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Net and configurational effects of determinants on cloud computing adoption by SMEs under cloud promotion policy using PLS-SEM and fsQCA

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A B S T R A C T

A deeper understanding of cloud computing is required to accelerate its adoption and leverage its cost, performance, reliability, and security. However, information about the combined effect of factors influencing cloud computing adoption using traditional statistical methods is limited. Based on a literature review of firms' adoption of cloud computing, we identified 12 determinants to explore how antecedent factors influence cloud computing adoption by small and medium-sized enterprises (SMEs). We used symmetric and asymmetric techniques to analyze data from 203 Chinese SMEs. The partial least squares structural equation modeling (PLS-SEM) assessed the net impact of each antecedent, and the fuzzy-set qualitative comparative analysis (fsQCA) provided a supplementary analysis by highlighting the configurations of the causal conditions associated with cloud computing adoption. The PLS-SEM results show that security concerns, top management support, IT competence, competitive pressure, trading partner pressure, and provider support influence SMEs' decisions to adopt cloud computing. Interestingly, fsQCA provides a deeper understanding of the complex causality that PLS-SEM does not capture. That is, fsQCA revealed seven configurations resulting in high-level cloud computing adoption and eight causal paths leading to the negation of cloud computing adoption. These findings indicate that several conditions with no significant influence in PLS-SEM were adequate when combined with other conditions in the configurations. The results of the complementary analysis provide theoretical and practical insights.

Introduction

The COVID-19 pandemic has affected the global economy, compelling small- and medium-sized enterprises (SMEs), which contribute toward economic and social development, to adapt to increased digital transformation (e.g., both online and offline business operations) and changes in customer needs and behavior (Pillai et al., 2021; Venkatesh, 2020). During the COVID-19 lockdowns, there was a strong need for digital technologies to operate businesses with restricted budgets and resources (Dey, Al-Karaghouli, & Muhammad, 2020; Dwivedi et al., 2020). In the information and technology (IT) industry, cloud computing, a representative cutting-edge technology, is a major shift from the traditional IT investment mode owing to its on-demand payment characteristics, scalability, configurability, and fast and low-cost implementation (Deng, Wang, Teo, & Song, 2021).

With its specific characteristics (Deng et al., 2021; Dwivedi & Mustafee, 2010; S. Liu, Chan, Yang, & Niu, 2018; Y. Liu, Soroka, Han, Jian, & Tang, 2020; F.-K. Wang & He, 2014), cloud computing can reduce physical infrastructure and personnel costs and innovate to achieve sustainable organizational performance (S. Gupta, Meissonier, Drave, & Roubaud, 2020) and agility (S. Liu et al., 2018), especially for SMEs. SMEs can use cloud computing to enhance their competitiveness against their larger counterparts. In fact, they can afford and manage key business applications (e.g., password, customer relationship, and e-mails) that cannot be supported by shrinking internal funds (Senarathna, Wilkin, Warren, Yeoh, & Salzman, 2018).

The benefits of moving to the cloud are obvious; however, several enterprises are concerned about transitioning from traditional IT infrastructure to new cloud platforms. This concern will be even greater for SMEs that have inadequate time or funds to adapt to the

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new system (Khayer, Talukder, Bao, & Hossain, 2020). Recent surveys show that the actual cloud computing adoption rate among SMEs is low, lagging behind large firms (Skare & Riberio Soriano, 2021). For example, a report on the Chinese cloud computing industry's prospects and investment strategy planning (2021−2026) states that Chinese industrial enterprises migrating to the cloud increased from 43.50% in 2018 to 49.40% in 2021, which is much lower than in Europe (70%) and the United States (US) (80%). To encourage enterprises to adopt cloud services, thereby accelerating their digital transformation and promoting the cloud-computing industry, it is important to encourage SMEs to adopt cloud computing.

From the perspective of primary technology adoption theories, numerous empirical studies have explored the determinants of cloud-computing adoption at different levels (Al Hadwer, Tavana, Gillis, & Rezania, 2021; Senyo, Addae, & Boateng, 2018), such as individual (Song, Kim, & Sohn, 2020), enterprise, healthcare (Gao & Sunyaev, 2019), and government (Liang, Qi, Wei, & Chen, 2017). At the firm level, several factors have been found to significantly influence cloud computing adoption. However, unified results on the impact of these factors have not been established. For example, relative advantage was found to have a significantly positive effect on cloud computing adoption in several studies (Gangwar, Date, & Ramaswamy, 2015; C.-L. Hsu & Lin, 2016; Khayer et al., 2020; Kumar, Samalia, & Verma, 2017; Martins, Oliveira, & Thomas, 2016; Oliveira, Thomas, & Espadanal, 2014; Senarathna et al., 2018; Shih & Lin, 2016), a significantly negative effect in one study of Low, Chen, and Wu (2011) and no effect in some studies (Gutierrez, Boukrami, & Lumsden, 2015; Skafi, Yunis, & Zekri, 2020; Yang, Sun, Zhang, & Wang, 2015). The results may vary owing to different samples in varying contexts. Another possible reason for this is the drawbacks of the data analysis techniques used. The dominant techniques employed in empirical studies to analyze the relationships between independent variables (IV) and dependent variables (DV) are conventional symmetric-based approaches such as multiple regression models, covariance-based structural equation modeling (CB-SEM), and partial least squares structural equation modeling (PLS-SEM). These approaches can lead to similar results, as all IVs are set as predictors of a single DV (Pappas & Woodside, 2021). They focus only on the net effect of individual variables that have been criticized for causing multicollinearity and symmetric assumptions, while the relationships between antecedents and outcomes in social sciences are more asymmetric (Phung, Ly, Nguyen, & Nguyen-Thanh, 2020). Therefore, as a holistic approach, qualitative comparative analysis (QCA) has been recommended to address these shortcomings by offering a case-based investigation developed from the causal complexity theory (Kraus, Ribeiro-Soriano, & Schüssler, 2018; Liang, Zhang, Xu, & Wang, 2020; Ragin, 2008; Rihoux & Ragin, 2009; Roig-Tierno, Gonzalez-Cruz, & Llopis-Martinez, 2017; Romero-Castro, López-Cabarcos, & Piñeiro-Chousa, 2022; Woodside, 2013).

This study responds to the call for a holistic approach to understanding SMEs' decision to adopt cloud computing. First, based on a systematic review of related studies on cloud computing adoption by enterprises, the primary constructs used in most studies have been selected as the elements of our model elements and classified according to technological, organizational, and environmental dimensions. Second, using a sample of 203 SMEs in China, we apply both symmetric (PLS-SEM) and asymmetric (fuzzy-set QCA, fsQCA) methods to analyze the role of these factors in accelerating cloud computing adoption. We begin by analyzing the net effects of each antecedent on cloud computing adoption using the conventional approach (PLS-SEM). Subsequently, we use fsQCA to provide a deeper understanding of the complex reality associated with adopting cloud computing that PLS-SEM does not capture (Gligor & Bozkurt, 2020; Jahanmir, Silva, Gomes, & Gonçalves, 2020). The fsQCA can explore how antecedent factors fit together to produce multiple causal equifinality pathways that can result in cloud computing adoption or negation of cloud computing adoption (causal asymmetry). The PLS-SEM and fsQCA results provide relevant insights and suggestions for incentivizing SMEs to adopt cloud computing.

Literature review

Unlike traditional IT outsourcing, cloud computing provides users access to sophisticated computing services via the Internet on a fee-for-service basis (Gao & Sunyaev, 2019). With specific characteristics of cloud computing, including scalability and rapid configurability (Deng et al., 2021), cloud computing is likely to yield substantial benefits and change the nature of competition in the IT industry. It offers three service models—Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS)—and three types of deployment—public cloud, private cloud, and hybrid cloud (Song et al., 2020). However, there are several challenges in cloud computing, such as privacy and data security, availability, data jurisdiction, technical challenges, cultural resistance, data ownership, and data/service reliability (S. Gupta et al., 2020). To facilitate the diffusion of cloud computing, studies across different disciplines and perspectives have examined the factors driving organizations to accept cloud computing (Al Hadwer et al., 2021). Table 1 summarizes previous studies on the adoption of cloud computing by enterprises.

As shown in Table 1, the technology-organization-environment (TOE) framework, diffusion of innovation (DOI), institutional theory (INT), and technology acceptance model (TAM) have been used as single-theory or integrated theories to study the factors affecting the adoption of cloud computing in enterprises. Most empirical studies have employed conventional symmetric-based methods, such as regression models, structural equation modeling (SEM), and partial least squares (PLS), to investigate the outcomes between variables. However, these methods emphasize the net effect of each IV on each DV while ignoring possible asymmetric relations between variables in complex contexts (Chaparro-Peláez, Agudo-Peregrina, & Pascual-Miguel, 2016), resulting in correlations and significance that may vary across different models. In a real-life context, the outcome often results from various combinations of antecedents rather than from individual ones (Kaya, Abubakar, Behravesh, Yildiz, & Mert, 2020). QCA has been recommended for analyzing complex causality and logical relations, specifically to understand the combined effects of determinants on adopting cloud-computing (Ragin, 2008; Rihoux & Ragin, 2009). Therefore, we also answer this call and use fsQCA to provide a more nuanced understanding of how these antecedent conditions fit together to affect SMEs' decision to adopt cloud computing.

Conceptual model and hypotheses

As shown in Table 2, we identified 12 determinants and classified them into technology, organization, and environmental contexts based on the TOE framework.

Technology context

Relative advantage is the perception that an innovation is considered more beneficial to an organization than its predecessor (Rogers, 2010). This resembles the notion of perceived usefulness in TAM (Gangwar et al., 2015; Palos-Sanchez et al., 2017; Shih & Lin, 2016; Wu, 2011). It has been identified as a strong driver of IT innovation adoption, such as blockchain (Wong, Leong, Hew, Tan, & Ooi, 2020) and mobile marketing (Maduku, Mpinganjira, & Duh, 2016). Organizations tend to adopt innovations with a unique advantage in improving their strategic and operational effectiveness. Compared with traditional on-premise IT, cloud computing provides many benefits for SMEs, including reduced IT costs, flexibility, scalability, reliability (business continuity), and efficiency (Kumar et al., 2017; Lin & Chen, 2012; S. Liu et al., 2018). SMEs are more likely to adopt cloud

Table 1
Determinants of the adoption of cloud computing by enterprises.

Reference	Theory	Sample/methodology	DV	IV
Adjei, Adams, and Mamattah (2021)	INT	79 organizations in Ghana PLS-SEM	Cloud computing adoption	Mimetic pressure*, coercive pressure*, and normative pressure*
Skafi et al. (2020)	TOE, and the contextual theory	139 SMEs in Lebanon Logistic regression	Cloud computing adoption decision making	Relative advantage, cost, security and privacy*, compatibility, complexity*, trialability, size, top management support*, innovativeness, prior IT experience*, competitive pressure, market scope, supplier computing support, political issues and instability, poor infrastructure*, and lack of government initiatives*
Khayer et al. (2020)	TOE	311 firms in Bangladesh PLS-SEM and artificial neural network	Cloud adoption	Relative advantage*, service quality*, perceived risk*, top management support*, facilitating conditions*, social influence, cloud providers influence*, server location*, computer self-efficacy*, and resistance to change*
Dincă, Dima, and Rozsa (2019)	TOE, and DOI	198 Romanian SMEs Logistic regression	Cloud computing adoption	Competing business scene, government support, cooperation with cloud providers*, collaboration with other business units, employee's cloud know-how, employee's information access, manager's innovation capacity, manager's cloud expertise*, perceived business benefit, cost reduction*, security and privacy, complexity, compatibility, and trialability
Oliveira, Martins, Sarker, Thomas, and Popovič (2019)	TOE and INT	259 firms in Portugal PLS-SEM	SaaS adoption	Technology competence*, top management support*, and environment context* (coercive pressures, normative pressures, mimetic pressures) Control: industry sector, firm size
N. Wang, Xue, Liang, Wang, and Ge (2019)	INT	376 Chinese firms PLS-SEM	Cloud computing assimilation	Government regulation*, government support*, and top management support* Control: IT staff, IT budget, firm size, industry type
N. Wang, Liang, Ge, Xue, and Ma (2019)	No specific theory	376 Chinese firms PLS-SEM	Cloud computing assimilation	Top management support*, government support*, organization inertia, and data security risk*
Senarathna et al. (2018)	TOE, and DOI	149 Australian SMEs multiple regression analysis	SMEs' adoption of cloud computing	Relative advantage*, flexibility, quality of service*, awareness*, security, and privacy Control: organizational size and industry type
Maqueira-Marín, Bruque-Cámara, and Minguela-Rata (2017)	No specific theory	281 high-technology firms in Southern Europe SEM	Cloud computing adoption	Killer applications, R&D institutions, technology providers*, public administrations, and success cases*
Hassan (2017)	No specific theory	90 Malaysian SMEs PLS-SEM	Cloud computing adoption	Top management support, IT resources*, and employee knowledge
Palos-Sanchez, Arenas-Marquez, and Aguayo-Camacho (2017)	TAM	150 companies in Spain PLS-SEM	Behavioral intention to use cloud computing (SaaS model)	Perceived usefulness*, perceived ease of use, attitude toward using*, top management support, training, communication, organization size*, and technological complexity*
Priyadarshinee, Raut, Jha, and Gardas (2017)	TOE	660 Indian private organizations SEM and artificial neural network	Cloud computing adoption	Perceived IT security risk*, risk analysis*, technology innovation*, usage of technology, industry usage, management style*, and trust*
Kumar et al. (2017)	TOE, TAM, and DOI	271 SMEs from the northern region of India SEM (Amos)	Cloud computing adoption intention	Perceived usefulness, perceived ease of use, relative advantage*, compatibility, security concerns*, technology readiness, top management support*, firm size, external pressure*, and service providers' support*
Tomás, Thomas, and Oliveira (2017)	TOE, INT, and process virtualization theory	317 firms in Portugal SEM	Intention to adopt SaaS	Representation capability of SaaS, reach capability of SaaS*, monitoring capability of SaaS*, technology competence*, top management support*, coercive pressure, normative pressure*, and mimetic pressures Control: industry sector, firm size
Hassan, Nasir, Khairudin, and Adon (2017)	TOE, and IOS model	132 SMEs in Malaysia PLS-SEM	Cloud computing adoption	perceived benefits, top management support, IT resources*, and external pressure*

(*continued*)

Table 1 (*Continued*)

Reference	Theory	Sample/methodology	DV	IV
Martins et al. (2016)	TOE, DOI, INT	265 firms in Portugal PLS-SEM	SaaS diffusion: intention, adoption, routinization	Cost saving, security concerns, relative advantage*, compatibility, complexity*, technology competence*, top management support*, coercive pressures*, normative pressures*, and mimetic pressures Control: industry sector, firm size
C.-L. Hsu and Lin (2016)	TOE	102 enterprises in Taiwan PLS-SEM	Cloud service adoption	Relative advantage*, ease of use, compatibility, trialability, observability*, security*, firm size, global scope, financial costs*, satisfaction with existing IS*, competition intensity*, and regulatory environment Control: Industry type
Shih and Lin (2016)	SLA, DOI, trust theory, TAM	214 firms in Taiwan SEM and fsQCA	Cloud service adoption intention	Foundation characteristics, management characteristics, compatibility, relative advantage, trust*, and perceived usefulness*
Gangwar et al. (2015)	TOE, and TAM	280 companies in IT, manufacturing, and finance sectors in India SEM (Amos)	Cloud computing adoption intention	Relative advantage, compatibility, complexity, organizational readiness, top management support, training and education, perceived ease of use*, perceived usefulness*, competitive pressure*, and trading partner support*
Yang et al. (2015)	TOE	173 organizations in China PLS-SEM	Intention to use SaaS	Technological readiness (relative advantage, simplicity, compatibility, experience ability), organizational readiness (IT infrastructure, top management support), environmental readiness (competitor pressure, partner pressure), and SaaS readiness*
M. Li, Zhao, and Yu (2015)	TOE	107 SMEs in China PLS-SEM	Cloud service transformation intention	Cloud service trust*, reliability, information security, institutional pressure, structure assurance, vendor scarcity Control: size, international scope, IT competence, and entrepreneurship*
Gutierrez et al. (2015)	TOE	257 in the UK Logistic regression	Cloud computing adoption	Relative advantage, complexity*, compatibility, top management support, firm size, technology readiness*, competitive pressure*, and trading partner pressure*
P.-F. Hsu, Ray, and Li-Hsieh (2014)	TOE	200 Taiwanese firms SEM	Cloud adoption intention	Perceived benefits*, business concerns*, IT capability*, and external pressure
Oliveira et al. (2014)	DOI and TOE	369 firms in services and manufacturing sectors in Portugal PLS-SEM	Cloud computing adoption	Security concerns, cost savings, relative advantage*, complexity*, compatibility, technology readiness*, top management support*, firm size*, competitive pressure, and regulatory support
P. Gupta, Seetharaman, and Raj (2013)	No specific theory	211 micro and small businesses in the APAC region PLS-SEM	Cloud computing usage and adoption	Reliability, ease of use & convenience*, cost reduction*, sharing & collaboration, and security & privacy*
Low et al. (2011)	TOE	111 firms in the high-tech industry in Taiwan logistic regression	Cloud computing adoption	Relative advantage*, complexity, compatibility, top management support*, firm size*, technology readiness, competitive pressure*, and trading partner pressure*
Wu (2011)	TAM	246 enterprises in Taiwan RST data mining	Behavioral intention to use the SaaS solutions	Social influence, perceived benefits, attitude toward technology innovation, security and trust, perceived usefulness*, and perceived ease of use*
Heart (2010)	No specific theory	143 services and manufacturing organizations PLS-Graph	Organizational intention to adopt SaaS	Trust in SaaS vendor community*, perceived reputation of SaaS vendor community*, perceived capabilities of SaaS vendor community, perceived risk*, perceived data insecurity, and perceived systems unavailability

Note: "*" indicates that factors are found to be significant.

computing in their business processes when they perceive its relative advantage (C.-L. Hsu & Lin, 2016; Khayer et al., 2020; Low et al., 2011; Martins et al., 2016; Oliveira et al., 2014; Senarathna et al., 2018).

H1. Relative advantage positively impacts cloud computing adoption.

Compatibility is measured by the degree to which cloud computing is compatible with an organization's business processes and existing IT infrastructure (Chatterjee, Rana, Dwivedi, & Baabdullah, 2021; Martins et al., 2016). It is an important determinant of innovation adoption, such as in social media marketing (Chatterjee & Kumar Kar,

Table 2
Determinants identified based on literature review.

Context	Construct identified in this study	Similar construct from previous studies	Statistically significant effect	Statistically insignificant effect
Technology	Relative advantage	Relative advantage	Low et al. (2011), Oliveira et al. (2014), Gangwar et al. (2015), Martins et al. (2016), C.-L. Hsu and Lin (2016), Shih and Lin (2016), Kumar et al. (2017), Senarathna et al. (2018), and Khayer et al. (2020)	Yang et al. (2015), Gutierrez et al. (2015), and Skafi et al. (2020)
		Perceived usefulness	Wu (2011), Gangwar et al. (2015), Shih and Lin (2016), and Palos-Sanchez et al. (2017)	Kumar et al. (2017)
		Perceived (business) benefits	Wu (2011), P.-F. Hsu et al. (2014)	Hassan et al. (2017) and Dincă et al. (2019)
	Compatibility	Compatibility	Gangwar et al. (2015)	Low et al. (2011), Oliveira et al. (2014), Yang et al. (2015), Gutierrez et al. (2015), Martins et al. (2016), C.-L. Hsu and Lin (2016), Shih and Lin (2016), Kumar et al. (2017), Dincă et al. (2019), and Skafi et al. (2020)
	Complexity	Complexity	Oliveira et al. (2014), Gangwar et al. (2015), Gutierrez et al. (2015), Martins et al. (2016), and Skafi et al. (2020)	Low et al. (2011) and Dincă et al. (2019)
		Technological complexity	Palos-Sanchez et al. (2017)	
		Perceived ease of use	Wu (2011), P. Gupta et al. (2013), and Gangwar et al. (2015)	C.-L. Hsu and Lin (2016), Palos-Sanchez et al. (2017), and Kumar et al. (2017)
	Security concern	Security concerns	Kumar et al. (2017)	Oliveira et al. (2014) and Martins et al. (2016)
		Security and privacy	P. Gupta et al. (2013), C.-L. Hsu and Lin (2016), and Skafi et al. (2020)	Dincă et al. (2019) and Senarathna et al. (2018)
		Perceived (IT security) risk	Heart (2010), Priyadarshinee et al. (2017), N. Wang, Liang, et al. (2019), Khayer et al. (2020)	
Organization	Top management support	Top management support	Low et al. (2011), Oliveira et al. (2014), Gangwar et al. (2015), Martins et al. (2016), Kumar et al. (2017), Tomás et al. (2017), Oliveira et al. (2019), N. Wang, Xue, et al. (2019), N. Wang, Liang, et al. (2019), Skafi et al. (2020), and Khayer et al. (2020)	Yang et al. (2015), Gutierrez et al. (2015), Hassan (2017), Palos-Sanchez et al. (2017), and Hassan et al. (2017)
	Adequate resource	IT resources	Hassan et al. (2017) and Hassan (2017)	
		Firm (or organization) size	Low et al. (2011), Oliveira et al. (2014), and Palos-Sanchez et al. (2017)	Gutierrez et al. (2015), C.-L. Hsu and Lin (2016), Kumar et al. (2017), and Skafi et al. (2020)
	IT competence	Technology competence	Martins et al. (2016), Tomás et al. (2017), and Oliveira et al. (2019)	
		Prior IT experience/ capability	P.-F. Hsu et al. (2014) and Skafi et al. (2020)	
		Technology readiness	Oliveira et al. (2014) and Gutierrez et al. (2015)	Low et al. (2011) and Kumar et al. (2017)
		Employee knowledge		Hassan (2017) and Dincă et al. (2019)
Environment	Competitive pressure	Competitive pressure	Low et al. (2011), Gangwar et al. (2015), and Gutierrez et al. (2015)	Oliveira et al. (2014) and Skafi et al. (2020)
		Competing business scene		Dincă et al. (2019)
		Competition intensity	C.-L. Hsu and Lin (2016)	
	Trading partner pressure	Trading partner pressure	Low et al. (2011) and Gutierrez et al. (2015)	
		Collaboration with other business units		Dincă et al. (2019)
	Coercive pressure	Coercive pressure	Martins et al. (2016), Oliveira et al. (2019), and Adjei et al. (2021)	Tomás et al. (2017)
		Government regulation	N. Wang, Xue, et al. (2019)	Dincă et al. (2019)
	Government support	Government support	N. Wang, Xue, et al. (2019) and N. Wang, Liang, et al. (2019)	
		Regulatory support		Oliveira et al. (2014),
	Provider support	Service providers' support	Kumar et al. (2017)	
		Supplier computing support		Skafi et al. (2020)
		Trading partner support	Gangwar et al. (2015)	

2020). An organization may perceive more benefits from adopting cloud computing and reduction in related uncertainties if cloud computing has a greater fit with its present values, systems, procedures, and needs (Kumar et al., 2017; Lin & Chen, 2012; Martins et al., 2016). Thus, compatibility increases the likelihood of cloud computing adoption (Gangwar et al., 2015).

H2. Compatibility positively influences cloud computing adoption.

Complexity can be defined as the degree of the perceived difficulty in understanding or using innovation (Chatterjee et al., 2021; Martins et al., 2016). This is analogous to the perceived ease of use from the TAM (Gangwar et al., 2015; Wu, 2011), which has been identified as an inhibitor of new technology adoption, such as master data management (Haneem, Kama, Taskin, Pauleen, & Abu Bakar, 2019), blockchain (Wong et al., 2020), and big data analytics (Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020). Migrating from existing systems to a specialized cloud may be difficult for companies. Moreover, companies may be reluctant to adopt cloud computing if it requires their employees to acquire extensive new skills (Gutierrez et al., 2015; Oliveira et al., 2014; Skafi et al., 2020).

H3. Complexity negatively influences cloud computing adoption.

Security concerns refer to the perceived security breach wherein a company loses information, personal records, or other sensitive data by adopting cloud computing (Oliveira et al., 2014). Several studies on IT adoption have reported this as a major obstacle to cloud computing (P. Gupta et al., 2013; Kumar et al., 2017; Priyadarshinee et al., 2017; Skafi et al., 2020), social commerce (Abed, 2020), and big data analytics (Maroufkhani et al., 2020). Cloud computing allows multiple users to share computing, storage, networking infrastructure, software, analytics, and intelligence over the Internet, which heightens certain security concerns (Kumar et al., 2017). SMEs' main concern in adopting cloud services is data security (Z. Wang, Wang, Su, & Ge, 2020), including malicious manipulation and disclosure of enterprises' private information and reduced auditability of enterprise data. These security concerns not only cause economic losses to the enterprise but could also damage the enterprise's reputation and consumers' trust (Zhang, Wang, & Liang, 2021). In contrast to the relative advantage, security concerns may weigh on the decisions of SMEs to adopt cloud computing.

H4. Security concern negatively impacts cloud computing adoption.

Organization context

Top management support is the vision, support, and commitment provided to create the desired environment for adopting an innovation (Martins et al., 2016). It has proven to be an essential condition for overcoming the resistance to organizational change and ensuring the successful implementation of IT in various contexts, including social commerce (Abed, 2020), master data management (Haneem et al., 2019), mobile marketing (Maduku et al., 2016), and big data analytics (Maroufkhani et al., 2020). Top management support is particularly important for adopting technology in centralized SMEs, where the top management often makes the final decisions on the organization's information and communication technology (ICT) strategy and investments (Kumar et al., 2017). When top managers recognize the advantages of cloud services, they may allocate the necessary resources to adopt cloud services and encourage employees to use them (Oliveira et al., 2014).

H5. Top management support is positively associated with cloud computing adoption.

Resource availability positively affects the organizational adoption of innovative technology (Abed, 2020). Some empirical studies have reported that large firms tend to adopt more innovations as they have adequate resources for changing business strategies and taking risks (Low et al., 2011; Sun, Hall, & Cegielski, 2020). As most small enterprises have limited human and financial resources, their IT adoption strategy often varies from that of a larger business with more resources (F.-K. Wang & He, 2014). The adoption of cloud computing is typically a large project for SMEs. However, if an SME has sufficient funds, adequate human resources, and ample time, it can successfully adopt cloud-computing technology (Chang, Hwang, Hung, Lin, & Yen, 2007; van de Weerd, Mangula, & Brinkkemper, 2016).

H6. Adequate resource positively affects cloud computing adoption.

IT competence (or technology competence) refers to technological characteristics that are available, including IT infrastructure and human resources, to impact a firm's innovation adoption (Martins et al., 2016). Several studies have shown that it is an important determinant of IT adoption across contexts such as master data management (Haneem et al., 2019) and mobile marketing (Maduku et al., 2016). Cloud-based architecture transfers the responsibilities of maintenance and security procedures from the client to the provider. However, the diversity of cloud-based solutions and specialized requirements may require ongoing monitoring of legal and organizational compliance (Oliveira et al., 2019). IT competence is crucial for implementing appropriate procedures. Therefore, IT competence can provide a higher degree of technological readiness to adopt a new IT solution (Tomás et al., 2017).

H7. IT competence positively impacts cloud computing adoption.

Environment context

Competitive pressure refers to the constraint companies experience from their industry peers (Low et al., 2011). It has been proved to be an important factor in studies on innovation adoption, such as blockchain (Wong et al., 2020) and business analytics (Nam, Lee, & Lee, 2019). In an uncertain environment of globalization and customization, SMEs with weak funds and poor ability to withstand risks are more likely to experience pressure from competitors and follow them in using new technologies (Zhang et al., 2021). Introducing new technologies is an effective way to gain a first-mover competitive advantage. By embracing cloud computing, companies can better understand market visibility, collect data more accurately, and achieve higher operational efficiency, which makes them more profitable (Oliveira et al., 2014). Therefore, companies can operate more efficiently and remain competitive in the industry.

H8. Competitive pressure is positively correlated with cloud computing adoption.

Organizations also depend on their trading partners to design and implement a technology (Chatterjee et al., 2021; Kalaitzi & Tsolakis, 2022). Many studies have demonstrated that demand from business partners is an important factor in the adoption of innovations such as radio frequency identification (RFID) (Y.-M. Wang, Wang, & Yang, 2010), social commerce (Abed, 2020), and mobile marketing (Maduku et al., 2016). Trading partner pressure to adopt cloud computing may exist because it provides a platform for information exchange and supply chain management among suppliers, manufacturers, wholesalers, and retailers (Yang et al., 2015). A firm may adopt an innovation if its dominant customers or suppliers have implemented it, thereby demonstrating its fitness as a business partner.

H9. Trading partner pressure positively affects cloud computing adoption.

Coercive pressure is formal or informal pressure exerted by organizations on which a firm depends (Martins et al., 2016), such as resource-dominant organizations, governments, and parent corporations. The degree of coercive strength from these entities determines the specific formal or informal pressure on a firm's actions (Oliveira et al., 2019). Several studies have indicated that coercive pressure has a significant positive relationship with IT adoption, such as in cloud computing (Adjei et al., 2021; Oliveira et al., 2019) and enterprise architecture (Ahmad, Drus, & Kasim, 2020).

H10. Coercive pressure has a significant positive impact on cloud computing adoption.

Government support refers to the support provided by a government to firms for their strategic initiatives and operational activities through political, economic, and social resources to encourage IT innovation and adoption (N. Wang, Xue, et al., 2019), including cloud-specific standards and protocols (Oliveira et al., 2014), financial incentives, direct investment, related funds, privilege policies, and specific guidance for a company's business activities (Nam et al., 2019). Government support is a form of social capital, that helps companies overcome resource shortages (Luk et al., 2008).

H11. Government support is positively associated with cloud computing adoption.

Cloud computing provides organizations with on-demand and pay-per-usage access to computing resources hosted at a remote data center managed by cloud service providers (CSPs) (F.-K. Wang & He, 2014) without installing and maintaining them on-premises (Gangwar et al., 2015). CSPs must handle all services that migrate to the cloud; therefore, CSPs' reputation, reliability, capability, and support are crucial to ensure data availability at all times (Gangwar et al., 2015; Lai, Lin, & Tseng, 2014). As a new technology, support from CSPs plays an important role in having a constructive impact on SMEs' cloud computing adoption (Kumar et al., 2017). Provider support is considered a significant factor in IT adoption, such as cloud computing (Alshamaila, Papagiannidis, & Li, 2013; Gangwar et al., 2015), digital transformational outsourcing (Mazumder & Garg, 2021), and big data analytics (Maroufkhani et al., 2020).

H12. Provider support positively affects cloud computing adoption.

Configurational effect based on complexity theory

Table 1 shows several studies that have examined the possible antecedents of cloud-computing adoption in isolation (Gligor & Bozkurt, 2020). However, mixed results on the significance of the above variables for explaining cloud-computing adoption suggest that no single variable is either necessary or sufficient to fully explain cloud-computing adoption (Duarte & Pinho, 2019). Previous studies have also shown that the relationship between antecedent variables and adoption is complex and requires further research in various contexts such as mobile health (Duarte & Pinho, 2019) and Internet of Vehicles services (G. Li, Liang, Wang, Chen, & Chang, 2022; Liang et al., 2020). Complexity theory supports the argument that different antecedents in a combination can negatively or positively impact the outcome, depending on the absence or presence of other elements in the combination (Fiss, 2007). Complexity theory argues this as equifinality; that is, the outcome of interest may be explained similarly by alternative sets of causal conditions that combine into sufficient configurations for the outcome (Kourouthanassis, Mikalef, Pappas, & Kostagiolas, 2017; Mazumder & Garg, 2021). The identified determinants are essentially causal conditions, and they may combine in different configurational forms to produce the same outcome (i.e., cloud computing adoption) (Ali, Seny Kan, & Sarstedt, 2016). Therefore, we believe that multiple combinations of these antecedents can lead to cloud computing adoption. This study posits the following propositions, consistent with complexity theory.

Proposition 1. There are disparate configurations of determinants in the technological, organizational, and environmental dimensions associated with cloud computing adoption.

Previous studies suggest that configurations leading to an outcome (e.g., high performance) may not be the reciprocals of configurations engendering negated outcomes (i.e., low performance) (Afonso, Silva, Gonçalves, & Duarte, 2018; Bigerna, Bollino, & Micheli, 2016; Jahanmir et al., 2020; Liang et al., 2020). In the context of our study, while tremendous competitive pressure may be the underlying reason for the adoption of cloud computing, a deficiency in the same pressure may not be the reason for low adoption, as it could be driven by a different set of enablers, such as support from top management, legislative governments, and providers. Similarly, while a firm may demonstrate low adoption of cloud computing owing to strong concerns about security, the absence of security concerns does not assure adoption. As the two-factor theory explains, despite the presence of other enablers, security concerns (as inhibitors) could hinder cloud-computing adoption; however, their absence does not necessarily encourage adoption (S. C. Park & Ryoo, 2013). Complexity theory argues this as asymmetry (Afonso et al., 2018; Mazumder & Garg, 2021; Woodside, 2013); that is, the set of causal conditions leading to the presence of the outcome may frequently differ from the set of conditions leading to the absence of the outcome (Fiss, 2011). Thus, the following proposition is suggested.

Proposition 2. The multiple configurations of determinants that lead to a high level of cloud-computing adoption differ from those that result in a low level of cloud computing adoption.

Based on the above analysis, the integrative research model is shown in Fig. 1.

Fig. 1 illustrates the proposed research model. This model includes the hypothesized relationships (H1 to H12) for each factor that the PLS-SEM tests (Jahanmir et al., 2020). These factors can combine in multiple ways to achieve cloud computing adoption. We use a holistic approach to analyze possible combinations between the factors (conditions) and the outcome of interest (cloud-computing adoption), and test the propositions (1 and 2) with fsQCA for a deeper understanding of the interconnected structures of the constructs and the complex nature of their interdependencies (Ali et al., 2016).

Methodology

We conducted a survey to gather empirical data on SMEs in China. We developed and examined our instruments using a PLS-SEM measurement model based on theoretical models. The structural model of PLS-SEM was used to test our model and hypotheses and provide a symmetrical "net effect" explanation (Valaei, Rezaei, & Ismail, 2017). In addition, considering the limitations of symmetric statistical approaches and the occurrence of multiple realities (i.e., complex causality), the same data were calibrated and analyzed by fsQCA to explore the cause-effect relations between antecedent conditions and outcomes, and to offer a holistic view of the interrelationships that jointly impact cloud computing adoption.

Measurement instrument

The measurement instruments for the constructs were adapted from previously validated and reliable literature. Subsequently, a pilot study comprising 30 companies was conducted to confirm the instruments' reliability, validity, and translational equivalence. As seen in Table 3, the final instrument had 42 items rated on a five-point Likert-type scale ranging from "strongly disagree" to "strongly agree."

Data collection

Using Wenjuanxing (http://www.wenjuan.com), a professional online questionnaire survey and voting platform, an online questionnaire was sent to key informants in Chinese firms involved in and knowledgeable about cloud computing. These included chief information officers (CIOs), managers in IT departments, and other managers in non-IT departments. To target respondents who assumed the role of key informants, we provided a clear description of cloud

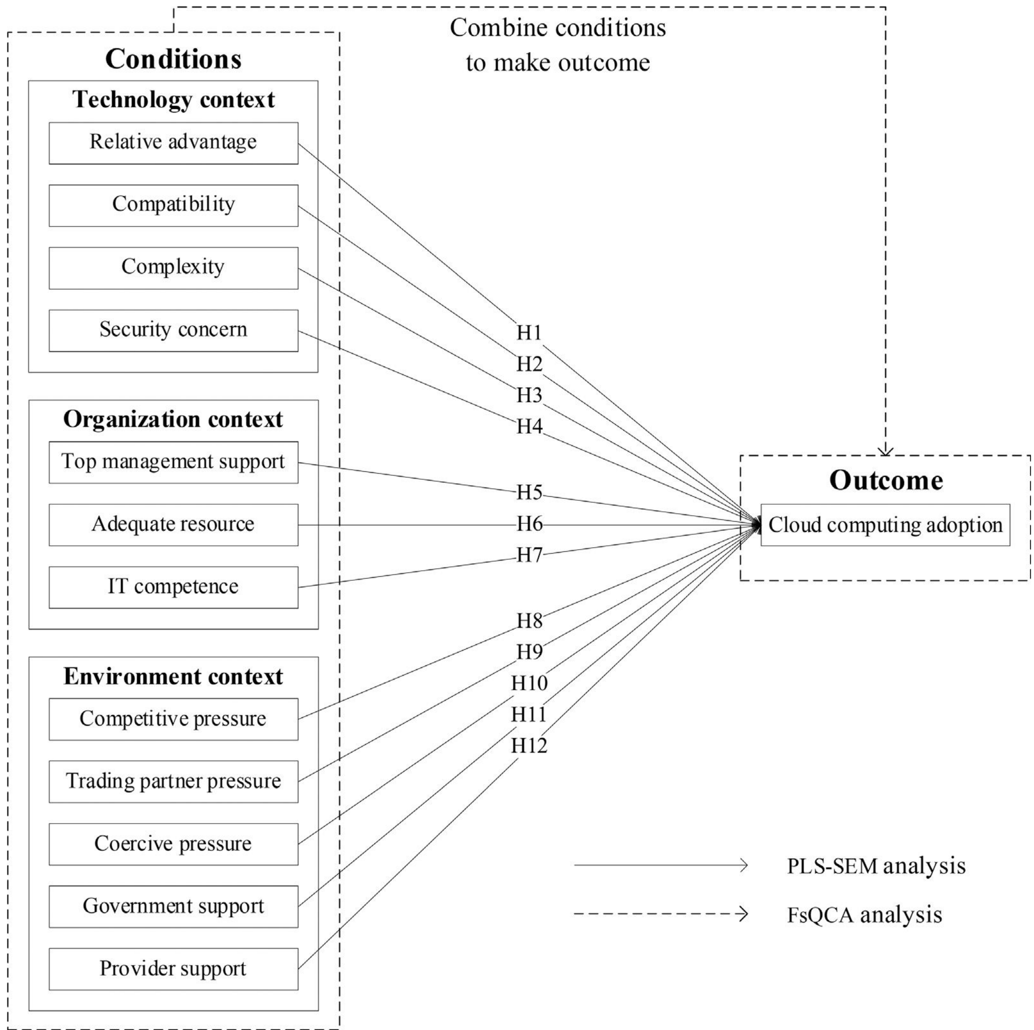

Fig. 1. Research model

computing. A total of 480 responses were received between March and April 2020. After excluding invalid responses with unusually short completion time, nonconformity (reversed items), incomplete data, or excessively similar options, 203 valid responses were obtained for this study. Among the valid responses, 62% (125 firms) were received from medium-sized enterprises, and 38% (78 firms) were received from small-sized enterprises, drawing on the "statistical division standard of large, medium, small and micro enterprises" issued by China's National Bureau of Statistics. This standard determines the classification matrix using thresholds of indicators (e.g., number of employees, total assets, and annual revenue) for different sectors (China's industry classification categories). The participants' demographic characteristics are presented in Table 4.

Data analysis approach

Data were analyzed using PLS-SEM to estimate the measurement and structural model (Hair, Risher Jeffrey, Sarstedt, & Ringle Christian, 2019), and fsQCA to reveal the configurations of the antecedent conditions on the outcome (Ragin, 2008).

PLS-SEM approach

Compared with other approaches, PLS-SEM provides greater flexibility in modeling (e.g., complex models and formative constructs) and data requirements (e.g., small samples and non-normally distributed data) (Hair et al., 2019). Therefore, PLS-SEM has been widely used in various study domains such as organization management, information management (Liang, Wang, Dong, Zhang, & Qi, 2021), supply chain (Kalaitzi & Tsolakis, 2022), and transportation management (Lee, Lee, Park, Lee, & Ha, 2019).

Following these recommendations (Hair et al., 2019), our research aims to identify the key "driver" constructs, and our proposed structural model is complex. Therefore, we selected the PLS-SEM approach using SmartPLS 3.2.9 software.

Qualitative comparative analysis approach

QCA, originally developed by Ragin, is a methodology for an in-depth analysis of the causal contribution of different conditions to an outcome of interest, based on set theory (Damian & Manea, 2019). QCA can distinguish various complex forms of causation, such as the configurations of causal conditions (not just single causes), equifinality (multiple causal pathways leading to the same outcome), multifinality (identical conditions generating different outcomes), and causal asymmetry (failure may not simply be the absence of causes of success) (Fiss, 2007; Kusa, Duda, & Suder, 2021; Ragin, 2008).

In everyday life, the outcome often results from different combinations of antecedent conditions rather than from any individual condition, in the context of great causal complexity. FsQCA is particularly suitable for analyzing causal processes, providing a configurational understanding of how causes combine to produce outcomes, and dealing with significant causal complexity (Fiss, 2007; Ott, Williams, Saker, & Staley, 2019; Romero-Castro et al., 2022). Therefore,

Table 3
Measurement instruments.

Construct	Items	Description	References
Relative advantage	RA1	Cloud computing reduces costs	C.-L. Hsu and Lin (2016)
	RA2	Cloud computing saves time	
	RA3	Cloud computing increases business productivity	
Compatibility	CMPT1	Cloud computing fits the company's work style	Oliveira et al. (2014)
	CMPT2	Cloud computing is fully compatible with current business operations	
	CMPT3	Cloud computing is compatible with my company's corporate culture and value system	
	CMPT4	Cloud computing will be compatible with the company's existing hardware and software	
Complexity	CX1	Cloud computing requires much mental effort	Oliveira et al. (2014)
	CX2	Cloud computing is frustrating	
	CX3	Cloud computing is too complex for business operations	
	CX4	Skills required for adopting cloud computing are too complex for employees	
Security concern	SC1	Company's concern about data security in cloud computing	Oliveira et al. (2014)
	SC2	Concern for customers with data security in cloud computing	
	SC3	Concern about privacy in cloud computing	
Top management support	TMS1	My company's top management supports the implementation of cloud computing	Oliveira et al. (2014)
	TMS2	My company's top management provides strong leadership and engages in the process when it comes to information systems	
	TMS3	My company's management is willing to take risks (financial and organizational) involved in the adoption of cloud computing	
Adequate resource	AR1	My company has enough resources to support the development of cloud computing	Lian, Yen, and Wang (2014)
	AR2	My company has ample time to develop cloud computing	
	AR3	My company has a sufficient budget to develop cloud computing	
IT competence	ITC1	My company's technology infrastructure is available to support cloud computing	Martins et al. (2016)
	ITC2	My company is dedicated to ensuring that employees are familiar with cloud computing	
	ITC3	My company has good knowledge of cloud computing	
Competitive pressure	ComP1	My company thinks that cloud computing influences competition in the industry	Oliveira et al. (2014)
	ComP2	My company is under pressure from competitors to adopt cloud computing	
	ComP3	Some of our competitors have already started using cloud computing	
Trading partner pressure	TPP1	My company's major trading partners encouraged the implementation of cloud computing	Y.-M. Wang et al. (2010)
	TPP2	My company's major trading partners recommended the implementation of cloud computing	
	TPP3	My company's major trading partners requested the implementation of cloud computing	
Coercive pressure	CoeP1	The local government requires our firm to use cloud computing	Martins et al. (2016)
	CoeP2	The industry association requires our firm to use cloud computing	
	CoeP3	Competitive conditions require our firm to use cloud computing	
Government support	GS1	Governments have initiated plans for promoting firms to use cloud computing	N. Wang, Xue, et al. (2019)
	GS2	Governments have set up relevant funds to support companies to use cloud computing	
	GS3	Governments have introduced some privileged policies for firms that have already used cloud computing	
	GS4	Governments will provide financial support to firms planning to use cloud computing	
Provider support	PS1	Cloud providers' reputation is an important factor when determining cloud computing implementation	Kumar et al. (2017)
	PS2	It is necessary to have adequate technical support after the adoption of cloud computing	
	PS3	It is important to have a good relationship with cloud providers	
Cloud computing adoption	CCA1	My company invests resources in cloud computing	Martins et al. (2016)
	CCA2	My company's business activities require the use of cloud computing	
	CCA3	My company's functional areas require the use of cloud computing	

fsQCA appeals to many researchers and is widely used in different contexts to assess cause-effect relations, such as strategy management (Fiss, 2007) and information management (Pappas & Woodside, 2021; Ribeiro-Navarrete, Palacios-Marqués, Lassala, & Ulrich, 2021).

PLS-SEM and fsQCA rely on distinct principles. PLS-SEM is a variable-oriented approach that verifies each IV's net effect and significance on the DV through a series of regression analyses. It does not determine which variables are sufficient or necessary for a certain outcome. Conversely, fsQCA is a case-oriented approach that analyzes the causal contributions of different conditions. Instead of considering the unique influence of each variable on the outcome, the fsQCA examines how causal conditions (IV) combine into several configurations entailing equifinality, resulting in the same outcome (DV) (Duarte & Pinho, 2019; Fiss, 2007; Kourouthanassis et al., 2017; Woodside, 2013). Therefore, fsQCA is a complementary analysis approach that is suitable for PLS-SEM when effects due to unobserved heterogeneity are detected, as it explains how factors work together to produce the outcome (Pappas & Woodside, 2021). Thus, many studies have empirically tested the proposed models, employing both a symmetrical approach with PLS-SEM and an asymmetrical approach with fsQCA, to analyze the causal and outcome conditions in complex situations such as technology adoption (McLeay, Olya, Liu, Jayawardhena, & Dennis, 2022), organizational learning (Valaei et al., 2017), SME performance (Kusa et al., 2021), and mobile shopping (Bawack, Wamba, & Carillo, 2021; L. Wang, Wang, Wang, & Zhao, 2021).

Results

PLS-SEM results

Measurement model

A reflective measurement model assessment includes indicator and internal consistency reliability and convergent and discriminant validity (Hair et al., 2019).

Indicator reliability, obtained by squaring the outer loadings of reflective constructs, clearly describes the relationship between the latent variable and its measures (Liang et al., 2021). Table 5 shows that the constructs' outer loadings are greater than 0.708 (Hair et al., 2019), except for one indicator (i.e., TPP3). As previously recommended (Hair, Hult, Ringle, & Sarstedt, 2017), removing this indicator is unnecessary, as the deletion will reduce the composite reliability (CR), average variance extracted (AVE), and content validity. Therefore, the indicator reliability is acceptable.

Internal consistency reliability was assessed using Cronbach's alpha (CA), rho_A, and CR (Fornell & Larcker, 1981; Hair et al., 2019).

Table 4
Demographic characteristics (N=203).

Characteristic		Freq	%	Characteristic		Freq	%
Respondent's position	CIO/CTO/IT managers	67	33	Number of employees	Less than 20 employees	2	0.99
	Other managers	136	67		21–50 employees	19	9.36
Sector	Mining and manufacturing	39	19.21		51–100 employees	28	13.79
	Construction	2	0.99		100–200 employees	63	31.03
	Production and supply of electricity, heat, gas, and water	11	5.42		more than 200 employees	91	44.83
	Real estate	4	1.97	Annual revenue (RMB)	Less than 1 million	2	0.99
	Transport, storage, and post	15	7.39		1-5 million	16	7.88
	Financial intermediation	8	3.94		5-10 million	23	11.33
	Wholesale and retail trades	11	5.42		10-50 million	54	26.6
	Information transmission, software, and information technology	102	50.25		50-100 million	50	24.63
	Leasing and business services	3	1.48		100-300 million	31	15.27
	Culture, sports, and entertainment	4	1.97		300-500 million	15	7.39
	Others	4	1.97		More than 500 million	12	5.91
Firm age	2–5 years	29	14.29	Cloud computing is used in functional areas	Accounting/Finance	135	66.5
	6–10 years	83	40.89		Production	81	39.9
	11–20 years	76	37.44		Logistics	117	57.64
	more than 20 years	15	7.39		Marketing	157	77.34
Size	Small	78	38.42		Human resources	118	58.13
	Medium	125	61.58		Customer relationship	157	77.34

Table 5
Loadings and cross-loadings.

	RA	CMPT	CX	SC	TMP	AR	ITC	ComP	TPP	CoeP	GS	PS	CCA
RA1	**0.790**	0.549	-0.402	-0.132	0.243	0.238	0.234	0.183	0.262	0.236	0.206	0.357	0.275
RA2	**0.841**	0.521	-0.333	-0.192	0.281	0.158	0.195	0.237	0.113	0.087	0.085	0.318	0.336
RA3	**0.811**	0.415	-0.269	-0.145	0.342	0.130	0.243	0.179	0.220	0.172	0.245	0.291	0.299
CMPT1	0.518	**0.785**	-0.329	-0.169	0.242	0.273	0.362	0.298	0.126	0.188	0.084	0.249	0.322
CMPT2	0.385	**0.745**	-0.381	-0.303	0.269	0.280	0.272	0.286	0.156	0.154	0.082	0.357	0.357
CMPT3	0.433	**0.712**	-0.350	-0.207	0.279	0.162	0.255	0.273	0.246	0.143	0.275	0.358	0.320
CMPT4	0.500	**0.757**	-0.377	-0.140	0.272	0.243	0.288	0.216	0.177	0.139	0.151	0.320	0.242
CX1	-0.245	-0.284	**0.724**	0.352	-0.214	-0.309	-0.375	-0.097	-0.049	0.035	0.078	-0.181	-0.256
CX2	-0.321	-0.357	**0.725**	0.309	-0.330	-0.238	-0.358	-0.121	-0.015	0.028	-0.038	-0.242	-0.325
CX3	-0.349	-0.418	**0.750**	0.297	-0.338	-0.356	-0.428	-0.153	-0.211	-0.111	-0.125	-0.350	-0.296
CX4	-0.273	-0.334	**0.731**	0.340	-0.225	-0.374	-0.406	-0.129	-0.180	-0.106	-0.034	-0.245	-0.308
SC1	-0.204	-0.249	0.335	**0.792**	-0.195	-0.295	-0.288	-0.237	-0.147	-0.038	-0.076	-0.344	-0.344
SC2	-0.108	-0.183	0.319	**0.817**	-0.253	-0.282	-0.338	-0.206	-0.250	-0.099	-0.069	-0.320	-0.349
SC3	-0.154	-0.250	0.415	**0.788**	-0.202	-0.288	-0.299	-0.102	-0.119	-0.058	-0.049	-0.189	-0.290
TMS1	0.214	0.206	-0.207	-0.167	**0.773**	0.219	0.228	0.407	0.159	0.116	0.108	0.247	0.433
TMS2	0.270	0.249	-0.245	-0.218	**0.787**	0.191	0.234	0.235	0.231	0.121	0.191	0.363	0.413
TMS3	0.350	0.373	-0.435	-0.256	**0.814**	0.284	0.396	0.424	0.215	0.188	0.129	0.460	0.491
AR1	0.164	0.214	-0.351	-0.329	0.246	**0.796**	0.419	0.174	0.283	0.099	0.150	0.156	0.220
AR2	0.140	0.322	-0.337	-0.187	0.180	**0.724**	0.437	0.217	0.298	0.097	0.263	0.230	0.162
AR3	0.195	0.258	-0.358	-0.323	0.267	**0.865**	0.470	0.279	0.321	0.341	0.275	0.217	0.272
ITC1	0.182	0.301	-0.441	-0.257	0.287	0.432	**0.809**	0.194	0.211	0.014	0.106	0.338	0.380
ITC2	0.273	0.373	-0.455	-0.314	0.379	0.463	**0.854**	0.343	0.295	0.176	0.246	0.399	0.467
ITC3	0.181	0.241	-0.374	-0.373	0.172	0.424	**0.713**	0.155	0.170	0.122	0.151	0.278	0.291
ComP1	0.212	0.255	-0.089	-0.081	0.347	0.179	0.235	**0.820**	0.211	0.280	0.247	0.474	0.437
ComP2	0.251	0.327	-0.184	-0.302	0.353	0.289	0.299	**0.757**	0.281	0.488	0.120	0.363	0.451
ComP3	0.143	0.295	-0.141	-0.178	0.395	0.216	0.210	**0.838**	0.236	0.221	0.205	0.397	0.506
TPP1	0.154	0.164	-0.146	-0.174	0.224	0.340	0.276	0.282	**0.884**	0.239	0.328	0.305	0.369
TPP2	0.267	0.269	-0.178	-0.245	0.239	0.351	0.294	0.249	**0.873**	0.254	0.392	0.291	0.325
TPP3	0.151	0.111	0.011	-0.067	0.124	0.159	0.060	0.178	**0.610**	0.333	0.513	0.154	0.157
CoeP1	0.184	0.200	-0.045	-0.118	0.060	0.250	0.087	0.202	0.268	**0.793**	0.458	0.118	0.181
CoeP2	0.150	0.122	0.066	0.005	0.098	0.241	0.049	0.248	0.425	**0.713**	0.521	0.155	0.082
CoeP3	0.139	0.158	-0.080	-0.050	0.226	0.141	0.143	0.441	0.181	**0.832**	0.172	0.174	0.237
GS1	0.255	0.208	-0.049	-0.076	0.142	0.199	0.219	0.234	0.380	0.316	**0.867**	0.280	0.266
GS2	0.109	0.175	0.031	-0.066	0.166	0.248	0.157	0.220	0.394	0.357	**0.845**	0.191	0.149
GS3	0.202	0.151	-0.106	-0.061	0.168	0.219	0.170	0.163	0.370	0.401	**0.872**	0.207	0.186
GS4	0.130	0.125	-0.019	-0.074	0.145	0.329	0.186	0.190	0.462	0.377	**0.854**	0.223	0.206
PS1	0.325	0.363	-0.231	-0.300	0.300	0.150	0.342	0.438	0.242	0.219	0.276	**0.827**	0.495
PS2	0.251	0.303	-0.309	-0.400	0.404	0.219	0.346	0.334	0.286	0.111	0.211	**0.770**	0.518
PS3	0.366	0.363	-0.296	-0.162	0.384	0.222	0.346	0.448	0.253	0.123	0.159	**0.794**	0.497
CCA1	0.291	0.303	-0.300	-0.343	0.486	0.228	0.389	0.435	0.243	0.169	0.207	0.530	**0.812**
CCA2	0.327	0.387	-0.430	-0.349	0.360	0.224	0.375	0.510	0.331	0.216	0.149	0.553	**0.808**
CCA3	0.273	0.312	-0.234	-0.288	0.508	0.220	0.404	0.431	0.325	0.185	0.232	0.419	**0.763**

Note: The bold diagonal elements are loadings. RA-Relative advantage; CMPT-Compatibility; CX-Complexity; SC-Security concern; TMP-Top management support; AR-Adequate resource; ITC-IT competence; ComP-Competitive pressure; TPP-Trading partner pressure; CoeP-Coercive pressure; GS-Government support; PS-Provider support; CCA-Cloud computing adoption.

Table 6
Construct reliability and validity

	Cronbach's Alpha	rho_A	CR	AVE	VIF Values
Relative advantage	0.747	0.754	0.855	0.663	1.755
Compatibility	0.743	0.745	0.837	0.563	1.939
Complexity	0.713	0.714	0.822	0.537	1.950
Security concern	0.718	0.722	0.841	0.638	1.394
Top management support	0.703	0.707	0.834	0.627	1.538
Adequate resource	0.718	0.758	0.839	0.635	1.742
IT competence	0.712	0.747	0.836	0.631	1.897
Competitive pressure	0.729	0.734	0.847	0.649	1.772
Trading partner pressure	0.724	0.812	0.838	0.639	1.485
Coercive pressure	0.713	0.751	0.824	0.610	1.425
Government support	0.884	0.918	0.919	0.739	1.502
Provider support	0.713	0.712	0.840	0.636	1.849
Cloud computing adoption	0.707	0.709	0.837	0.631	

Table 6 suggests that all the criteria are above 0.7, indicating good measurement reliability.

Convergent validity, the extent to which a construct converges to explain the variance of its items, was examined according to AVE (Fornell & Larcker, 1981). Table 6 shows that the AVE was greater than 0.5, indicating good convergent validity (Hair et al., 2019).

Discriminant validity, the extent to which a construct is empirically distinct from other constructs, was evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981), heterotrait-monotrait (HTMT) ratio of the correlations, and cross-loadings criterion. The Fornell-Larcker criterion requires the square root of AVE to be higher than the correlations between the constructs (Fornell & Larcker, 1981); the cross-loadings criterion requires factor loading to be higher than all cross-loadings; and the HTMT criterion requires HTMT to be significantly lower than the threshold value of 0.90 or 0.85 (Hair et al., 2019). As shown in Tables 5, 7, and 8, all the criteria satisfy discriminant validity.

Structural model

The standard assessment criteria of the structural model include the coefficient of determination (R^2) and the significance and relevance of the path coefficients (Hair et al., 2019; Liang et al., 2021).

Before assessing the structural model, multicollinearity must be tested through the variance inflation factor (VIF) (Hair et al., 2019). Table 6 shows that all VIF values are between 1.394 and 1.950, far less than 3 (Hair et al., 2019), indicating no multicollinearity issues.

To ensure the stability of the study results, the statistical significance of various PLS-SEM results was tested using the PLS bootstrapping procedure with 5000 iterations of resampling recommended by Hair et al. (2017) and Sarstedt et al. (2014). Fig. 2 shows the final results of the structural model assessment, where the explained variance of the endogenous variables (R2) and the standardized path coefficients (β) are presented.

Generally, R^2 is used to assess the goodness-of-fit in regression analysis (Benitez, Henseler, Castillo, & Schuberth, 2020). In PLS-SEM research, R^2 measures the variance, which is explained in each endogenous construct, and is a measure of the model's explanatory power (Hair et al., 2019). As a guideline, R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak, respectively (Hair et al., 2019). As depicted in Fig. 2, our proposed model explains 58.26% of the variance (R^2) in cloud-computing adoption, indicating a moderate explanatory power (Hair et al., 2019).

Table 7
Fornell-Larcker criterion

	RA	CMPT	CX	SC	TMP	AR	ITC	ComP	TPP	CoeP	GS	PS	CCA
Relative advantage	**0.814**												
Compatibility	0.606	**0.750**											
Complexity	-0.408	-0.479	**0.733**										
Security concern	-0.194	-0.282	0.441	**0.799**									
Top management support	0.355	0.354	-0.382	-0.272	**0.792**								
Adequate resource	0.212	0.321	-0.434	-0.361	0.295	**0.797**							
IT competence	0.273	0.392	-0.535	-0.386	0.368	0.551	**0.794**						
Competitive pressure	0.247	0.363	-0.172	-0.233	0.454	0.283	0.306	**0.806**					
Trading partner pressure	0.237	0.234	-0.156	-0.219	0.255	0.375	0.293	0.301	**0.799**				
Coercive pressure	0.196	0.210	-0.055	-0.082	0.181	0.247	0.135	0.404	0.316	**0.781**			
Government support	0.213	0.195	-0.046	-0.082	0.178	0.286	0.218	0.237	0.466	0.417	**0.860**		
Provider support	0.393	0.430	-0.350	-0.362	0.456	0.248	0.433	0.509	0.327	0.188	0.270	**0.797**	
Cloud computing adoption	0.375	0.421	-0.407	-0.412	0.565	0.282	0.489	0.579	0.377	0.240	0.245	0.632	**0.794**

Note: The bold diagonal elements are AVE's square root.

Table 8
Heterotrait-Monotrait Ratio (HTMT)

	RA	CMPT	CX	SC	TMP	AR	ITC	ComP	TPP	CoeP	GS	PS	CCA
Relative advantage													
Compatibility	0.822												
Complexity	0.558	0.652											
Security concern	0.262	0.375	0.624										
Top management support	0.483	0.481	0.521	0.378									
Adequate resource	0.288	0.451	0.611	0.487	0.402								
IT competence	0.368	0.525	0.745	0.552	0.487	0.774							
Competitive pressure	0.337	0.485	0.235	0.332	0.624	0.386	0.405						
Trading partner pressure	0.333	0.310	0.238	0.285	0.342	0.490	0.359	0.405					
Coercive pressure	0.280	0.275	0.189	0.108	0.224	0.344	0.187	0.524	0.545				
Government support	0.255	0.241	0.138	0.099	0.231	0.365	0.257	0.292	0.638	0.613			
Provider support	0.542	0.587	0.486	0.494	0.635	0.351	0.596	0.710	0.432	0.263	0.329		
Cloud computing adoption	0.511	0.568	0.564	0.573	0.802	0.383	0.673	0.802	0.494	0.295	0.298	0.887	

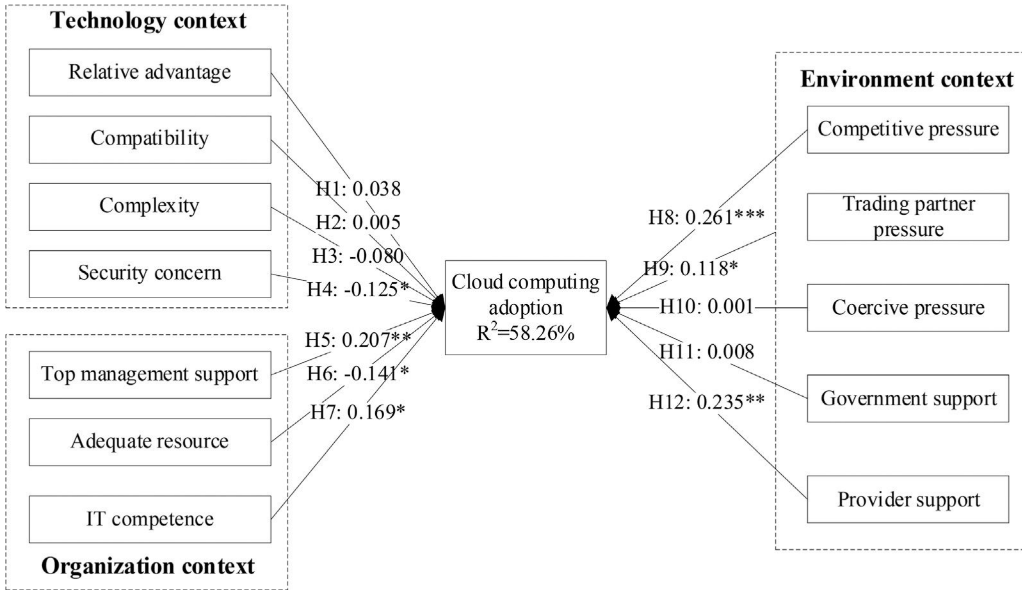

Fig. 2. The results of the structural model of cloud computing adoption. *Note*: * p <0.05, ** p <0.01, *** p <0.001.

The PLS analysis shows that security concern (β = -0.125, p<0.05), top management support (β = 0.207, p<0.01), IT competence (β = 0.169, p<0.05), competitive pressure (β = 0.261, p<0.001), trading partner pressure (β = 0.118, p<0.05), and provider support (β =0.235 , p<0.01) significantly influence SMEs' decisions to adopt cloud computing, supporting H4, H5, H7, H8, H9, and H12. Among these variables, competitive pressure has the greatest influence on cloud computing adoption. Relative advantage (β = 0.038, p>0.05), compatibility (β = 0.005, p>0.05), complexity (β = -0.08, p>0.05), coercive pressure (β = 0.001, p>0.05), and government support (β = 0.008, p>0.05) have no significant impact on cloud computing adoption. Thus H1, H2, H3, H10, and H11 are not supported. Interestingly, adequate resource (β = -0.141, p<0.05) has a significantly negative impact, rejecting H6. Table 9 summarizes the results for the 12 hypotheses.

Qualitative comparative analysis

The same constructs and datasets used in the PLS-SEM analysis were analyzed using fsQCA to compare them with the PLS-SEM results presented earlier. The key procedures of fsQCA include model development, sampling, data calibration, analysis of necessary conditions, analysis of sufficient conditions, and interpretation of the findings (Pappas & Woodside, 2021).

Calibration

The dataset used in the PLS-SEM was calibrated into fuzzy sets for fsQCA analysis. The fuzzy set ranges from 0 to 1 on a continuous scale, where 0 represents full non-set membership, and 1 indicates full set membership (Pappas & Woodside, 2021). As our actual data were not normally distributed, the mean value of each condition was selected as the crossover point (Fiss, 2007; L. Wang et al., 2021). Using fsQCA 3.0, data calibration was automatically calculated (see Table 10).

Analysis of necessary conditions

This should always be preceded by identifying the necessary conditions before analyzing the sufficient conditions, which is the core of fsQCA. Analysis of the necessary conditions examines whether any causal conditions can be considered necessary to produce an outcome, which is cloud computing adoption in our study. According to previous studies (Ragin, 2008), a condition is necessary when its consistency is more than 0.9 (L. Wang et al., 2021). As seen in Table 11, a single condition cannot be deemed necessary for cloud computing adoption ("CCA") and the negation of cloud computing adoption ("~CCA"). The results suggest that no single condition can result in an output CCA or ~CCA.

Analysis of sufficient conditions for cloud computing adoption

Analysis of sufficient conditions determines all conditions that are sufficient for an outcome. This study sets a frequency cutoff of 2 and

Table 9
Summary of the hypothesis test.

Hypothesis	Structural path	β	STDEV	T values	P values	Supported
H1	Relative advantage → Adoption	0.038	0.059	0.641	0.521	No
H2	Compatibility → Adoption	0.005	0.071	0.070	0.944	No
H3	Complexity → Adoption	-0.080	0.083	0.968	0.333	No
H4	Security concern → Adoption	-0.125*	0.062	2.008	0.045	Yes
H5	Top management support → Adoption	0.207**	0.072	2.876	0.004	Yes
H6	Adequate resource → Adoption	-0.141*	0.067	2.104	0.035	No
H7	IT competence → Adoption	0.169*	0.074	2.294	0.022	Yes
H8	Competitive pressure → Adoption	0.261***	0.072	3.636	0.000	Yes
H9	Trading partner pressure → Adoption	0.118*	0.060	1.977	0.048	Yes
H10	Coercive pressure → Adoption	0.001	0.062	0.011	0.991	No
H11	Government support → Adoption	0.008	0.060	0.128	0.898	No
H12	Provider support → Adoption	0.235**	0.083	2.844	0.004	Yes

Note: * p <0.05, ** p <0.01, *** p <0.001.

Table 10
Data calibration.

	Full nonmembership	Crossover point	Full membership
Relative advantage	2.00	4.18	5.00
Compatibility	1.25	4.05	5.00
Complexity	1.00	1.92	4.25
Security concern	1.00	2.34	4.33
Top management support	1.00	4.22	5.00
Adequate resource	1.33	4.00	5.00
IT competence	1.33	4.14	5.00
Competitive pressure	1.33	4.14	5.00
Trading partner pressure	1.33	3.64	5.00
Coercive pressure	1.00	3.30	5.00
Government support	1.00	3.56	5.00
Provider support	1.67	4.35	5.00

Table 11
Analysis of necessary conditions.

	CCA (adoption)		~CCA (Negation of adoption)	
	Consistency	Coverage	Consistency	Coverage
RA	0.831	0.840	0.824	0.569
~RA	0.573	0.827	0.769	0.757
CMPT	0.843	0.845	0.827	0.566
~CMPT	0.567	0.828	0.774	0.771
CX	0.577	0.830	0.775	0.762
~CX	0.834	0.845	0.827	0.571
SC	0.579	0.759	0.783	0.700
~SC	0.771	0.839	0.729	0.544
TMP	0.869	0.859	0.847	0.571
~TMP	0.566	0.844	0.791	0.805
AR	0.821	0.820	0.819	0.559
~AR	0.559	0.818	0.737	0.737
ITC	0.870	0.846	0.823	0.547
~ITC	0.534	0.816	0.768	0.801
ComP	0.873	0.849	0.799	0.531
~ComP	0.518	0.791	0.773	0.806
TPP	0.772	0.824	0.754	0.549
~TPP	0.577	0.774	0.758	0.695
CoeP	0.737	0.824	0.768	0.587
~CoeP	0.631	0.800	0.770	0.666
GS	0.771	0.806	0.764	0.545
~GS	0.564	0.778	0.728	0.685
PS	0.858	0.811	0.819	0.529
~PS	0.501	0.802	0.706	0.772

Note: The tilde sign "~" indicates the negation of the conditions.

a consistency cutoff of 0.8 (the actual value is 0.924) to avoid the distractions of less important configurations. Based on the “standard analysis” procedure for fsQCA 3.0, complex, intermediate, and parsimonious solutions were automatically obtained (Ragin, 2008). Combining parsimonious and intermediate solutions presents all core (i.e., a strong causal relationship with the outcome) and peripheral (i.e., a weak relationship with the outcome) conditions, thereby offering a better interpretation of the findings (Fiss, 2007; Pappas, Papavlasopoulou, Mikalef, & Giannakos, 2020).

The fsQCA results shown in Table 12 suggest that any isolated condition is not sufficient for “CCA,” and there are seven equivalent sufficient configurations (divided into six types by the core conditions of top management support, IT competence, competitive pressure, and provider support) of conditions that result in high-level cloud computing adoption (CCA), indicating equifinality and supporting Proposition 1. As shown in Table 12, the overall solution consistency of 0.952 and solution coverage of 0.595 were larger than the 0.75 and 0.25, respectively, recommended by Ragin (2008). The overall solution coverage, similar to R^2 in regression-based methods (Woodside, 2013), presented seven solutions, accounting for 59.5% of the samples related to high-level cloud computing adoption. Moreover, the consistency of each solution was greater than 0.8, indicating that all solutions were sufficient. The coverage of every solution was greater than zero, suggesting that they were empirically relevant (Ragin, 2008). Among these solutions, Solution 1 demonstrated a high level of consistency (0.990) and clarified a substantial number of cases (raw coverage = 0.494), thus representing the best solution for high-level cloud computing adoption. This indicates that the presence of all core conditions (i.e., top management support, IT competence, competitive pressure, and provider support) combined with the presence of other peripheral conditions (i.e., relative advantage, compatibility, adequate resources, trading partner pressure, coercive pressure, and government support) would lead to high-level cloud computing adoption.

Analysis of sufficient conditions for the negation of cloud computing adoption

Contrary to conventional approaches, such as SEM and regression models, fsQCA is good at dealing with causal asymmetry (Ragin, 2008). Therefore, this study also explored the conditions that work together to negate cloud computing adoption (~CCA), by applying the same cutoff settings related to frequency and consistency. The fsQCA results listed in Table 13 reveal eight distinct solutions (divided into five types by the core conditions of complexity, security concerns, and government support) that lead to the negation of cloud-computing adoption (~CCA), indicating asymmetry. The overall solution consistency (0.803) and coverage (0.659) are more than 0.75 and 0.25, respectively (Ragin, 2008), suggesting that the overall solutions account for 65.9% of cases associated with low-level cloud computing adoption (~CCA). In addition, the consistency of each solution was greater than 0.8, indicating that all these solutions were sufficient. The coverage of every solution was greater than zero, suggesting that they were empirically relevant (Ragin, 2008). Solutions 3 (raw coverage = 0.469) and 4 (raw coverage = 0.450) have significant coverage and explain a substantial number of cases, thus representing the two best solutions for low-level cloud computing adoption. Solution 3 implies that notwithstanding other positive conditions, the presence of complexity is the key condition for low-level cloud computing adoption. Solution 4 is similar to Solution 3 except that the presence of security concerns substitutes the presence of complexity. These findings indicate the presence of causal asymmetry, with seven configurations consistently leading to CCA, and eight different configurations being consistently associated with ~CCA, indicating equifinality and supporting Proposition 2.

Discussion

Using both PLS-SEM and fsQCA (Afonso et al., 2018), we show that analyzing the net and combined effects of specific antecedent variables can improve the understanding of cloud computing adoption. The results obtained from SEM-PLS and fsQCA confirm the impact of each investigated factor on cloud computing adoption. The fsQCA results identify seven configurations that lead to high-level cloud computing adoption and eight configurations that result in low-level cloud computing adoption.

Remarkably, in contrast to the results reported by previous studies on cloud computing (Khayer et al., 2020; Kumar et al., 2017; Martins et al., 2016; Oliveira et al., 2014; Shih & Lin, 2016), the PLS-SEM results show that relative advantage (H1) has no significant positive effect on cloud computing adoption, as indicated by the value of the path coefficient ($\beta = 0.038$) and probability ($p > 0.05$). This result contradicts most previous studies that have found that relative advantage has a positive relationship with IT adoption, such as enterprise resource planning (ERP) (Lutfi et al., 2022), accounting systems

Table 12
Sufficient configurations for high-level cloud computing adoption.

	Solutions						
	1a	1b	2	3	4	5	6
Relative advantage	●	●	●	●	●	○	○
Compatibility	●	●	●	●	●	○	○
Complexity		○	○	○	○	●	●
Security concern		○	●	○	○	●	●
Top management support	⊙	⊙	⊙	⊙	⊙	○	○
Adequate resource	●	○	●	●	●	○	○
IT competence	⊙	⊙	○	⊙	○	○	○
Competitive pressure	⊙	⊙	⊙	○	○		○
Trading partner pressure	●	●	○	●	○	○	●
Coercive pressure	●	○	●	●	○	○	●
Government support	●	○	○	○	○	○	○
Provider support	⊙	⊙	⊙	⊙	⊙	○	○
Raw coverage	0.494	0.270	0.249	0.260	0.238	0.216	0.209
Unique coverage	0.219	0.019	0.008	0.008	0.011	0.010	0.003
Consistency	0.990	0.999	0.995	0.997	0.993	0.916	0.962
Solution consistency				0.952			
Solution coverage				0.595			

Note: The symbols "⊙" or "•" shows the presence of core or peripheral conditions, respectively. The symbols "⊗" or "○" shows the absence of core or peripheral conditions, respectively. Blank cells show a "do not care" situation.

Table 13
Sufficient configurations for the negation of cloud computing adoption

	Solutions							
	1a	1b	2	3	4	5a	5b	5c
Relative advantage	○	○	●	●	●	●	●	●
Compatibility	○	○	●	●	●	●	●	●
Complexity	⊙	⊙	○	⊙		○	○	○
Security concern	⊙	⊙	⊙		⊙	○	○	○
Top management support	○	○	●	●	●	○	●	●
Adequate resource	○	○	●	●	●	●	○	●
IT competence	○	○	○	●	●	○	●	●
Competitive pressure		○	●	●	●	○	●	○
Trading partner pressure	○	●	○	●	●	○	●	●
Coercive pressure	○	●	●	●	●	○	○	●
Government support	⊗	⊗	⊗	●	●	⊗	⊗	⊗
Provider support	○	○	●	●	●	●	●	●
Raw coverage	0.339	0.307	0.349	0.469	0.450	0.341	0.358	0.356
Unique coverage	0.034	0.004	0.011	0.036	0.021	0.016	0.012	0.011
Consistency	0.982	0.965	0.953	0.836	0.826	0.971	0.904	0.933
Solution consistency					0.803			
Solution coverage					0.659			

Note: The symbols "⊙" or "•" shows the presence of core or peripheral conditions, respectively. The symbols "⊗" or "○" shows the absence of core or peripheral conditions, respectively. Blank cells show a "do not care" situation.

(Azmi, Sapiei, Mustapha, & Abdullah, 2016), remote work systems (Ofosu-Ampong & Acheampong, 2022), mobile reservation systems (Y.-S. Wang, Li, Li, & Zhang, 2016), 3D printing (Yeh & Chen, 2018), blockchain (Gökalp, Gökalp, & Çoban, 2022; Kumar Bhardwaj, Garg, & Gajpal, 2021; Malik, Chadhar, Vatanasakdakul, & Chetty, 2021), artificial intelligence (AI) (Chen, Li, & Chen, 2021), robotics (Pizam et al., 2022), big data (Baig, Shuib, & Yadegaridehkordi, 2021; J.-H. Park & Kim, 2021; Sun et al., 2020), and hospital IS (Ahmadi, Nilashi, Shahmoradi, & Ibrahim, 2017). However, past studies have also found that relative advantage does not impact IT adoption, such as smart farms (C. Yoon, Lim, & Park, 2020), virtual worlds (T. E. Yoon & George, 2013), RFID (Wei, Lowry, & Seedorf, 2015), e-commerce (Mohtaramzadeh, Ramayah, & Jun-Hwa, 2018), AI (Pan, Froese, Liu, Hu, & Ye, 2022), and open government data (H. Wang & Lo, 2020). Similarly, fsQCA results show that the presence of relative advantage is just a peripheral condition in five of the seven solutions for cloud-computing adoption (i.e., the presence of CCA), indicating that it is less important and perhaps even expendable or exchangeable for a causal relationship with CCA. A possible reason for this insignificant result is that most of the respondents in SMEs have low cloud-computing know-how. In terms of cost advantage, SMEs should consider the initial costs of technology investment in the early stage and consider the costs of continuous cost in the later stage, such as, operating costs, long-term maintenance, and software and application expenses.

Surprisingly, unlike previous adoption studies indicating a significant effect of compatibility (Ahmadi et al., 2017; Azmi et al., 2016; Baig et al., 2021; Chen et al., 2021; Henderson, Sheetz, & Trinkle, 2012; Kumar Bhardwaj et al., 2021; Malik et al., 2021; Maroufkhani, Iranmanesh, & Ghobakhloo, 2022; Nilashi, Ahmadi, Ahani, Ravangard, & Ibrahim, 2016; Pillai et al., 2021; Shi & Yan, 2016; Y.-S. Wang et al., 2016; C. Yoon et al., 2020), compatibility (H2) is not significantly related to cloud-computing adoption in the PLS-SEM results (β = 0.005, p>0.05). This result is consistent with similar studies, such as ERP (Lutfi et al., 2022), remote work systems (Ofosu-Ampong & Acheampong, 2022), virtual worlds (T. E. Yoon & George, 2013), robotics (Pizam et al., 2022), RFID (Wei et al., 2015), big data (J.-H. Park & Kim, 2021), and supply chain analytics (Kalaitzi & Tsolakis, 2022). Similar to the relative advantage, fsQCA results find that the presence of compatibility is also a peripheral condition in five of seven solutions for cloud computing adoption, indicating a weaker causal relationship between compatibility and the outcome (CCA). The non-significance of compatibility may be attributable to the preference for the work/production style and requirements for internet-based business operations in different industries. For example, Oliveira et al. (2014) found that compatibility facilitates cloud computing adoption in the service sector but is not significant in the manufacturing sector.

Complexity (H3) has been frequently cited as a major barrier to cloud computing adoption; however, in our study, PLS-SEM failed to identify its significantly negative influence on cloud computing adoption (β = -0.08, p>0.05). This PLS-SEM result aligns with previous innovation adoption studies on smart farming (C. Yoon et al., 2020), enterprise architecture (Ahmad et al., 2020), hospital IS (Ahmadi et al., 2017), and AI (Pan et al., 2022). Interestingly, fsQCA provides opposite results, showing that the presence of complexity is a core condition in three (Solutions 1a, 1b, and 3) of the eight solutions for the negation of cloud-computing adoption (~CCA), indicating that the higher the complexity perception by SMEs, the lower the probability of the adoption of cloud-based services. This fsQCA result corroborates previous studies that have observed a significantly negative effect of complexity on the adoption of innovative technologies, such as accounting systems (Azmi et al., 2016), remote work systems (Ofosu-Ampong & Acheampong, 2022), mobile reservation systems (Y.-S. Wang et al., 2016), robotics (Pizam et al., 2022), AI (Chen et al., 2021), blockchain (Kumar Bhardwaj et al., 2021; Malik et al., 2021), big data analytics (Baig et al., 2021; Maroufkhani et al., 2022), and hospital IS (Nilashi et al., 2016). These findings imply that complexity plays a role in cloud computing adoption to a certain extent, particularly for SMEs with no or low intent to adopt cloud computing. Complexity is often considered a barrier to cloud computing adoption because many SMEs may not be aware or have adequate knowledge of cloud technology. They may believe that the adoption process of cloud computing is complex and involves organizational structure reengineering, cloud strategy, promotion plans, data migration, and cloud service delivery.

Conversely, PLS-SEM suggests that security concerns (H4) inhibit Chinese SMEs from adopting cloud computing (β = -0.125, p<0.05). This result is consistent with earlier findings that organizations are concerned about the adoption of emerging technologies, such as social commerce (Abed, 2020), big data (Baig et al., 2021), and hospital IS (Ahmadi et al., 2017), particularly cloud computing (Khayer et al., 2020). However, it contrasts with the research finding that security concerns have an insignificant negative effect on the adoption of IT such as virtual worlds (T. E. Yoon & George, 2013), blockchain (Kumar Bhardwaj et al., 2021), and supply chain analytics (Kalaitzi & Tsolakis, 2022). Besides, the fsQCA findings reinforce that security concerns (as a core condition) are present in four (Solutions 1a, 1b, 2, and 4) out of eight solutions for the negation of cloud computing adoption (~CCA), and (as a peripheral condition) absent (~SC) in three out of seven solutions that explain cloud computing adoption (CCA), indicating that presence of security concern (SC) has a strong causal relationship with "~CCA" while the absence of security concern (~SC) has a weaker causal relationship with "CCA." The fsQCA finding implies that inhibitors (security concerns) can hinder intent (CCA) despite the presence of enablers facilitating the same objective, as explained by the two-factor theory (S. C. Park & Ryoo, 2013).With the implementation of cloud computing across various business activities (e.g., finance, logistics, and marketing), SMEs are concerned about the breach of security and privacy related to the use of cloud computing, such as customer data leakage and loss of control over application security. Therefore, ensuring security and privacy is a major challenge in cloud computing implementation.

In contrast to the existing literature suggesting no significant effect (Ahmad et al., 2020; Ahmadi et al., 2017; Y.-S. Wang et al., 2016; T. E. Yoon & George, 2013), PLS-SEM analysis provides empirical evidence that top management support (H5) is significant in explaining the adoption of cloud computing (β = 0.207, p<0.01). This concurs with previous research findings that a significant positive relationship exists between top management support and the adoption of technology, such as customer relationship management (CRM) (Cruz-Jesus, Pinheiro, & Oliveira, 2019), ERP (Lutfi et al., 2022), social commerce (Abed, 2020), agile innovation management (Sharma, Singh, Jones, Kraus, & Dwivedi, 2022), 3D printing (Henao Ramírez & López-Zapata, 2022; Yeh & Chen, 2018), robotics (Pizam et al., 2022), blockchain (Kumar Bhardwaj et al., 2021; Malik et al., 2021), big data (Baig et al., 2021; Maroufkhani et al., 2022; J.-H. Park & Kim, 2021; Sun et al., 2020), RFID (Shi & Yan, 2016), AI (Chen et al., 2021), B2B e-commerce (Mohtaramzadeh et al., 2018; Ocloo, Xuhua, Akaba, Shi, & Worwui-Brown, 2020), and open government data (H. Wang & Lo, 2020). Furthermore, the fsQCA results indicate that top management support (as a core condition) is present in five (Solutions 1a, 1b, 2, 3, and 4) of the seven solutions that lead to cloud computing adoption, thus reinforcing the PLS-SEM results. Our findings indicate that top management can determine cloud-computing adoption by creating a supportive environment in terms of committing and allocating financial and organizational resources that involve the entire implementation process.

Surprisingly, inconsistent with our hypothesis (H6), a significant negative effect of adequate resources on the adoption of cloud computing was observed, with the lowest degree of influence. Besides, the fsQCA results show that, as a peripheral condition, adequate resources are absent (∼AR) in three out of seven solutions, resulting in cloud computing adoption (CCA), and are present (AR) in five out of eight solutions for the negation of cloud computing adoption (∼CCA), confirming a weaker negative relationship between AR and CCA. This empirical result is contrary to the findings of prior studies that established the positive role of adopting innovations, such as hospital clouds (Lian et al., 2014), big data (Baig et al., 2021), supply chain analytics (Kalaitzi & Tsolakis, 2022), B2B e-commerce (Ocloo et al., 2020), and remote work systems (Ofosu-Ampong & Acheampong, 2022). A possible explanation is that SMEs (particularly small and micro-sized enterprises) have insufficient budgets and resources for IT investment, so they do not invest much in IT construction. Instead, they can choose to deploy reputable industry clouds or public clouds, focusing on core business development and conducting more business at a minimum cost.

IT competence (H7) is found to be a significant determinant of cloud-computing adoption in the SEM-PLS results (β = 0.169, $p<0.05$), consistent with previous research on the adoption of emerging technologies such as CRM (Cruz-Jesus et al., 2019), mobile reservation systems (Y.-S. Wang et al., 2016), hospital IS (Ahmadi et al., 2017), RFID (Shi & Yan, 2016), 3D printing (Henao Ramírez & López-Zapata, 2022), AI (Pan et al., 2022), industrial robots (Pillai et al., 2021), and big data (J.-H. Park & Kim, 2021; Sun et al., 2020). Furthermore, fsQCA results indicate IT competence, as a core condition, is present in three (Solutions 1a, 1b, and 3) out of seven configurations for cloud computing adoption, showing a strong causal relationship with the outcome of interest (CCA). Unlike previous findings that IT competence or technology competence may not necessarily influence cloud computing adoption (Kumar et al., 2017; Low et al., 2011), our findings suggest that IT competence to implement cloud computing is considered in the adoption process. As cloud-based solutions are a complex process, SMEs should ensure that adequate technology infrastructure and IT specialists are available for data migration, architecture reconstruction, and integration of cloud-based solutions.

Contrary to previous studies that found no significant effect on technology adoption (Chen et al., 2021; Y.-S. Wang et al., 2016; Wei et al., 2015; C. Yoon et al., 2020), the PLS-SEM results show that competitive pressure (H8) had the strongest positive influence on cloud-computing adoption (β = 0.261, $p<0.001$), suggesting that it is the most important factor in the structural model. This result corroborates previous findings on adopting innovations, such as CRM (Cruz-Jesus et al., 2019), ERP (Lutfi et al., 2022), robotics (Pillai et al., 2021; Pizam et al., 2022), 3D printing (Henao Ramírez & López-Zapata, 2022), blockchain (Gökalp et al., 2022; Malik et al., 2021), big data (Baig et al., 2021; Sun et al., 2020), RFID (Shi & Yan, 2016), B2B e-commerce (Mohtaramzadeh et al., 2018; Ocloo et al., 2020), and open government data (H. Wang & Lo, 2020). In addition, the fsQCA results indicate that competitive pressure (as a core condition) is present in three (Solutions 1a, 1b, and 2) out of seven solutions that lead to cloud computing adoption, and it (as a peripheral condition) is absent (∼ComP) in three out of eight solutions that explain the negation of cloud computing adoption (∼CCA), reinforcing the PLS-SEM results and providing additional support for H8. This result is not surprising when competitors choose innovative technology as a competitive instrument. Other SMEs face strong competition and are under pressure to adopt innovative technology to maintain a competitive edge (Gangwar et al., 2015). Specifically, in the currently shrinking market environment due to the economic slowdown caused by the COVID-19 pandemic (Akpan, Udoh, & Adebisi, 2022), firms changed their strategies and adopted digital technologies, such as remote work systems (Ofosu-Ampong & Acheampong, 2022) and mobile payment (Upadhyay, Upadhyay, Abed, & Dwivedi, 2022), to adjust to customers' needs and lifestyle changes.

The significant net effect of trading partner pressure (H9) on cloud computing adoption was also found in the PLS-SEM analysis, with the lowest degree of influence among all the factors (β = 0.118, $p<0.05$). Furthermore, the fsQCA results indicate that, as a peripheral condition, trading partner pressure (TPP) is present in four out of seven solutions that explain cloud computing adoption (CCA), and is absent (∼TPP) in three out of eight solutions for "∼CCA," reinforcing a certain significant positive correlation with cloud computing adoption. This result corresponds to those of previous studies on the adoption decisions of various innovations such as 3D printing (Yeh & Chen, 2018), social commerce (Abed, 2020), supply chain analytics (Kalaitzi & Tsolakis, 2022), and blockchain (Gökalp et al., 2022; Malik et al., 2021). To survive in a turbulent competitive environment, most firms are deeply interconnected in enterprise ecosystems (e.g., Alibaba's e-commerce ecosystem) and require interorganizational collaboration with other partners for information exchange and data sharing, which positively affects a firm's propensity for cloud computing adoption.

The PLS-SEM results show that coercive pressure (H10) does not significantly impact the adoption of cloud computing (β = 0.001, $p>0.05$). This finding is similar to those of previous studies on the adoption of accounting systems (Azmi et al., 2016), hospital IS (Ahmadi et al., 2017), agile innovation management (Sharma et al., 2022), and virtual worlds (T. E. Yoon & George, 2013). Nevertheless, the fsQCA results indicate that coercive pressure, just as a peripheral condition, is present in four out of seven configurations for CCA and absent in three out of eight configurations for the negation of CCA, suggesting a weak causal relationship with the outcome (CCA). This aligns with studies proposing that coercive pressure drives technological innovation adoption, such as social CRM entrepreneurship (Al-Omoush, Simón-Moya, Al-ma'aitah, & Sendra-García, 2021) and enterprise architecture (Ahmad et al., 2020). An explanation for the weak and insignificant impact of coercive pressure on cloud adoption may be that the mandatory nature of such pressure forces firms to act; however, they enjoy the right to business autonomy in the market economy because a government agency is prohibited from interfering with firms' legitimate business operations.

The PLS-SEM results show that government support (H11) has no significant net effect on cloud-computing adoption (β = 0.008, $p>0.05$), which is consistent with previous studies that have found an insignificant impact of government support on the adoption of various innovations, such as remote work systems (Ofosu-Ampong & Acheampong, 2022), smart farms (C. Yoon et al., 2020), RFID (Wei et al., 2015), industrial robots (Pillai et al., 2021), and open government data (H. Wang & Lo, 2020). Nevertheless, in the fsQCA result, government support was absent (∼GS) as a core condition in six out of eight solutions for the negation of cloud computing adoption (∼CCA), suggesting the conditional relevance of GS on CCA. This result confirms previous findings on adopting technology, such as ERP (Lutfi et al., 2022), blockchain (Malik et al., 2021; Orji, Kusi-Sarpong, Huang, & Vazquez-Brust, 2020), RFID (Shi & Yan, 2016), AI (Chen et al., 2021; Pan et al., 2022), B2B e-commerce (Mohtaramzadeh et al., 2018; Ocloo et al., 2020), and big data (J.-H. Park & Kim, 2021; Sun et al., 2020). The absence of government support as a core condition for "∼CCA," especially in Solutions 5a, 5b, and 5c (absence of government support, even if all other conditions are either present, absent or do not matter, determines the absence of CCA) further indicates that the lack of privileged policies and government financial support is a key factor that makes it difficult for SMEs to adopt cloud computing. This is possible because of the special institutional environment in China, as the government provides various forms of support such as financial aid, tax reductions, favorable policies, and reduced land-use fees (N. Wang, Liang, et al., 2019; N. Wang, Xue, et al., 2019). Therefore, government support can help overcome uncertainties in data security and information privacy regarding cloud computing, which can directly facilitate firms' adoption of cloud computing, regardless of their size.

The PLS-SEM results show that the positive effect of provider support (H12) has the second-strongest influence on the adoption of cloud computing (β=0.235, $p<0.01$). In addition, the presence of provider support was a core condition in five (Solutions 1a, 1b, 2, 3, and 4) of the seven configurations for cloud computing adoption. The significance of a strong causal relationship of provider support in shaping adoption intention corroborates previous studies on hospital IS (Nilashi et al., 2016), blockchain (Kumar Bhardwaj et al., 2021), industrial robots (Pillai et al., 2021), and AI (Chen et al., 2021). A cloud provider improves access to cloud-computing services, such as infrastructure, platforms, and software, that SMEs would otherwise have to provide on their own. Thus, SMEs will likely depend on service providers' support for the uninterrupted availability of cloud services.

Overall, the PLS-SEM results indicate that security concerns, top management support, IT competence, competitive pressure, trading partner pressure, and provider support have significantly positive net effects on cloud computing adoption by SMEs. The results of fsQCA confirm that "the presence of top management support," "presence of IT competence," "presence of competitive pressure," and "presence of provider support" are indeed core conditions in four of the seven configurations for "the presence of cloud computing adoption." "The presence of security concern" is a core condition in four of the eight configurations for "the absence of cloud computing adoption (∼CCA)," providing additional support for the supported hypotheses of PLS-SEM.

Despite relative advantage, compatibility, complexity, coercive pressure, and government support being frequently cited as significant determinants for adopting IT innovations, PLS-SEM has failed to explore their significant net effects on cloud computing adoption. This does not mean they will be ignored for the impact on cloud computing adoption. The fsQCA results indicate that "the presence of complexity" and "the absence of government support" are indeed core conditions in the configurations for "the absence of cloud computing adoption (∼CCA)." Moreover, relative advantage, compatibility, adequate resources, trading partner pressure, and coercive pressure, as peripheral conditions, combined with other core conditions, are sufficient for cloud computing adoption. These findings supplement the PLS-SEM analysis and demonstrate the existence of causal asymmetry in a complex context.

Theoretical contributions and implications

This study offers several theoretical contributions and implications. First, from a theoretical perspective, our study uses a holistic approach to explore cloud-computing adoption. Although previous studies focused on cloud-computing adoption, the advantage of our study is that it combines technological, organizational, and environmental constructs from several technology adoption theories. Empirical studies show that our integrated model overcomes the shortcomings of a single model and explains 58.26% of the variance (R2) in cloud-computing adoption, indicating high explanatory power.

Second, from a methodological perspective, our study illustrates the complementarity of PLS-SEM and fsQCA in the context of cloud computing adoption. Several studies on cloud-computing adoption by firms have used the multiple regression model, SEM, and PLS-SEM techniques to test the net effect of each isolated antecedent on an organization's decision to accept cloud computing. Hence, we applied the QCA methodology to complex behavioral studies (Pappas & Woodside, 2021). Specifically, the PLS-SEM methodology is appropriate for identifying the key "driver" constructs for cloud computing adoption. By contrast, fsQCA provides a deeper understanding of the configuration of conditions that must be considered to explain the complex, nonlinear, and asymmetric influences of causal conditions on the outcome (cloud-computing adoption).

Implications for practice

Our findings show that high levels of complexity and security concerns lead to low-level cloud computing adoption, whereas relative advantage and compatibility are either unimportant or less significant for cloud computing adoption. This may be attributed to a lack of knowledge regarding cloud computing (Oliveira et al., 2014). Information and knowledge about cloud computing can help SMEs eliminate more uncertainty, which is helpful for increasing the expected advantages of successful implementation of cloud-computing services and reducing concerns about complexity and security risk. However, cloud computing has been widely used to offer services to users. Except for certain fundamental concepts (e.g., definition, benefits, services models, and deployment types), most SMEs are not sufficiently aware of cloud computing, for example, how to integrate cloud computing into their business and realize the expected value in the post-adoption stage (Liang, Qi, Zhang, & Li, 2019).

CSPs should focus on helping SMEs understand the benefits of cloud computing, provide information regarding the cloud computing techniques and service choices, and emphasize their competence in providing secure and reliable cloud services by holding workshops, seminars, conferences, press releases, and advertising in business media read by CIOs or IT managers. They should explain how cloud computing works and the service it provides, present information regarding service prices, and promote security mechanisms to enhance knowledge. First, to reduce security concerns, CSPs can provide information on cloud computing security mechanisms, such as data encryption, data dissemination and communication security, data recovery, identity, and access management, and demonstrate that cloud computing can safeguard cloud environments, data, information, and applications against data breaches, data hijacks, unauthorized access, distributed denial of service (DDOS) attacks, malware, hackers, and other similar threats. In addition, CSPs can educate SMEs on improving staff knowledge of disaster management and recovery handling. They can ease SMEs' uncertainty by signing contracts promising short- or long-term support for regular maintenance, disaster management, and recovery. Second, to increase the expectation of advantage, CSPs can provide information on how SMEs can leverage cloud computing to grow and improve their business, rather than expertise on promoting products, by endorsing real use cases of reputable early adopter firms in related industries. In addition, CSPs can explain why cloud computing is ultimately an investment that can result in considerable savings despite the initial costs, provide a reasonable price mechanism, and offer SMEs the freedom to choose the most cost-effective solutions.

Given the importance of organizational readiness for cloud computing adoption, CSPs can offer free or contracted cloud computing training programs, workshops, and seminars to facilitate managers and employees becoming familiar with these cloud services, because users' expertise in cloud computing services improves the overall acceptance of the technologies in the organization and results in a higher return on investment. As executives are the main initiators of the cloud in real economy enterprises, CSPs can offer suggestions to senior executives on how firms can adapt to routine changes, organizational structure alterations, and workforce modifications brought about by the introduction of cloud computing. Through training, SMEs' members can understand cloud computing and reduce their resistance to it.

Given SMEs' resource constraints, governments and providers must offer the necessary support. Governments should issue free cloud-service vouchers to encourage and support SMEs to purchase cloud services from CSPs to accelerate digital transformation. However, CSPs must also offer sales promotions; for example, CSPs can provide cloud services that offer free trials to new users. Most SMEs are keen to test a cloud server before buying it, and a free trial can help SMEs obtain free hands-on experience with computing, networking, databases, storage, security, enterprise applications, analytics, AI, and developer services to evaluate whether cloud computing will suit their operations (Liang et al., 2021). Converting free-trial users to paying users is an effective marketing strategy. Other possible actions include offering discounts, special offers, and compensation for the costs involved in cloud computing acquisition, repair, and maintenance. In addition, CSPs can offer free assessments at the initial stage, cloud computing consultant hiring, and personnel training programs.

The provider can maintain good cooperative relationships through a 24/7 response and technical support program for firms' business plans, policies, executions, and operations with the highest standards of security and compliance.

Limitations and future research directions

This study has some limitations. First, it only identifies and tests key antecedents of cloud-computing adoption based on previous literature at the firm level. However, several other factors may influence organizations' decisions to use cloud computing. Therefore, future studies should consider a more comprehensive range of factors. Second, our study relies on a sample from a single country, China. However, SMEs in other countries may have different attitudes toward cloud computing because of potentially different legal regulations and technology levels. Hence, future studies should consider a comparative analysis across multiple regions to enhance generalizability.

Conclusion

With the increasingly fierce commercial competition, SMEs have been experiencing survival pressure, especially during the COVID-19 lockdown (Dwivedi et al., 2020). Cloud computing could help SMEs considerably improve their operations and productivity, even staying ahead of the competition. However, SMEs have not widely adopted cloud computing without understanding its diffusion. Thus, this study aims to explore the net and configurational effects of determinants leading to SMEs' adoption of cloud computing. Based on a literature review of cloud computing adoption, this study has identified 12 determinants (i.e., relative advantage, compatibility, complexity, security concern, top management support, adequate resources, IT competence, competitive pressure, trading partner pressure, coercive pressure, government support, and provider support), and has explored how these determinant antecedent conditions suit SMEs' decision to adopt cloud computing. Both PLS-SEM and fsQCA approaches were employed to analyze the survey data collected from 203 SMEs in China. PLS-SEM examines the relationship between variables, whereas fsQCA assesses the cause-and-effect process. Briefly, the PLS-SEM results reveal that security concerns, top management support, IT competence, competitive pressure, trading partner pressure, and provider support significantly impact cloud computing adoption. The fsQCA results reveal seven different configurations, including the factors identified by PLS-SEM, resulting in high-level cloud computing adoption, and eight causal paths leading to the negation of cloud computing adoption. These findings indicate that several conditions that had no significant effect in PLS-SEM are sufficient conditions when combined with other conditions in the configurations, providing relevant insights and suggestions for incentivizing SMEs to adopt cloud computing.

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References

Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. *International Journal of Information Management, 53*, 102118. doi:10.1016/j.ijinfomgt.2020.102118.

Adjei, J. K., Adams, S., & Mamattah, L. (2021). Cloud computing adoption in Ghana; accounting for institutional factors. *Technology in Society, 65*, 101583. doi:10.1016/j.techsoc.2021.101583.

Afonso, C., Silva, G. M., Gonçalves, H. M., & Duarte, M. (2018). The role of motivations and involvement in wine tourists' intention to return: SEM and fsQCA findings. *Journal of Business Research, 89*, 313–321. doi:10.1016/j.jbusres.2017.11.042.

Ahmad, N. A., Drus, S. M., & Kasim, H. (2020). Factors that influence the adoption of enterprise architecture by public sector organizations: An empirical study. *IEEE Access, 8*, 98847–98873. doi:10.1109/ACCESS.2020.2996584.

Ahmadi, H., Nilashi, M., Shahmoradi, L., & Ibrahim, O. (2017). Hospital Information System adoption: Expert perspectives on an adoption framework for Malaysian public hospitals. *Computers in Human Behavior, 67*, 161–189. doi:10.1016/j.chb.2016.10.023.

Akpan, I. J., Udoh, E. A. P., & Adebisi, B. (2022). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship, 34*(2), 123–140. doi:10.1080/08276331.2020.1820185.

Al-Omoush, K. S., Simón-Moya, V., Al-ma'aitah, M. A., & Sendra-García, J. (2021). The determinants of social CRM entrepreneurship: An institutional perspective. *Journal of Business Research, 132*, 21–31. doi:10.1016/j.jbusres.2021.04.017.

Al Hadwer, A., Tavana, M., Gillis, D., & Rezania, D (2021). A systematic review of organizational factors impacting cloud-based technology adoption using Technology-Organization-Environment framework. *Internet of Things, 15*, 100407. doi:10.1016/j.iot.2021.100407.

Ali, M., Seny Kan, K. A., & Sarstedt, M. (2016). Direct and configurational paths of absorptive capacity and organizational innovation to successful organizational performance. *Journal of Business Research, 69*(11), 5317–5323. doi:10.1016/j.jbusres.2016.04.131.

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England: A multi-perspective framework. *Journal of Enterprise Information Management, 26*(3), 250–275. doi:10.1108/17410391311325225.

Azmi, A., Sapiei, N. S., Mustapha, M. Z., & Abdullah, M. (2016). SMEs' tax compliance costs and IT adoption: The case of a value-added tax. *International Journal of Accounting Information Systems, 23*, 1–13. doi:10.1016/j.accinf.2016.06.001.

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2021). A model for decision-makers' adoption of big data in the education sector. *Sustainability, 13*,(24) 13995. doi:10.3390/su132413995.

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management, 58*, 102309. doi:10.1016/j.ijinfomgt.2021.102309.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*,(2) 103168. doi:10.1016/j.im.2019.05.003.

Bigerna, S., Bollino, C. A., & Micheli, S. (2016). Italian youngsters' perceptions of alternative fuel vehicles: A fuzzy-set approach. *Journal of Business Research, 69*(11), 5426–5430. doi:10.1016/j.jbusres.2016.04.149.

Chang, I. C., Hwang, H.-G., Hung, M.-C., Lin, M.-H., & Yen, D. C. (2007). Factors affecting the adoption of electronic signature: Executives' perspective of hospital information department. *Decision Support Systems, 44*(1), 350–359. doi:10.1016/j.dss.2007.04.006.

Chaparro-Peláez, J., Agudo-Peregrina, Á. F., & Pascual-Miguel, F. J (2016). Conjoint analysis of drivers and inhibitors of e-commerce adoption. *Journal of Business Research, 69*(4), 1277–1282. doi:10.1016/j.jbusres.2015.10.092.

Chatterjee, S., & Kumar Kar, A. (2020). Why do small and medium enterprises use social media marketing and what is the impact: Empirical insights from India. *International Journal of Information Management, 53*, 102103. doi:10.1016/j.ijinfomgt.2020.102103.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, 120880. doi:10.1016/j.techfore.2021.120880.

Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics, 8*(1), 36–68. doi:10.1080/23270012.2020.1852895.

Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding CRM adoption stages: Empirical analysis building on the TOE framework. *Computers in Industry, 109*, 1–13. doi:10.1016/j.compind.2019.03.007.

Damian, D., & Manea, C. (2019). Causal recipes for turning fin-tech freelancers into smart entrepreneurs. *Journal of Innovation & Knowledge, 4*(3), 196–201. doi:10.1016/j.jik.2019.01.003.

Deng, C.-P., Wang, T., Teo, T. S. H., & Song, Q. (2021). Organizational agility through outsourcing: Roles of IT alignment, cloud computing and knowledge transfer. *International Journal of Information Management, 60*, 102385. doi:10.1016/j.ijinfomgt.2021.102385.

Dey, B. L., Al-Karaghouli, W., & Muhammad, S. S. (2020). Adoption, adaptation, use and impact of information systems during pandemic time and beyond: Research and managerial implications. *Information Systems Management, 37*(4), 298–302. doi:10.1080/10580530.2020.1820632.

Dincă, V. M., Dima, A. M., & Rozsa, Z. (2019). Determinants of cloud computing adoption by Romanian SMEs in the digital economy. *Journal of Business Economics and Management, 20*(4), 798–820. doi:10.3846/jbem.2019.9856.

Duarte, P., & Pinho, J. C. (2019). A mixed methods UTAUT2-based approach to assess mobile health adoption. *Journal of Business Research, 102*, 140–150. doi:10.1016/j.jbusres.2019.05.022.

Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management, 55*, 102211. doi:10.1016/j.ijinfomgt.2020.102211.

Dwivedi, Y. K., & Mustafee, N. (2010). It's unwritten in the Cloud: The technology enablers for realising the promise of Cloud Computing. *Journal of Enterprise Information Management, 23*(6), 673–679. doi:10.1108/17410391011088583.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review, 32*(4), 1180–1198. doi:10.5465/amr.2007.26586092.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal, 54*(2), 393–420. doi:10.5465/amj.2011.60263120.

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.

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management, 28*(1), 107–130. doi:10.1108/JEIM-08-2013-0065.

Gao, F., & Sunyaev, A. (2019). Context matters: A review of the determinant factors in the decision to adopt cloud computing in healthcare. *International Journal of Information Management, 48*, 120–138. doi:10.1016/j.ijinfomgt.2019.02.002.

Gligor, D., & Bozkurt, S. (2020). FsQCA versus regression: The context of customer engagement. *Journal of Retailing and Consumer Services, 52*, 101929. doi:10.1016/j.jretconser.2019.101929.

Gökalp, E., Gökalp, M. O., & Çoban, S. (2022). Blockchain-based supply chain management: Understanding the determinants of adoption in the context of organizations. *Information Systems Management, 39*(2), 100–121. doi:10.1080/10580530.2020.1812014.

Gupta, P., Seetharaman, A., & Raj, J. R. (2013). The usage and adoption of cloud computing by small and medium businesses. *International Journal of Information Management, 33*(5), 861–874. doi:10.1016/j.ijinfomgt.2013.07.001.

Gupta, S., Meissonier, R., Drave, V. A., & Roubaud, D. (2020). Examining the impact of cloud ERP on sustainable performance: A dynamic capability view. *International Journal of Information Management, 51*, 102028. doi:10.1016/j.ijinfomgt.2019.10.013.

Gutierrez, A., Boukrami, E., & Lumsden, R. (2015). Technological, organisational and environmental factors influencing managers' decision to adopt cloud computing in the UK. *Journal of Enterprise Information Management, 28*(6), 788–807. doi:10.1108/JEIM-01-2015-0001.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.

Hair, J. F., Risher Jeffrey, J., Sarstedt, M., & Ringle Christian, 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.

Haneem, F., Kama, N., Taskin, N., Pauleen, D., Bakar, Abu, & N, A (2019). Determinants of master data management adoption by local government organizations: An empirical study. *International Journal of Information Management, 45*, 25–43. doi:10.1016/j.ijinfomgt.2018.10.007.

Hassan, H. (2017). Organisational factors affecting cloud computing adoption in small and medium enterprises (SMEs) in service sector. *Procedia Computer Science, 121*, 976–981. doi:10.1016/j.procs.2017.11.126.

Hassan, H., Nasir, M. H. M., Khairudin, N., & Adon, I. (2017). Factors influencing cloud computing adoption in small medium enterprises. *Journal of Information and Communication Technology, 16*(1), 21–41. Retrieved from http://e-journal.uum.edu.my/index.php/jict/article/view/8216.

Heart, T. (2010). Who is out there?: Exploring the effects of trust and perceived risk on saas adoption intentions. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 41*(3), 49–68. doi:10.1145/1851175.1851179.

Henao Ramírez, A. M., & López-Zapata, E. (2022). Analysis of the factors influencing adoption of 3D design digital technologies in Colombian firms. *Journal of Enterprise Information Management, 35*(2), 429–454. doi:10.1108/JEIM-10-2020-0416.

Henderson, D., Sheetz, S. D., & Trinkle, B. S. (2012). The determinants of inter-organizational and internal in-house adoption of XBRL: A structural equation model. *International Journal of Accounting Information Systems, 13*(2), 109–140. doi:10.1016/j.accinf.2012.02.001.

Hsu, C.-L., & Lin, J. C.-C. (2016). Factors affecting the adoption of cloud services in enterprises. *Information Systems and e-Business Management, 14*(4), 791–822. doi:10.1007/s10257-015-0300-9.

Hsu, P.-F., Ray, S., & Li-Hsieh, Y.-Y. (2014). Examining cloud computing adoption intention, pricing mechanism, and deployment model. *International Journal of Information Management, 34*(4), 474–488. doi:10.1016/j.ijinfomgt.2014.04.006.

Jahanmir, S. F., Silva, G. M., Gomes, P. J., & Gonçalves, H. M. (2020). Determinants of users' continuance intention toward digital innovations: Are late adopters different? *Journal of Business Research, 115*, 225–233. doi:10.1016/j.jbusres.2019.11.010.

Kalaitzi, D., & Tsolakis, N. (2022). Supply chain analytics adoption: Determinants and impacts on organisational performance and competitive advantage. *International Journal of Production Economics, 248*, 108466. doi:10.1016/j.ijpe.2022.108466.

Kaya, B., Abubakar, A. M., Behravesh, E., Yildiz, H., & Mert, I. S. (2020). Antecedents of innovative performance: Findings from PLS-SEM and fuzzy sets (fsQCA). *Journal of Business Research, 114*, 278–289. doi:10.1016/j.jbusres.2020.04.016.

Khayer, A., Talukder, M. S., Bao, Y., & Hossain, M. N. (2020). Cloud computing adoption and its impact on SMEs' performance for cloud supported operations: A dual-stage analytical approach. *Technology in Society, 60*, 101225. doi:10.1016/j.techsoc.2019.101225.

Kourouthanassis, P. E., Mikalef, P., Pappas, I. O., & Kostagiolas, P. (2017). Explaining travellers online information satisfaction: A complexity theory approach on information needs, barriers, sources and personal characteristics. *Information & Management, 54*(6), 814–824. doi:10.1016/j.im.2017.03.004.

Kraus, S., Ribeiro-Soriano, D., & Schüssler, M. (2018). Fuzzy-set qualitative comparative analysis (fsQCA) in entrepreneurship and innovation research – the rise of a method. *International Entrepreneurship and Management Journal, 14*(1), 15–33. doi:10.1007/s11365-017-0461-8.

Kumar Bhardwaj, A., Garg, A., & Gajpal, Y (2021). Determinants of blockchain technology adoption in supply chains by small and medium enterprises (SMEs) in India. *Mathematical Problems in Engineering, 2021*, 5537395. doi:10.1155/2021/5537395.

Kumar, D., Samalia, H. V., & Verma, P. (2017). Factors influencing cloud computing adoption by small and medium-sized enterprises (SMEs) In India. *Pacific Asia Journal of the Association for Information Systems, 9*(3), 25–48. doi:10.17705/1pais.09302.

Kusa, R., Duda, J., & Suder, M. (2021). Explaining SME performance with fsQCA: The role of entrepreneurial orientation, entrepreneur motivation, and opportunity perception. *Journal of Innovation & Knowledge, 6*(4), 234–245. doi:10.1016/j.jik.2021.06.001.

Lai, H.-M., Lin, I. C., & Tseng, L.-T. (2014). High-level managers' considerations for RFID adoption in hospitals: An empirical study in Taiwan. *Journal of Medical Systems, 38*, 3. doi:10.1007/s10916-013-0003-z.

Lee, J., Lee, D., Park, Y., Lee, S., & Ha, T. (2019). Autonomous vehicles can be shared, but a feeling of ownership is important: Examination of the influential factors for intention to use autonomous vehicles. *Transportation Research Part C: Emerging Technologies, 107*, 411–422. doi:10.1016/j.trc.2019.08.020.

Li, G., Liang, Y., Wang, H., Chen, J., & Chang, X. (2022). Factors influencing users' willingness to adopt connected and autonomous vehicles: Net and configurational effects analysis using PLS-SEM and FsQCA. *Journal of Advanced Transportation, 2022*, 7489897. doi:10.1155/2022/7489897.

Li, M., Zhao, D., & Yu, Y. (2015). TOE drivers for cloud transformation: Direct or trust-mediated? *Asia Pacific Journal of Marketing and Logistics, 27*(2), 226–248. doi:10.1108/APJML-03-2014-0040.

Lian, J.-W., Yen, D. C., & Wang, Y.-T. (2014). An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital. *International Journal of Information Management, 34*(1), 28–36. doi:10.1016/j.ijinfomgt.2013.09.004.

Liang, Y., Qi, G., Wei, K., & Chen, J. (2017). Exploring the determinant and influence mechanism of e-Government cloud adoption in government agencies in China. *Government Information Quarterly, 34*(3), 481–495. doi:10.1016/j.giq.2017.06.002.

Liang, Y., Qi, G., Zhang, X., & Li, G. (2019). The effects of e-government cloud assimilation on public value creation: An empirical study of China. *Government Information Quarterly, 36*,(4) 101397. doi:10.1016/j.giq.2019.101397.

Liang, Y., Wang, W., Dong, K., Zhang, G., & Qi, G. (2021). Adoption of mobile government cloud from the perspective of public sector. *Mobile Information Systems, 2021*, 8884594. doi:10.1155/2021/8884594.

Liang, Y., Zhang, G., Xu, F., & Wang, W. (2020). User acceptance of Internet of Vehicles services: Empirical findings of partial least square structural equation modeling (PLS-SEM) and fuzzy sets qualitative analysis (fsQCA). *Mobile Information Systems, 2020*, 6630906. doi:10.1155/2020/6630906.

Lin, A., & Chen, N.-C. (2012). Cloud computing as an innovation: Percepetion, attitude, and adoption. *International Journal of Information Management, 32*(6), 533–540. doi:10.1016/j.ijinfomgt.2012.04.001.

Liu, S., Chan, F. T. S., Yang, J., & Niu, B. (2018). Understanding the effect of cloud computing on organizational agility: An empirical examination. *International Journal of Information Management, 43*, 98–111. doi:10.1016/j.ijinfomgt.2018.07.010.

Liu, Y., Soroka, A., Han, L., Jian, J., & Tang, M. (2020). Cloud-based big data analytics for customer insight-driven design innovation in SMEs. *International Journal of Information Management, 51*, 102034. doi:10.1016/j.ijinfomgt.2019.11.002.

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems, 111*(7), 1006–1023. doi:10.1108/02635571111161262.

Luk, C.-L., Yau, O. H. M., Sin, L. Y. M., Tse, A. C. B., Chow, R. P. M., & Lee, J. S. Y. (2008). The effects of social capital and organizational innovativeness in different institutional contexts. *Journal of International Business Studies, 39*(4), 589–612. doi:10.1057/palgrave.jibs.8400373.

Lutfi, A., Alshira'h, A. F., Alshirah, M. H., Al-Okaily, M., Alqudah, H., Saad, M., Ibrahim, N., & Abdelmaksoud, O. (2022). Antecedents and impacts of enterprise resource planning system adoption among Jordanian SMEs. *Sustainability, 14*,(6) 3508. doi:10.3390/su14063508.

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework. *International Journal of Information Management, 36*(5), 711–723. doi:10.1016/j.ijinfomgt.2016.04.018.

Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors affecting the organizational adoption of blockchain technology: Extending the technology–organization–environment (TOE) framework in the Australian context. *Sustainability, 13*,(16) 9404. doi:10.3390/su13169404.

Maqueira-Marín, J. M., Bruque-Cámara, S., & Minguela-Rata, B. (2017). Environment determinants in business adoption of cloud computing. *Industrial Management & Data Systems, 117*(1), 228–246. doi:10.1108/IMDS-11-2015-0468.

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems, 123*(1), 278–301. doi:10.1108/IMDS-11-2021-0695.

Maroufkhani, P., Tseng, M.-L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, 102190. doi:10.1016/j.ijinfomgt.2020.102190.

Martins, R., Oliveira, T., & Thomas, M. A. (2016). An empirical analysis to assess the determinants of SaaS diffusion in firms. *Computers in Human Behavior, 62*, 19–33. doi:10.1016/j.chb.2016.03.049.

Mazumder, S., & Garg, S. (2021). Decoding digital transformational outsourcing: The role of service providers' capabilities. *International Journal of Information Management, 58*, 102295. doi:10.1016/j.ijinfomgt.2020.102295.

McLeay, F., Olya, H., Liu, H., Jayawardhena, C., & Dennis, C. (2022). A multi-analytical approach to studying customers motivations to use innovative totally autonomous vehicles. *Technological Forecasting and Social Change, 174*, 121252. doi:10.1016/j.techfore.2021.121252.

Mohtaramzadeh, M., Ramayah, T., & Jun-Hwa, C. (2018). B2B e-commerce adoption in Iranian manufacturing companies: Analyzing the moderating role of organizational culture. *International Journal of Human–Computer Interaction, 34*(7), 621–639. doi:10.1080/10447318.2017.1385212.

Nam, D., Lee, J., & Lee, H. (2019). Business analytics adoption process: An innovation diffusion perspective. *International Journal of Information Management, 49*, 411–423. doi:10.1016/j.ijinfomgt.2019.07.017.

Nilashi, M., Ahmadi, H., Ahani, A., Ravangard, R., & Ibrahim, O.b. (2016). Determining the importance of Hospital Information System adoption factors using Fuzzy Analytic Network Process (ANP). *Technological Forecasting and Social Change, 111*, 244–264. doi:10.1016/j.techfore.2016.07.008.

Ocloo, C. E., Xuhua, H., Akaba, S., Shi, J., & Worwui-Brown, D. K. (2020). The determinant factors of business to business (B2B) e-commerce adoption in small- and medium-sized manufacturing enterprises. *Journal of Global Information Technology Management, 23*(3), 191–216. doi:10.1080/1097198X.2020.1792229.

Ofosu-Ampong, K., & Acheampong, B. (2022). Adoption of contactless technologies for remote work in Ghana post-Covid-19: Insights from technology-organisation-environment framework. *Digital Business, 2*,(2) 100023. doi:10.1016/j.digbus.2022.100023.

Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovič, A. (2019). Understanding SaaS adoption: The moderating impact of the environment context. *International Journal of Information Management, 49*, 1–12. doi:10.1016/j.ijinfomgt.2019.02.009.

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*(5), 497–510. doi:10.1016/j.im.2014.03.006.

Orji, I. J., Kusi-Sarpong, S., Huang, S., & Vazquez-Brust, D. (2020). Evaluating the factors that influence blockchain adoption in the freight logistics industry. *Transportation Research Part E: Logistics and Transportation Review, 141*, 102025. doi:10.1016/j.tre.2020.102025.

Ott, U. F., Williams, D., Saker, J., & Staley, L. (2019). A configurational analysis of the termination scenarios of international joint ventures: All is well that ends well. *Journal of Innovation & Knowledge, 4*(3), 202–210. doi:10.1016/j.jik.2019.01.004.

Palos-Sanchez, P. R., Arenas-Marquez, F. J., & Aguayo-Camacho, M. (2017). Cloud computing (SaaS) adoption as a strategic technology: Results of an empirical study. *Mobile Information Systems, 2017*, 2536040. doi:10.1155/2017/2536040.

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management, 33*(6), 1125–1147. doi:10.1080/09585192.2021.1879206.

Pappas, I. O., Papavlasopoulou, S., Mikalef, P., & Giannakos, M. N. (2020). Identifying the combinations of motivations and emotions for creating satisfied users in SNSs: An fsQCA approach. *International Journal of Information Management, 53*, 102128. doi:10.1016/j.ijinfomgt.2020.102128.

Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management, 58*, 102310. doi:10.1016/j.ijinfomgt.2021.102310.

Park, J.-H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems, 61*(3), 285–293. doi:10.1080/08874417.2019.1631133.

Park, S. C., & Ryoo, S. Y. (2013). An empirical investigation of end-users' switching toward cloud computing: A two factor theory perspective. *Computers in Human Behavior, 29*(1), 160–170. doi:10.1016/j.chb.2012.07.032.

Phung, M. T., Ly, P. T. M., Nguyen, T. T., & Nguyen-Thanh, N. (2020). An fsQCA investigation of eWOM and social influence on product adoption intention. *Journal of Promotion Management, 26*(5), 726–747. doi:10.1080/10496491.2020.1729318.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control, 33*(16), 1517–1533. doi:10.1080/09537287.2021.1882689.

Pizam, A., Ozturk, A. B., Balderas-Cejudo, A., Buhalis, D., Fuchs, G., Hara, T., Meira, J., Revilla, M. R. G., Sethi, D., Shen, Y., State, O., Hacikara, A., & Chaulagain, S. (2022). Factors affecting hotel managers' intentions to adopt robotic technologies: A global study. *International Journal of Hospitality Management, 102*, 103139. doi:10.1016/j.ijhm.2022.103139.

Priyadarshinee, P., Raut, R. D., Jha, M. K., & Gardas, B. B. (2017). Understanding and predicting the determinants of cloud computing adoption: A two staged hybrid SEM - Neural networks approach. *Computers in Human Behavior, 76*, 341–362. doi:10.1016/j.chb.2017.07.027.

Ragin, C. C. (2008). *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. University of Chicago Press.

Ribeiro-Navarrete, S., Palacios-Marqués, D., Lassala, C., & Ulrich, K. (2021). Key factors of information management for crowdfunding investor satisfaction. *International Journal of Information Management, 59*, 102354. doi:10.1016/j.ijinfomgt.2021.102354.

Rihoux, B., & Ragin, C. C. (2009). *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. Sage Publications.

Rogers, E. M. (2010). *Diffusion of Innovations* (4th Edition). Free Press.

Roig-Tierno, N., Gonzalez-Cruz, T. F., & Llopis-Martinez, J. (2017). An overview of qualitative comparative analysis: A bibliometric analysis. *Journal of Innovation & Knowledge, 2*(1), 15–23. doi:10.1016/j.jik.2016.12.002.

Romero-Castro, N., López-Cabarcos, M.Á., & Piñeiro-Chousa, J. (2022). Uncovering complexity in the economic assessment of derogations from the European industrial emissions directive. *Journal of Innovation & Knowledge, 7*,(1) 100159. doi:10.1016/j.jik.2021.11.001.

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy, 5*(1), 105–115. doi:10.1016/j.jfbs.2014.01.002.

Senarathna, I., Wilkin, C., Warren, M., Yeoh, W., & Salzman, S. (2018). Factors that influence adoption of cloud computing: An empirical study of Australian SMEs. *Australasian Journal of Information Systems, 22*, 1–31. doi:10.3127/ajis.v22i0.1603.

Senyo, P. K., Addae, E., & Boateng, R. (2018). Cloud computing research: A review of research themes, frameworks, methods and future research directions. *International Journal of Information Management, 38*(1), 128–139. doi:10.1016/j.ijinfomgt.2017.07.007.

Sharma, S., Singh, G., Jones, P., Kraus, S., & Dwivedi, Y. K. (2022). Understanding agile innovation management adoption for SMEs. *IEEE Transactions on Engineering Management, 69*(6), 3546–3557. doi:10.1109/TEM.2022.3148341.

Shi, P., & Yan, B. (2016). Factors affecting RFID adoption in the agricultural product distribution industry: Empirical evidence from China. *Springerplus, 5*,(1) 2029. doi:10.1186/s40064-016-3708-x.

Shih, T.-Y., & Lin, C.-W. (2016). Cloud service adoption by firms in Taiwan: Advancing trust theory and applications. *Information Development, 33*(5), 495–511. doi:10.1177/0266666916671985.

Skafi, M., Yunis, M. M., & Zekri, A. (2020). Factors influencing SMEs' adoption of cloud computing services in Lebanon: An empirical analysis using TOE and contextual theory. *IEEE Access, 8*, 79169–79181. doi:10.1109/ACCESS.2020.2987331.

Skare, M., & Riberio Soriano, D. (2021). How globalization is changing digital technology adoption: An international perspective. *Journal of Innovation & Knowledge, 6* (4), 222–233. doi:10.1016/j.jik.2021.04.001.

Song, C.-h., Kim, S. W., & Sohn, Y.-W (2020). Acceptance of public cloud storage services in South Korea: A multi-group analysis. *International Journal of Information Management, 51*, 102035. doi:10.1016/j.ijinfomgt.2019.11.003.

Sun, S., Hall, D. J., & Cegielski, C. G. (2020). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management, 86*, 109–121. doi:10.1016/j.indmarman.2019.09.003.

Tomás, S., Thomas, M., & Oliveira, T. (2017). Evaluating the impact of virtualization characteristics on SaaS adoption. *Enterprise Information Systems, 12*(3), 259–278. doi:10.1080/17517575.2017.1355484.

Upadhyay, N., Upadhyay, S., Abed, S. S., & Dwivedi, Y. K. (2022). Consumer adoption of mobile payment services during COVID-19: Extending meta-UTAUT with perceived severity and self-efficacy. *International Journal of Bank Marketing, 40*(5), 960–991. doi:10.1108/IJBM-06-2021-0262.

Valaei, N., Rezaei, S., & Ismail, W. K. W. (2017). Examining learning strategies, creativity, and innovation at SMEs using fuzzy set Qualitative Comparative Analysis and PLS path modeling. *Journal of Business Research, 70*, 224–233. doi:10.1016/j.jbusres.2016.08.016.

van de Weerd, I., Mangula, I. S., & Brinkkemper, S. (2016). Adoption of software as a service in Indonesia: Examining the influence of organizational factors. *Information & Management, 53*(7), 915–928. doi:10.1016/j.im.2016.05.008.

Venkatesh, V. (2020). Impacts of COVID-19: A research agenda to support people in their fight. *International Journal of Information Management, 55*, 102197. doi:10.1016/j.ijinfomgt.2020.102197.

Wang, F.-K., & He, W. (2014). Service strategies of small cloud service providers: A case study of a small cloud service provider and its clients in Taiwan. *International Journal of Information Management, 34*(3), 406–415. doi:10.1016/j.ijinfomgt.2014.01.007.

Wang, H., & Lo, J. (2020). Factors influencing the adoption of open government data at the firm level. *IEEE Transactions on Engineering Management, 67*(3), 670–682. doi:10.1109/TEM.2019.2898107.

Wang, L., Wang, Z., Wang, X., & Zhao, Y. (2021). Explaining consumer implementation intentions in mobile shopping with SEM and fsQCA: Roles of visual and technical perceptions. *Electronic Commerce Research and Applications, 49*, 101080. doi:10.1016/j.elerap.2021.101080.

Wang, N., Liang, H., Ge, S., Xue, Y., & Ma, J. (2019). Enablers and inhibitors of cloud computing assimilation: An empirical study. *Information Technology & People, 32*(1), 147–170. doi:10.1108/INTR-03-2018-0126.

Wang, N., Xue, Y., Liang, H., Wang, Z., & Ge, S. (2019). The dual roles of the government in cloud computing assimilation: An empirical study in China. *Information Technology & People, 32*(1), 147–170. doi:10.1108/ITP-01-2018-0047.

Wang, Y.-M., Wang, Y.-S., & Yang, Y.-F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change, 77*(5), 803–815. doi:10.1016/j.techfore.2010.03.006.

Wang, Y.-S., Li, H.-T., Li, C.-R., & Zhang, D.-Z. (2016). Factors affecting hotels' adoption of mobile reservation systems: A technology-organization-environment framework. *Tourism Management, 53*, 163–172. doi:10.1016/j.tourman.2015.09.021.

Wang, Z., Wang, N., Su, X., & Ge, S. (2020). An empirical study on business analytics affordances enhancing the management of cloud computing data security. *International Journal of Information Management, 50*, 387–394. doi:10.1016/j.ijinfomgt.2019.09.002.

Wei, J., Lowry, P. B., & Seedorf, S. (2015). The assimilation of RFID technology by Chinese companies: A technology diffusion perspective. *Information & Management, 52*(6), 628–642. doi:10.1016/j.im.2015.05.001.

Wong, L.-W., Leong, L.-Y., Hew, J.-J., Tan, G. W.-H., & Ooi, K.-B. (2020). Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs. *International Journal of Information Management, 52*, 101997. doi:10.1016/j.ijinfomgt.2019.08.005.

Woodside, A. G. (2013). 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. *Journal of Business Research, 66*(4), 463–472. doi:10.1016/j.jbusres.2012.12.021.

Wu, W.-W. (2011). Developing an explorative model for SaaS adoption. *Expert Systems with Applications, 38*(12), 15057–15064. doi:10.1016/j.eswa.2011.05.039.

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. *Computers in Human Behavior, 45*, 254–264. doi:10.1016/j.chb.2014.12.022.

Yeh, C.-C., & Chen, Y.-F. (2018). Critical success factors for adoption of 3D printing. *Technological Forecasting and Social Change, 132*, 209–216. doi:10.1016/j.techfore.2018.02.003.

Yoon, C., Lim, D., & Park, C. (2020). Factors affecting adoption of smart farms: The case of Korea. *Computers in Human Behavior, 108*, 106309. doi:10.1016/j.chb.2020.106309.

Yoon, T. E., & George, J. F. (2013). Why aren't organizations adopting virtual worlds? *Computers in Human Behavior, 29*(3), 772–790. doi:10.1016/j.chb.2012.12.003.

Zhang, G., Wang, W., & Liang, Y. (2021). Understanding the complex adoption behavior of cloud services by SMEs based on complexity theory: A fuzzy sets Qualitative Comparative Analysis (fsQCA). *Complexity, 2021*, 5591446. doi:10.1155/2021/5591446.