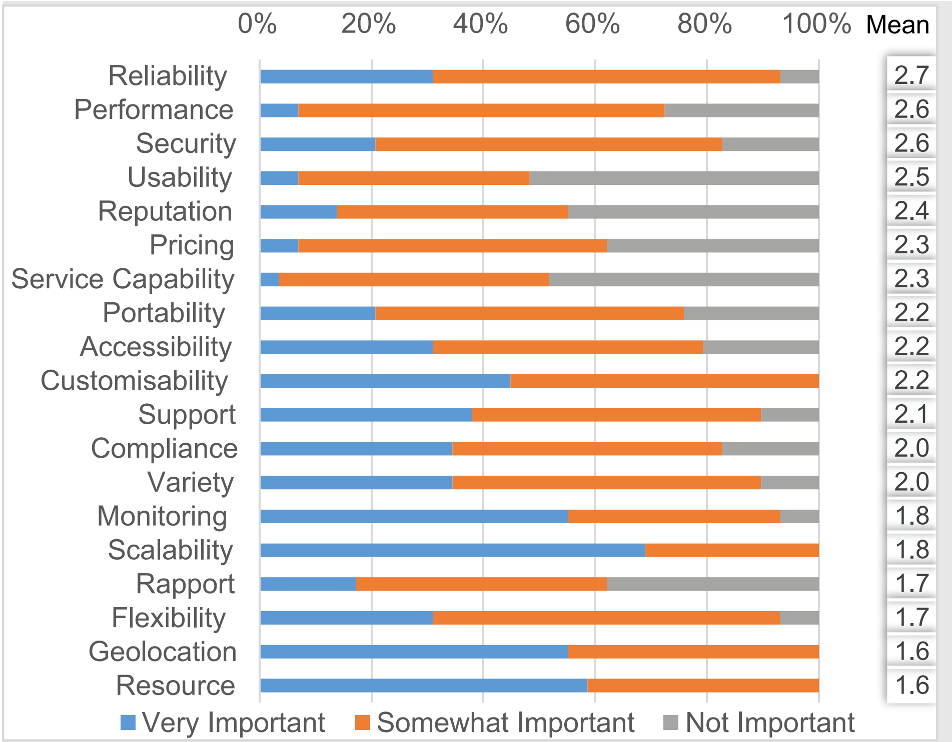


**Figure 1.** Prioritizing the attributes affecting the selection of CSP.

conditions (reputation, cost, service capability) for CSP selection.

## The configurational research model

Our research is grounded in complexity and configurational theories, proposing that CSP selection is a complex decision[44,45] that cannot be fully explained by the symmetrical relationships among technical and operational factors, as asymmetrical relationships may also exist.[46] These theories rely on three main tenets: conjunction, equifinality, and asymmetry.[47] Recent studies, such as Mallon and Fainshmidt,[48] argue that these tenets form the basis of a configurational approach, such as fsQCA, which explains causal complexity and distinguishes fsQCA from conventional regression methods. Based on these three tenets, our research model is articulated with three propositions.

The *conjunction principle*, also known as the *recipe principle*, suggests that a single condition (e.g., reliability) can be necessary but is rarely sufficient for predicting an outcome (e.g., CSP selection). Instead, conditions (e.g., reliability and reputation) need to be combined into distinct configurations. This principle indicates that an individual condition rarely operates in isolation but rather combines with one or more conditions. This represents a fundamental difference between regression-based linear approaches and configurational approaches. For example, by applying fsQCA, Zhang, Wang and Liang[4] found that not only the technological factors (e.g., relative advantage) but also the organizational (e.g., top management support) and environmental (e.g., government support) factors drive cloud service adoption by businesses. Therefore, our configurational model postulates that:

**P1:** A single condition may be necessary but is rarely sufficient for predicting the selection or rejection of a CSP; instead, a combination of conditions is required.

The *equifinality principle* suggests that "reality usually includes more than one combination of conditions that lead to high values in an outcome condition".[13(464)] In other words, the same outcome can be achieved through multiple configurations.[49,50] This tenet explains why two different businesses with varied perceived attributes can still select the same CSP. In contrast, traditional linear regression-based methodologies rely on the assumption of unifinality, where only one optimal model fits the data. Our second proposition is based on the equifinality principle.

**P2:** Different equally effective configurations may lead to the selection or rejection of a CSP.

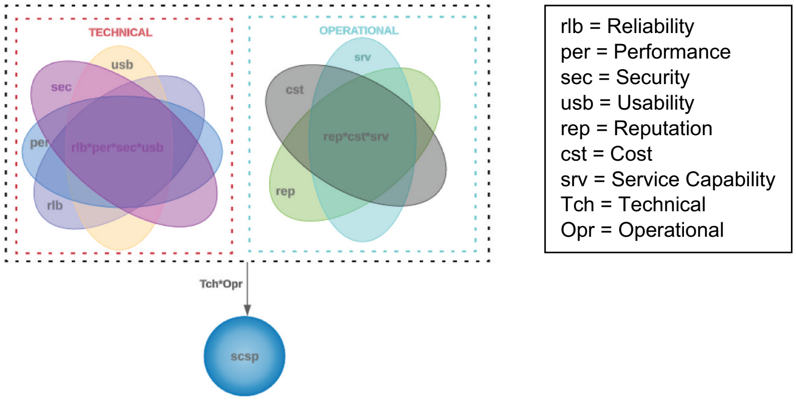


**Figure 2.** The configurational research model.

Finally, the *causal asymmetry principle* posits that the causes leading to the presence of an outcome may differ significantly from those leading to its absence.[46,50] In other words, "the explanation for the non-occurrence of the outcome cannot automatically be derived from the explanation for the occurrence of the outcome."[47] Our third proposition is based on this principle.

**P3:** The conditions leading to the selection of a CSP may be different from those leading to its rejection.

Although the tenets of conjunction, equifinality, and asymmetry are relevant for exploring the relationship between CSP attributes and CSP selection/rejection, to our knowledge, this study is among the first to utilize fsQCA to analyze the interplay of both technical and operational factors for both CSP selection and rejection. Our configurational research model, illustrated in Figure 2 as a Venn diagram, integrates the technical and operational attributes influencing CSP selection: [scsp = *f*(rel,per,sec,usb,rep,cst,srv)]. Alternatively, the rejection of a CSP becomes: [~scsp = *f*(rlb,per,sec,usb,rep,cst,srv)].

## Research design and methodology

### *Construct operationalization*

Since prior studies have not developed or validated measures for these constructs, we first identified potential items from various sources. Measures for *reliability* and *performance* were sourced from Benlian, Koufaris and Hess[22] and Garg, Versteeg and Buyya.[19] *Security* measures were adapted from Benlian, Koufaris and Hess,[22] and *usability* measures were drawn from Godse and Mulik.[11] For the reputation attribute, we considered perceived trustworthiness, reliability, and quality of a CSP, using scales from Schneider and Sunyaev,[2] Benlian, Koufaris and Hess,[22] and Godse and Mulik.[11] To measure *cost*, we examined the typical cost structures of cloud services, which often include usage-based fees and subscription fees.[21] Items for this measure were adapted from several sources.[11,16,19,51] *Service capability* items were taken from Schneider and Sunyaev[2] and Wulf, Westner and Strahringer.[1] Finally, *CSP selection* was measured using items adapted from Shiau and Chau[52] and Song, Kim and Sohn.[53]

To assess item placements within various construct categories, we employed the Q-sort technique, a recognized method for verifying discriminant validity and eliminating items that do not align with the posited construct.[54] Q-sort allows systematic assessment of item-construct alignment through expert sorting based on similarity. Q-sort provides robust evidence of construct validity by demonstrating the convergence and divergence of items.[54] The method has been extensively used in organizational research to validate constructs and ensure that items accurately reflect the intended theoretical domains.[55,56] Our diverse panel of judges, including cloud users, students, and academics, participated in the process. Cohen's Kappa scores (averaging 0.82) indicated good reliability, exceeding the threshold (Kappa >0.65).[57] Before conducting the survey, we performed a pilot test. To ensure diverse perspectives, we recruited three PhD students specializing in cloud computing, two academic staff members with Information Systems backgrounds from different Australian universities, and five professionals using CSPs, following the approaches of Stantchev, Colomo-Palacios, Soto-Acosta and Misra[58] and Roy, Das, Chatterjee, Kumar, Chattopadhyay and Rodrigues.[59] The questionnaire was revised based on feedback from the pilot test, including changes to unclear wording and adjustments to the sequence of questions. The final version of the survey items is presented in Appendix A.

**Table 2.** The demographics of the respondents.

| Attribute | | Percentage |
|---|---|---|
| Gender | Male | 50.2 |
| | Female | 48.4 |
| | Not to be included/non-binary | 1.4 |
| Education | Primary | 15.3 |
| | Secondary | 26.1 |
| | Bachelor | 31.6 |
| | Masters | 20.0 |
| | Doctoral | 7.4 |
| Age (years) | 18–20 | 0.5 |
| | 21–30 | 17.0 |
| | 31–45 | 44.0 |
| | 45–60 | 32.9 |
| | Older than 60 | 5.6 |
| Business type | Retail | 25.0 |
| | Agriculture | 12.3 |
| | Education | 19.6 |
| | Consulting | 9.9 |
| | Healthcare | 18.3 |
| | Finance | 3.3 |
| | Manufacturing | 11.6 |
| Size of business (number of full time employees) | Small: 1–49 | 47.4 |
| | Medium: 50–249 | 52.6 |

### Data collection

We collected data for this study through an electronic survey using convenience sampling, focusing on SMEs. A total of 213 respondents participated. While the gender distribution was balanced, most participants (aged 31–60) were mid-career to seasoned professionals. A significant percentage held tertiary qualifications. The survey covered diverse industry sectors, providing a comprehensive overview of SMEs using cloud services. Demographic details are in Table 2.

### Data analysis with fsQCA

We analyze our configurational research model using fsQCA,[49,60] with the *fsQCA 4.1* software.[60] Our analysis adheres to guidelines from recent studies.[61-63] Before proceeding to the fsQCA procedure, we have checked the psychometric properties of the variables. Following standard procedure, the validity of the constructs has been established by examining their reliability and convergent validity (see Apppendix B). Using the fsQCA software, we **first** calibrated the variables into fuzzy sets with values ranging from 0 to 1. We established three anchors for membership assessment: full membership, full non-membership, and the crossover point.[13] To determine these membership thresholds, we used percentiles (0.95, 0.50, and 0.05)[62] of the latent scores.[64] The percentile values for calibration are presented in Appendix C.

In the **second** step, we identified the necessary conditions.[61] "[A] necessary condition implies that the outcome of interest does not occur in the absence of the respective condition."[65(4)] For a condition to be deemed necessary, its consistency must exceed 0.9.[66] Our analysis found that no single condition met this criterion for either the selection or rejection of a CSP (see Appendix D). In the **third** step, we analyzed the truth table, which computes all possible combinations of causal conditions that sufficiently produce the outcome variable. The truth table initially generated 128 theoretically possible combinations. We refined the table by removing rows with no cases.[46] Following Mattke, Maier, Weitzel, Gerow and Thatcher,[61] we used a raw consistency threshold of 0.75 and a proportional reduction in inconsistency (PRI) threshold greater than 0.6. We also set the frequency threshold to 2.

In the **fourth** step, we analyzed sufficient condition. "[A] sufficient condition means that the outcome occurs whenever the respective condition is present."[65(4)] To confirm a configuration's sufficiency, consistency values must exceed 0.8 and coverage must be greater than 0.2.[64] Additionally, unique coverage values should be greater than zero. Our results showed that all consistency values exceeded 0.8 and raw coverage values were above 0.5, indicating robust configurations for the outcome variables (i.e., CSP selection). Among the complex, parsimonious, and intermediate solutions, we selected intermediate solutions as they are deemed most suitable for causal analysis[67] and provide theoretically plausible counterfactuals.[62] Data validation techniques are detailed in Appendix. We developed two sets of configurations for each sample-one for CSP selection and one for CSP rejection—covering the total sample as well as small and medium-sized enterprises.

**Table 3.** The diagrammatic representation of the sufficient configurations for total sample.

| | Selection of a CSP | | | | Rejection of a CSP | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Conditions** | **C1** | **C2** | **C3** | **C4** | **~C1** | **~C2** | **~C3** | **~C4** | **~C5** |
| Reliability | ● | | ● | ● | ⊗ | ⊗ | ● | ⊗ | ⊗ |
| Performance | ● | ● | | ● | ⊗ | ⊗ | | | |
| Security | | ● | ● | ● | ⊗ | ⊗ | ⊗ | ⊗ | ● |
| Usability | ● | ● | ● | | | ⊗ | ⊗ | ⊗ | ⊗ |
| Reputation | ● | ● | • | ⊗ | ⊗ | ⊗ | ⊗ | ● | ⊗ |
| Cost | ⊗ | | ⊗ | ⊗ | ● | | ● | ● | ● |
| Support Capability | | • | • | • | ⊗ | ⊗ | ⊗ | ⊗ | ⊗ |
| Raw Coverage | 0.552 | 0.546 | 0.521 | 0.293 | 0.503 | 0.375 | 0.312 | 0.367 | 0.326 |
| Unique Coverage | 0.058 | 0.052 | 0.026 | 0.035 | 0.132 | 0.018 | 0.015 | 0.004 | 0.029 |
| Consistency | 0.931 | 0.926 | 0.934 | 0.916 | 0.963 | 0.960 | 0.963 | 0.963 | 0.960 |
| Solution Coverage | 0.667 | | | | 0.623 | | | | |
| Solution Consistency | 0.905 | | | | 0.933 | | | | |

Key: The black circles (●) indicate the presence of a condition, a circle with "x" inside (⊗) indicates its absence, and blank space refers to "do not care" condition. Large circle (● or ⊗) refers to a peripheral condition.[a]

## Results

### *Configurations in the total sample*

Our analysis identified four distinct configurations sufficient for selecting a CSP and five configurations sufficient for rejecting a CSP, as detailed in Table 3.

Our analysis identified four distinct configurations for selecting a CSP (C1-C4), each suggesting different attribute combinations that can be effective for various firms. Among these, C1 stands out with the highest raw and unique coverage, as well as strong consistency, indicating it is the most empirically significant configuration. C1 combines high reliability, performance, and usability with a strong reputation and low costs, where security and support capability are less critical. C2 indicates that reliability and cost are less important if performance, security, usability, and reputation are high, though support capability remains somewhat relevant. C3 suggests that CSP performance is less critical if reliability, security, usability, and reputation are high and cost is low, with support capability having a lesser impact. Finally, C4 shows that a CSP may still be selected even with a low reputation if it offers high technical attributes and low costs, where usability is not influential and support capability has a minimal effect.

Our configurations (~C1–~C5) reveal several reasons why users may reject a CSP. For instance, ~C1 indicates that a CSP may be rejected if it has low reliability, performance, security, and support capability, combined with high costs, where usability has no influence and reputation has a minimal effect. Similarly, ~C2 suggests that users will reject a CSP if most attributes are poor, regardless of the cost. In configurations ~C3–~C5, high costs and low usability are significant factors leading to CSP rejection, with the lack of support capability also contributing to the decision.

[a]While core conditions appear in both parsimonious and intermediate solutions, the conditions that are eliminated in the parsimonious solution and appear only in the intermediate solution are called "peripheral conditions."

### *Configurations in the small vs. medium enterprise*

For a detailed analysis, we examined configurations for small and medium enterprises. Table 4 reveals that reliability and reputation are consistently present in all configurations for selecting CSPs across both small and medium organizations. Notably, the rejection configurations show that the absence of reputation has little impact on $\sim C_s2$ and $\sim C_m1$ and minimal impact on $\sim C_s1$ and $\sim C_m2$. This indicates that while reputation supports CSP selection, its absence does not solely drive rejection decisions. Table 4 also highlights that pricing (i.e., low cost) is crucial for small enterprises in selecting a CSP ($C_s1$ and $C_s2$). In contrast, for medium organizations, pricing is a peripheral (Cm1 and Cm2) or negligible when other attributes—such as reliability, security, reputation, usability, service capability, and performance—are met. This contrasts with findings from existing studies, such as Sun, Dong, Hussain, Hussain and Chang.[9] However, high

**Table 4.** The sufficient configurations for small vs. medium enterprises.

| | Selection of a CSP | | | | | Rejection of a CSP | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Small | | Medium | | | Small | | | Medium | |
| **Condition** | **$C_s1$** | **$C_s2$** | **$C_m1$** | **$C_m2$** | **$C_m3$** | **$\sim C_s1$** | **$\sim C_s2$** | **$\sim C_s3$** | **$\sim C_m1$** | **$\sim C_m2$** |
| Reliability | ● | ● | ● | ● | ● | | ⊗ | ● | ⊗ | ⊗ |
| Performance | ● | ● | ● | | ● | ⊗ | ⊗ | ● | ⊗ | ⊗ |
| Security | ● | ⊗ | ● | ● | ● | ⊗ | ⊗ | ⊗ | ⊗ | ⊗ |
| Usability | ⊗ | ● | ● | ● | ● | ⊗ | ⊗ | ⊗ | ⊗ | |
| Reputation | ● | ● | ● | ● | ● | ⊗ | | ● | | ⊗ |
| Pricing | ⊗ | ⊗ | ⊗ | ⊗ | | ● | ● | ⊗ | ● | ● |
| Support Capability | ● | ● | | • | • | ⊗ | ⊗ | ● | ⊗ | ⊗ |
| Raw Coverage | 0.321 | 0.549 | 0.524 | 0.508 | 0.505 | 0.496 | 0.511 | 0.269 | 0.503 | 0.472 |
| Unique Coverage | 0.038 | 0.265 | 0.045 | 0.030 | 0.027 | 0.014 | 0.030 | 0.051 | 0.065 | 0.034 |
| Consistency | 0.912 | 0.917 | 0.949 | 0.939 | 0.933 | 0.987 | 0.967 | 0.934 | 0.976 | 0.980 |
| Solution Coverage | 0.587 | | 0.581 | | | 0.584 | | | 0.537 | |
| Solution Consistency | 0.911 | | 0.931 | | | 0.950 | | | 0.977 | |

Key: The black circles (●) indicate the presence of a condition, a circle with "x" inside (⊗) indicates its absence, and blank space refers to "do not care" condition. Large circle (● or ⊗) refers to a peripheral condition.[b]

pricing does influence CSP rejection when other factors like reliability, performance, and security are lacking.

Furthermore, Table 4 shows that security is critically important for medium-sized enterprises, as it appears in all configurations for CSP selection. In contrast, small enterprises may accept lower security if usability is high ($C_s2$). Additionally, usability holds greater significance for medium organizations than for small ones. Small organizations are more likely to reject CSPs when both usability and security are lacking and the cost is high ($\sim C_s1$, $\sim C_s2$).

## Discussion

No single attribute alone determines the selection or rejection of a CSP; rather, it is the combination of attributes into distinct configurations that is crucial. This supports our first proposition that a combination of conditions is necessary to explain complex decisions. Specifically, CSP selection or rejection depends not only on technical attributes but also on operational attributes.[15,51]

One key implication of our study is the shift in focus from the isolated impact of individual attributes to the convergence of attributes in complex business decision-making processes. Across total and sub-samples, our findings indicate that no single attribute alone serves as a necessary or sufficient condition for the selection or rejection of a CSP. For instance, in the configurations for CSP selection (illustrated in Table 3), *cost* emerges as a common factor in three out of four configurations. Similarly, its negation is common in four out of five configurations for rejecting a CSP. The pivotal role of *cost* is echoed across both sub-samples as well (Table 4). However, *cost* alone is insufficient; it must be coupled with other capabilities. Interestingly, cost is a "does not care" condition when other capabilities are present (C2) or absent (~C2) for the selection or rejection of a CSP, respectively. Thus, the impact of an attribute (e.g., cost) on the selection or rejection of a CSP is always contingent upon the presence or absence of other attributes, exemplifying the concept of conjunctural causality in complexity theory.

In total and sub-samples, multiple distinct configurations lead to the same outcome (i.e., selection or rejection of a CSP). This confirms our second proposition: diverse yet equally effective configurations may yield the same outcome.[68] Consequently, our findings illustrate the concept of equifinal causality.

Finally, in contrast to a symmetric approach, our results show that the configurations of condition for rejecting a CSP (i.e., C ~ 1 – C ~ 5) are not mirror opposites of the causal models leading to the selection of a CSP (i.e., C1 – C4). This supports our third proposition: the causal asymmetry principle of complexity theory. Furthermore, attributes causally related in one

[b]While core conditions appear in both parsimonious and intermediate solutions, the conditions that are eliminated in the parsimonious solution and appear only in the intermediate solution are called "peripheral conditions."

configuration may be unrelated or inversely related in other configurations. For example, the presence of *reputation* is a core attribute in C3; however, C4 suggests that the absence of *reputation* may still lead to a sufficient configuration, ceteris paribus, when *performance* is present. Additionally, the presence of one attribute for selecting a CSP does not necessarily mean that its absence will lead to rejection. For example, C1 suggests that *reliability* is an important attribute for selecting a CSP, while its absence can lead to rejection (~C1); however, ~C3 argues that even high *reliability* may lead to rejection if other attributes are not suitable for users.

## Conclusion

The rise of digital technologies, including cloud computing, has opened new opportunities for SMEs to streamline their daily business operations. Consequently, the adoption of cloud services has surged among SMEs, leading to a proliferation of CSPs. While these CSPs offer similar functionalities, choosing the most suitable one remains a challenging yet crucial decision that demands careful consideration. CSP selection is not solely determined by a single variable; rather, customers must weigh various factors holistically. In our study, we explored CSP selection (and rejection) configurations by analyzing data from 213 SMEs using fsQCA. Our findings offer both theoretical implications and practical insights that are valuable to SMEs and CSPs.

### *Implications for research*

While regression-based methods oversimplify decision-making processes by focusing solely on linear and symmetrical relationships between variables, recent studies acknowledge the complexity of cloud computing service contexts. For instance, using technology-organization-environment (TOE) variables, Chen, Wang, Liang and Zhang[3] and Zhang, Wang and Liang[4] applied fsQCA to identify configurations predicting cloud computing adoption by SMEs. Similarly, Chanda, Vafaei-Zadeh, Hanifah and Ramayah[69] explored six configurations, based on the extended theory of planned behavior, that enhance adoption intention among individual users. These studies provide insights into the organizational and personal incentives for cloud service adoption i.e., *why* SMEs need to adopt them. However, they do not answer *how* CSP attributes are combined when selecting (or rejecting) a CSP, which is a complex challenge after the decision to adopt.

Our study contributes to the enrichment of cloud computing literature by exploring the nonlinear interdependencies among critical CSP attributes. Employing a MCDM process, we move beyond traditional regression-based methodologies, adopting a configurational approach to identify complex and asymmetric relationships. This opens avenues for new theoretical propositions and prescriptive configurational frameworks tailored to the cloud computing domain. Leveraging complexity theory, our study captures intricate relationships between technical and operational attributes, providing a deeper understanding of CSP selection (or rejection). Ultimately, it underscores the effectiveness of configurational models in information systems (IS) research, especially when navigating the inherent complexities of decision-making processes.

Our study offers a comprehensive understanding of cloud computing in SMEs. Rather than relying on conventional generalized models, we provide unique configurations tailored specifically to SMEs. This approach acknowledges the distinctiveness of SME business models and their corresponding needs. Furthermore, our application of a single configurational model across different samples within the same population demonstrates the versatility and adaptability of our theoretical framework—a distinctive contribution to cloud computing literature. By prioritizing key attributes for CSP selection, we establish a comprehensive yet succinct set of criteria that not only advances theoretical frameworks but also supports practical application and future research in this domain.

Finally, our study emphasizes the practicality and step-by-step procedures for utilizing configurational models in the context of CSP selection or rejection. We encourage IS researchers to explore the versatility of configurational models across various decision-making scenarios, including the selection or rejection of security service providers and data analytics vendors. Additionally, the comprehensive yet concise set of validated items tailored to the cloud computing context is poised to support future research endeavors within the same domain.

### *Implications for practice*

The practical implications of our study are extensive. It provides SMEs with a robust framework for selecting technological services, such as CSP. By applying the configurational model, businesses can streamline their decision-making processes, ensuring a more systematic and efficient approach. Our framework serves as a valuable tool for evaluating potential service providers across diverse domains, bolstering organizations' strategic decision-making capabilities.

Our study addresses a significant research gap by providing CSPs with a practical approach to configuring attributes customized for diverse firms. It underscores the idea that "one size doesn't fit all" when bundling services for different SMEs. By analyzing diverse configurations, CSPs can tailor attribute bundles to target specific SMEs. Packaging services with specific attributes offers CSPs competitive advantages, as unique combinations present replication challenges for competitors.

This study proposes configurations for both selecting and rejecting CSP providers. From a managerial perspective, the study's rejection configurations have significant implications for CSP executives and user-firm managers. While high costs and inadequate support capacity are closely associated with CSP rejection, other attributes also influence this decision. Notably, support capacity consistently emerges as a crucial criterion for CSP rejection. Interestingly, in three out of four configurations for selecting CSPs, support capacity appears as a peripheral condition with weaker influence. This suggests that while support capacity may not carry strong weight in CSP selection, its absence plays a crucial role in CSP rejection.

Our configurations also empower CSP executives to assess their weaknesses concerning technical and operational attributes. With this insight, CSPs can strategically address these areas, reducing the risk of rejection by SMEs. Furthermore, aligning attributes that may lead to CSP rejection with their in-house core capabilities and competencies allows CSPs to make informed strategic decisions for their business plans.

### *Limitations and future research direction*

While selecting a CSP, the needs and evaluation criteria of a business user may vary depending on the organization. This study explores the common focal points typically considered during service provider selection. However, the configurational model has limitations. One potential drawback is its reliance on accurately identifying and weighing selection criteria, which can vary greatly across organizations and industries. Additionally, the model's effectiveness depends on the quality and accessibility of data regarding options and attributes, potentially limiting its applicability in environments with less transparency.

Future research endeavors should focus on mitigating these limitations by developing methodologies that allow more accurate identification and weighting of decision criteria. This would accommodate the diverse needs of different organizations. Additionally, efforts should be directed toward enhancing the model's flexibility to suit various organizational contexts and decision-making scenarios. Expanding the model's application to assess emerging technologies or sustainability practices in service providers could significantly enhance its impact and relevance. Furthermore, examining the scalability of the model across different industries, refining its parameters for diverse decision-making contexts, and assessing its influence on organizational efficiency and strategic alignment would contribute to the ongoing refinement and practical applicability of the configurational model.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## ORCID

Mohammad Alamgir Hossain http://orcid.org/0000-0002-4292-8478
Alvedi Sabani http://orcid.org/0000-0001-6628-8092
Sachithra Lokuge http://orcid.org/0000-0003-4558-687X
Yee Ling Boo http://orcid.org/0000-0001-7188-9597
Shahriar Kaisar http://orcid.org/0000-0002-8103-0900
Preetha Menon http://orcid.org/0000-0002-5054-7536

## References

1. Wulf F, Westner M, Strahringer S. Cloud computing adoption: a literature review on what is new and what we still need to address. Commun of the Assoc for Inf Syst. 2021;48(1):44. doi:10.17705/1CAIS.04843.
2. Schneider S, Sunyaev A. Determinant factors of cloud-sourcing decisions: reflecting on the it outsourcing literature in the era of cloud computing. J Inf Technol. 2016;31(1):1–31. doi:10.1057/jit.2014.25.
3. Chen M, Wang H, Liang Y, Zhang G. Net and configurational effects of determinants on cloud computing adoption by SMEs under cloud promotion policy using PLS-SEM and fsQCA. J Innov & Knowl. 2023;8(3):100388. doi:10.1016/j.jik.2023.100388.
4. Zhang G, Wang W, Liang Y, Xie L. Understanding the complex adoption behavior of cloud services by SMEs based on complexity theory: a fuzzy sets qualitative comparative analysis (fsQCA). Complexity. 2021;2021(1):5591446. doi:10.1155/2021/5591446.
5. Saraswat M, Tripathi RC. Cloud computing: comparison and analysis of cloud service providers-AWs, Microsoft and Google. International Conference System Modeling and Advancement in Research Trends; 2020 Dec 04–05 Moradabad, India. IEEE, 2020; p. 281–285. doi:10.1109/SMART50582.2020.9337100.
6. Smiljanić D. 7 factors to help you choose the right cloud service provider. Binfire; 2023 [accessed 2024 Aug 1]. https://www.binfire.com/blog/7-factors-help-choose-right-cloud-service-provider/.
7. Cusack B, Adedokun A. Cloud disruption impacts business it role requirements. J Comput Inf Syst. 2022;62(5):1061–1071. doi:10.1080/08874417.2021.1978113.
8. Kumar A, Singh A, Garg A. Application of MCDM methods in cloud computing: a literature review. Artif Intel Blockchain Comput And Secur. 1(2024):868–873.

9. Sun L, Dong H, Hussain FK, Hussain OK, Chang E. Cloud service selection: state-of-the-art and future research directions. J Network And Comput Appl. 2014;45:134–150. doi:10.1016/j.jnca.2014.07.019.
10. Lang M, Wiesche M, Krcmar H. Criteria for selecting cloud service providers: a delphi study of quality-of-service attributes. Inf & Manag. 2018;55(6):746–758. doi:10.1016/j.im.2018.03.004.
11. Godse M, Mulik S. An approach for selecting software-as-a-service (SaaS) product. 2009 IEEE International Conference on Cloud Computing; 2009 Sep 21–25; Bangalore, India. IEEE, 2009. p. 155–158 doi:10.1109/CLOUD.2009.74.
12. Kumar S, Sahoo S, Lim WM, Kraus S, Bamel U. Fuzzy-set qualitative comparative analysis (fsQCA) in business and management research: a contemporary overview. Technol Forecast Soc Change. 2022;178 (121599):121599. doi:10.1016/j.techfore.2022.121599.
13. Woodside AG. Moving beyond multiple regression analysis to algorithms: calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. J Bus Res. 2013;66(4):463–472. doi:10.1016/j.jbusres.2012.12.021.
14. Lang M, Wiesche M, Krcmar H. What are the most important criteria for cloud service provider selection? A delphi study. European Conference on Information Systems; 2016; İstanbul, Turkey.
15. Kumar RR, Mishra S, Kumar C. A novel framework for cloud service evaluation and selection using hybrid MCDM methods. Arabian J For Sci Eng. 2018;43 (12):7015–7030. doi:10.1007/s13369-017-2975-3.
16. Xu H, Mahenthiran S. Users' perception of cybersecurity, trust and cloud computing providers' performance. Inf & Comput Secur. 2021;29(5):816–835. doi:10.1108/ICS-09-2020-0153.
17. Lehrig S, Eikerling H, Becker S. Scalability, elasticity, and efficiency in cloud computing: a systematic literature review of definitions and metrics. Proceedings of the 11th international ACM SIGSOFT conference on quality of software architectures; May 4–8. New York (NY): Association for Computing Machinery, 2015. p. 83–92. doi:10.1145/2737182.27371.
18. Nadeem F. A unified framework for user-preferred multi-level ranking of cloud computing services based on usability and quality of service evaluation. IEEE. 2020;8:180054–180066.
19. Garg SK, Versteeg S, Buyya R. SMICloud: a framework for comparing and ranking cloud services. Fourth IEEE International Conference on Utility and Cloud Computing; 2011 Dec 05–08; Melbourne, VIC, Australia. IEEE, 2011. p. 210–218.
20. Jagli D, Purohit S, Chandra NS. Evaluating service customizability of SaaS on the cloud computing environment. Int J Comput Appl. 2016;141(9):22–25. doi:10.5120/ijca2016909800.
21. Rahimi M, Jafari Navimipour N, Hosseinzadeh M, Moattar MH, Darwesh A. Toward the efficient service selection approaches in cloud computing. Kybernetes. 2022;51(4):1388–1412. doi:10.1108/K-02-2021-0129.
22. Benlian A, Koufaris M, Hess T. Service quality in software-as-a-service: developing the SaaS-Qual measure and examining its role in usage continuance. J Manag Inf Syst. 2011;28(3):85–126. doi:10.2753/MIS0742-1222280303.
23. McKinney V, Yoon K, Zahedi FM. The measurement of web-customer satisfaction: an expectation and disconfirmation approach. Inf Syst Res. 2002;13(3):296–315. doi:10.1287/isre.13.3.296.76.
24. Martens B, Teuteberg F, Gräuler M. Design and implementation of a community platform for the evaluation and selection of cloud computing services: a market analysis. European Conference on Information Systems (ECIS). AIS Electronic Library (AISeL), 2011.
25. Lee JY, Lee JW, Cheun DW, Kim SD. A quality model for evaluating software-as-a-service in cloud computing. Seventh ACIS international conference on software engineering research, management and applications; 2009 Dec 02–04; Haikou, China. IEEE, 2009; p. 261–266. doi:10.1109/SERA.2009.43.
26. Prasad Saripalli P. MADMAC. Multiple attribute decision methodology for adoption of clouds. In Pingali G, ed. IEEE 4th international conference on cloud computing; 2011 July 04–09; Washington, DC, USA; IEEE, 2011. p. 316–323. doi:10.1109/CLOUD.2011.61.
27. Repschlaeger J, Wind S, Zarnekow R, Turowski K. Decision model for selecting a cloud provider: a study of service model decision priorities. Americas Conference on Information Systems (AMCIS); 2013 Aug 15–17; Chicago (IL), 2013. p. 1–11.
28. Bagiwa IL, Ghani I, Younas M, Bello M. Systematic literature review on cloud adoption. Int J Internet, Broadcast And Commun. 2016;8(2):1–22.
29. Abid A, Manzoor MF, Farooq MS, Farooq U, Hussain M. Challenges and issues of resource allocation techniques in cloud computing. KSII Trans On Internet & Inf Syst. 2020;14(7):2815–2839.
30. Jaiswal C, Kumar V. Igod: identification of geolocation of cloud datacenters. J Inf Secur And Appl. 2016;27:85–102. doi:10.1016/j.jisa.2016.01.001.
31. Salim SA, Sedera D, Sawang S, Alarifi AHE, Atapattu M. Moving from evaluation to trial: how do SMEs start adopting cloud ERP? Australas J Inf Syst. 2015;19:S219–S254. doi:10.3127/ajis.v19i0.1030.
32. Walther S, Sedera D, Urbach N, Eymann T, Otto B, Sarker S. Should we stay, or should we go? Analyzing continuance of cloud enterprise systems. J Inf Technol Theory Application (JITTA). 2018;19(2):57–88.
33. Lokuge S, Duan SX. Exploring the enablers of digital transformation in small and medium-sized enterprises. In Rasmussen ES, Petersen NH, editors. Handbook of research on business model innovation through disruption and digitalization; 2023. p. 136–156.
34. Nagahawatta R, Warren M, Salzman S, Lokuge S. Security and privacy factors influencing the adoption of cloud computing in Australian SMEs. Pacific Asian Conference on Information Systems. Dubai: AIS, 2021.
35. Casalicchio E, Palmirani M. A cloud service broker with legal-rule compliance checking and quality assurance capabilities. Procedia Comput Sci. 2015;68:68(136–150. doi:10.1016/j.procs.2015.09.230.
36. QoS-driven service selection for multi-tenant saas. IEEE fifth international conference on cloud computing. IEEE, 2012. p. 566–573.

37. Garg SK, Versteeg S, Buyya R. A framework for ranking of cloud computing services. Future Gener Comput Syst. 2013;29(4):1012–1023. doi:10.1016/j.future.2012.06.006.
38. Selecting cloud computing service provider with fuzzy AHP. IEEE international conference on fuzzy systems, FUZZ-IEEE. IEEE, 2017. p. 1–5.
39. Sun L, Dong H, Hussain OK, Hussain FK, Liu AX. A framework of cloud service selection with criteria interactions. Future Gener Comput Syst. 2019;94:749–764. doi:10.1016/j.future.2018.12.005.
40. Sun L, Ma J, Zhang Y, Dong H, Hussain FK. Cloud-fuser: fuzzy ontology and MCDM based cloud service selection. Future Gener Comput Syst. 2016;57:42–55. doi:10.1016/j.future.2015.11.025.
41. Youssef AE. An integrated mcdm approach for cloud service selection based on topsis and bwm. IEEE. 2020:8:71851–71865.
42. Al-Faifi A, Song B, Hassan MM, Alamri A, Gumaei A. A hybrid multi criteria decision method for cloud service selection from smart data. Future generation computer systems. 2019: 9343–57
43. Tam MC, Tummala VR. An application of the ahp in vendor selection of a telecommunications system. Omega. 2001;29(2):171–182. doi:10.1016/S0305-0483(00)00039-6.
44. Macharia M. Cloud computing risk: a decision-making framework. J Comput Inf Syst. 2023;63(2):421–435. doi:10.1080/08874417.2022.2067793.
45. Changchit C, Chuchuen C. Cloud computing: an examination of factors impacting users' adoption. J Comput Inf Syst. 2018;58(1):1–9. doi:10.1080/08874417.2016.1180651.
46. Ragin CC. Redesigning social inquiry: fuzzy sets and beyond. University of Chicago Press; 2009.
47. Schneider CQ, Wagemann C. Set-theoretic methods for the social sciences: a guide to qualitative comparative analysis. Cambridge University Press; 2012.
48. Mallon MR, Fainshmidt S. Breaking new ground in family business research with neoconfigurational theorizing and analysis. J Fam Bus Manag. 2024;14(2):266–285. doi:10.1108/JFBM-02-2023-0019.
49. Ragin CC. Fuzzy-set social science. University of Chicago Press; 2000.
50. Woodside AG. Embrace• perform• model: complexity theory, contrarian case analysis, and multiple realities. J Bus Res. 2014;67(12):2495–2503. doi:10.1016/j.jbusres.2014.07.006.
51. Tricomi G, Merlino G, Panarello A, Puliafito A. Optimal selection techniques for cloud service providers. IEEE Access; 2020.
52. Shiau W-L, Chau PY. Understanding behavioral intention to use a cloud computing classroom: a multiple model comparison approach. Inf & Manag. 2016;53(3):355–365. doi:10.1016/j.im.2015.10.004.
53. C-H S, Kim SW. Sohn Y-w. Acceptance of public cloud storage services in South Korea: a multi-group analysis. Int J of Inf Manag. 2020: 102035:51.
54. Straub D, Boudreau M-C, Gefen D. Validation guidelines for is positivist research. Commun of the Assoc For Inf Syst. 2004;13(1):24. doi:10.17705/1CAIS.01324.
55. Fu S, Sun Y, Guo Y. Revealing product innovation practitioners' perspectives on design thinking: an exploratory research using Q-sort methodology. Technol in Soc. 2023;74(102281):102281. doi:10.1016/j.techsoc.2023.102281.
56. Ten Klooster PM, Visser M, De Jong MD. Comparing two image research instruments: the Q-sort method versus the Likert attitude questionnaire. Food Qual Preference. 2008;19(5):511–518. doi:10.1016/j.foodqual.2008.02.007.
57. Akter S, D'Ambra J, Ray P. Development and validation of an instrument to measure user perceived service quality of m-health. Inf & Manag. 2013;50(4):181–195. doi:10.1016/j.im.2013.03.001.
58. Stantchev V, Colomo-Palacios R, Soto-Acosta P, Misra S. Learning management systems and cloud file hosting services: a study on students' acceptance. Comput in Hum Behav. 2014;31:612–619. doi:10.1016/j.chb.2013.07.002.
59. Roy S, Das AK, Chatterjee S, Kumar N, Chattopadhyay S, Rodrigues JJ. Provably secure fine-grained data access control over multiple cloud servers in mobile cloud computing based healthcare applications. IEEE Trans on Ind Inf. 2018;15(1):457–468. doi:10.1109/TII.2018.2824815.
60. Ragin C, Sean, D. User's guide to fuzzy-set/qualitative comparative analysis 3.0. Irvine (CA): Department of Sociology, University of California; 2022.
61. Mattke J, Maier C, Weitzel T, Gerow JE, Thatcher JB. Qualitative comparative analysis (QCA) in information systems research: status quo, guidelines, and future directions. Commun of the Assoc For Inf Syst. 2022;50:50(556–588. doi:10.17705/1CAIS.05008.
62. Pappas IO, Woodside AG. Fuzzy-set qualitative comparative analysis (fsQCA): guidelines for research practice in information systems and marketing. Int J Inf Manag. 2021;58(102310):102310. doi:10.1016/j.ijinfomgt.2021.102310.
63. Park Y, Fiss PC, El Sawy OA. Theorizing the multiplicity of digital phenomena: the ecology of configurations, causal recipes, and guidelines for applying qca. MIS Q. 2020;44(4):1493–1520. doi:10.25300/MISQ/2020/13879.
64. Rasoolimanesh SM, Ringle CM, Sarstedt M, Olya H. The combined use of symmetric and asymmetric approaches: partial least squares-structural equation modeling and fuzzy-set qualitative comparative analysis. Int J Contemp Hosp Manag. 2021;33(5):1571–1592. doi:10.1108/IJCHM-10-2020-1164.
65. Ide T, Mello PA. QCA in international relations: a review of strengths, pitfalls, and empirical applications. Int Stud Rev. 2022;24(1):viac008. doi:10.1093/isr/viac008.
66. Pappas IO, Papavlasopoulou S, Mikalef P, Giannakos MN. Identifying the combinations of motivations and emotions for creating satisfied users in SNSS: an fsQCA approach. Int J Inf Manag. 2020;53(102128):102128. doi:10.1016/j.ijinfomgt.2020.102128.
67. Dușa A. Critical tension: sufficiency and parsimony in QCA. Sociological Methods & Res. 2022;51(2):541–565. doi:10.1177/0049124119882456.

68. Gonçalves HM, Lourenço TF, Silva GM. Green buying behavior and the theory of consumption values: a fuzzy-set approach. J Bus Res. 2016;69(4):1484–1491. doi:10.1016/j.jbusres.2015.10.129.
69. Chanda RC, Vafaei-Zadeh A, Hanifah H, Ramayah T. Investigating factors influencing individual user's intention to adopt cloud computing: a hybrid approach using PLS-SEM and fsQCA. Kybernetes. 2023; doi:10.1108/K-01-2023-0133.
70. Podsakoff PM, Sb M, Lee J-Y, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Phychol. 2003;88(5):879. doi:10.1037/0021-9010.88.5.879.
71. Kock N. Common method bias in pls-sem: a full collinearity assessment approach. Int J E-Collab (Ijec). 2015;11(4):1–10. doi:10.4018/ijec.2015100101.
72. De Jong MG, Pieters R, Fox J-P. Reducing social desirability bias through item randomized response: an application to measure underreported desires. J Mark Res. 2010;47(1):14–27. doi:10.1509/jmkr.47.1.14.
73. Fay MP, Proschan MA. Wilcoxon-Mann-Whitney or t-test? On assumptions for hypothesis tests and multiple interpretations of decision rules. Stat Surv. 2010;4 (none):1–39, 39. doi:10.1214/09-SS051.
74. Igbaria M, Guimaraes T, Davis GB. Testing the determinants of microcomputer usage via a structural equation model. J Manag Inf Syst. 1995;11(4):87–114. doi:10.1080/07421222.1995.11518061.
75. Hair JF, Jr, Hult GTM, Ringle CM, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications.

# Appendices

## Appendix A. The measures of the constructs and their reliability and validity tests

| Construct | Items | Loading |
|---|---|---|
| Reliability | 1. Most of the times, [your provider] operates without failure. | 0.690 |
| | 2. Most of the times, [your provider] provides services at the promised time. | 0.697 |
| | 3. Most of the times, [your provider] fulfills the obligations to the contract (e.g., service level agreement). | 0.606 |
| | 4. Most of the times, the services of [your provider] are accurate/error-free. | 0.798 |
| | 5. Overall, [your provider] is reliable. | 0.667 |
| Performance | 1. Most of the times, the service response time of [your provider] is quick. | 0.813 |
| | 2. The performance of [your provider] is stable. | 0.894 |
| | 3. [Your provider] meets most of the end-user requirements. | 0.784 |
| | 4. Most of the times, the services of [your provider] are available (e.g., no system crash or freeze). | 0.689 |
| Security | 1. As far I know, [your provider] has anti-virus protection. | 0.842 |
| | 2. As far I know, all data are encrypted in [your provider]. | 0.823 |
| | 3. As far I know, [your provider] ensures data confidentiality. | deleted |
| | 4. As far I know, [your provider] has secure data centers. | 0.847 |
| | 5. As far I know, [your provider] possesses access control security. | 0.758 |
| Usability | 1. [Your provider] has a simple user-interface for its contents. | 0.645 |
| | 2. [Your provider] has a simple layout for its contents. | 0.623 |
| | 3. The services of [your provider] are well organized e.g., navigation structure. | 0.877 |
| | 4. Overall, using the services of [your provider] is easy. | 0.821 |
| Reputation | 1. I believe that [your provider] has high brand value. | 0.833 |
| | 2. When it comes to user problems, [your provider] shows a sincere interest in solving them. | 0.811 |
| | 3. [Your provider] provides support that is tailored to individual needs. | 0.914 |
| | 4. Overall, I believe that [your provider] has a good reputation. | 0.801 |
| Cost | 1. The annual subscription cost of [your provider] is high. | 0.616 |
| | 2. The acquisition cost (i.e., subscription cost) of [your provider] is high. | deleted |
| | 3. The on-going cost of [your provider] is high. | 0.668 |
| | 4. The financial charges [your provider] is high. | 0.782 |
| | 5. The cost of using the service of [your provider] is significantly higher than buying and deploying relevant hardware and software by ourselves. | 0.775 |
| | 6. Overall, [your provider] is expensive. | 0.729 |
| Service Capability | 1. [Your provider] possesses a wealth of technical proficiency in delivering efficient cloud solutions. | 0.833 |
| | 2. [Your provider] employs industry best practices, leveraging the latest advancements in cloud technology. | 0.733 |
| | 3. [Your provider] demonstrates a deep understanding of cloud architecture. | 0.817 |
| | 4. [Your provider] combines their extensive knowledge and experience with a commitment to staying ahead of the curve in cloud technology. | 0.769 |
| | 5. [Your provider] consistently upgrades their capabilities to ensure they are well-equipped to address customers' dynamic demands of cloud computing. | 0.797 |
| | 6. [Your provider] exhibits a strong command of cloud processes, enabling them to streamline deployment, management, and monitoring procedures. | deleted |
| CSP Selection | 1. We use cloud services from [your provider] in our business operations. | 0.921 |
| | 2. Our business plans to continue to use cloud services from [your provider]. | 0.921 |
| | 3. I will recommend [your provider] to others. | 0.774 |

## Appendix B. Data validation

Before proceeding to data analysis, we addressed common method bias (CMB) using both procedural and statistical remedies.[70] Procedurally, we used established measurement items where possible, and conducted Q-sort and a pilot test as detailed in section 4.1. Statistically, the inner multicollinearity assessment indicated that all variance inflation factor (VIF) values were below the 3.3 threshold (see Table B1).[71] To minimize social desirability bias, respondents were assured of anonymity and confidentiality in the consent form.[72] We also conducted a non-response bias test by comparing early and late responses, with an independent sample Mann-Whitney U Test showing no significant demographic differences ($p < .05$) between the two groups. [73],[74]

**Table B1.** Collinearity statistics (variance inflation factor) – inner model matrix.

| | CSP Selection |
|---|---|
| Cost | 2.196 |
| Performance | 2.011 |
| Reliability | 1.925 |
| Reputation | 1.498 |
| Security | 2.104 |
| Service Capability | 1.800 |
| Usability | 1.974 |

### Construct validity tests

All items' loadings are higher than 0.6[75] (see Appendix A). The internal consistency of all constructs (composite reliability) are higher than the acceptable level of 0.7.[76] In addition, the average variance extracted (AVE) for every variable is greater than 0.5, indicative of acceptable convergent validity. To establish discriminant validity, we used the Heterotrait–Monotrait ratio of correlations (HTMT) criterion; we confirm that the HTMT values of all constructs are significantly ($p < .05$) lower than the conservative threshold of 0.85.[76]

| | | | HTMT ratio | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Constructs | CR | AVE | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| CSP Selection (1) | 0.857 | 0.667 | | | | | | | | |
| Cost (2) | 0.856 | 0.665 | 0.732 | | | | | | | |
| Performance (3) | 0.862 | 0.676 | 0.820 | 0.720 | | | | | | |
| Reliability (4) | 0.907 | 0.710 | 0.663 | 0.755 | 0.674 | | | | | |
| Reputation (5) | 0.896 | 0.683 | 0.662 | 0.619 | 0.533 | 0.546 | | | | |
| Security (6) | 0.896 | 0.743 | 0.744 | 0.722 | 0.795 | 0.592 | 0.483 | | | |
| Service Capability (7) | 0.918 | 0.790 | 0.646 | 0.622 | 0.630 | 0.588 | 0.404 | 0.685 | | |
| Usability (8) | 0.890 | 0.729 | 0.684 | 0.763 | 0.697 | 0.607 | 0.567 | 0.667 | 0.629 | |

Note: CR, composite reliability; AVE, average variance extracted.

## Appendix C. Computing thresholds using percentile of the latent scores (weighted average)

| | 95% | 50% | 5% |
|---|---|---|---|
| CSP Selection | 1.5 | 0.9 | −1.7 |
| Cost | 1.9 | −0.2 | −1.4 |
| Performance | 1.5 | 0.2 | −1.9 |
| Reliability | 1.4 | 0.2 | −1.9 |
| Reputation | 1.3 | −0.1 | −2.0 |
| Security | 1.4 | 0.2 | −1.8 |
| Service Capability | 1.3 | 0.2 | −1.9 |
| Usability | 1.4 | 0.1 | −1.9 |

Note. For the total sample and for the selection of a CSP.

## Appendix D. The necessary conditions check (total sample)

| | Selection of a CSP | | Rejection of a CSP | |
|---|---|---|---|---|
| Condition | Consistency | Coverage | Consistency | Coverage |
| Reliability | 0.780 | 0.792 | 0.553 | 0.545 |
| Performance | 0.817 | 0.826 | 0.541 | 0.531 |
| Security | 0.807 | 0.794 | 0.556 | 0.530 |
| Usability | 0.824 | 0.783 | 0.582 | 0.538 |
| Reputation | 0.825 | 0.752 | 0.615 | 0.545 |
| Cost | 0.550 | 0.561 | 0.794 | 0.786 |
| Service Capability | 0.807 | 0.795 | 0.568 | 0.543 |