Information Systems and e-Business Management
https://doi.org/10.1007/s10257-026-00744-7

ORIGINAL ARTICLE

Examining determinants of cloud analytics adoption in SMEs

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Received: 26 May 2025 / Revised: 28 June 2026 / Accepted: 9 September 2026
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Abstract

Small and medium-sized enterprises (SMEs) that aim to harness data & analytics often look to cloud-based solutions to reduce initial invest and to ensure scalability. To support that endeavor, this study examines individual-level adoption dynamics of cloud analytics in the specific organizational context of SMEs. A composite model was developed which integrates the socio-technical variables of the technology-organization-environment framework into the technology acceptance model. Data was collected from employees of SMEs operating in Germany (n = 368) using an online questionnaire and was analyzed using partial least squares structural equation modeling. The proposed model was found to explain 78 % of the variance in *intention to adopt*. *Relative advantage* and *compatibility* were shown as key determinants. Contrary to previous literature, *leadership support* was found to have no significant influence on individual perception. Overall, the findings provide guidance to SME managers, service providers and policy makers on how to successfully support the adoption of cloud analytics. In doing so, the paper helps to fill a research gap on cloud analytics in SMEs, advancing the understanding of the factors that influence the adoption of the technology.

Keywords Cloud · Data · Analytics · SME · Technology acceptance

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Published online: 13 October 2026

1 Introduction

In today's rapidly evolving digital landscape, small and medium-sized enterprises (SMEs) face increasing pressure to integrate data & analytics solutions to remain competitive (Justy et al. 2023). Such solutions offer a range of benefits that can significantly bolster overall performance, from improving decision-making processes to enhancing operational efficiency and customer insights (Coleman et al. 2016; Maroufkhani et al. 2020; Langer and Pütterich 2024). Nevertheless, SMEs encounter formidable obstacles when adopting these technologies, including resource constraints, limited technical expertise, and organizational inertia (Coleman et al. 2016; Lutfi et al. 2022). These issues are particularly pronounced in Germany, where SMEs, despite their pivotal role in the national economy, trail larger firms in implementing advanced analytics, resulting in diminished competitiveness and missed opportunities for innovation in a rapidly digitizing global marketplace (Eurostat 2023; Karunagaran et al. 2017).

Cloud-based analytics, delivered as software-as-a-service (SaaS), has emerged as one potential solution to these challenges, promising scalable, flexible, and cost-effective access to data analytics (Karunagaran et al. 2017; Pahl et al. 2018). By alleviating the need for extensive infrastructure investments, cloud analytics could enable SMEs to manage resources more efficiently and maintain a competitive edge (Karunagaran et al. 2017; Liu et al. 2020). Yet, stringent general data protection regulation (GDPR) requirements, data security concerns, and limited digital literacy continue to dampen actual adoption rates (Lutfi et al. 2022; Putzier et al. 2024). Indeed, only 47 % of German SMEs have thus far embraced cloud computing, which is significantly lower than countries like Finland, where 78 % of SMEs rely on the cloud (Eurostat 2024).

Practice indicates that these challenges are not solely technological or organizational but are also shaped by decision-makers' and employees' individual perceptions and intentions. Negative perceptions, such as concerns over data security or doubts about return on investment, can stall adoption, whereas a positive perception can act as a critical driver for embracing new technologies (Coleman et al. 2016; Lutfi et al. 2022). Consequently, improving individual perception and strengthening the intention to adopt is essential if SMEs are to fully capitalize on cloud analytics. To address this need, the present study attends to the following research question:

RQ *Which factors determine individual perception and adoption intention for cloud analytics in SMEs?*

To investigate which external factors influence individual-level perception and adoption intention in SMEs we propose a composite model based on the technology acceptance model (TAM) and technology-organization-environment (TOE) framework. Key constructs such as *perceived usefulness*, *perceived ease of use,* and *relative advantage*, as well as *organizational maturity*, *leadership support* and *compatibility* are investigated (cf., Gangwar et al. 2015; Tornatzky and Fleischer 1990; Venkatesh and Davis 2000). We then rely on a quantitative survey with German SMEs to test the model statistically using partial least squares structural equation modeling (PLS-

SEM). The results contribute to a better understanding of how established adoption mechanisms operate for cloud analytics in SMEs. The study also offers practical guidelines to SME managers, consultants, service providers and policy makers interested in developing digital transformation programs tailored to the needs of SMEs.

2 Background

2.1 Theoretical foundation

SMEs are essential to global economies, particularly in Germany, where they form the backbone of the "Mittelstand." SMEs account for 99.4 % of all German firms and employ over half the country's workforce, contributing significantly to innovation and economic stability (BMWK 2022; Söllner 2014). Their strengths include adaptability, niche market expertise, and strong regional ties, but they also face unique challenges in adopting advanced information systems (IS). Limited financial and technical resources, coupled with organizational resistance to change and stringent regulatory requirements, often impede their ability to integrate digital solutions (Nasrudin 2024; OECD 2023). These barriers underscore the need for tailored approaches to enable technological transformation in SMEs.

Data & analytics have emerged as key tools for addressing these challenges, offering methods to extract actionable insights from data to enhance decision-making and operational efficiency (Davenport 2006). However, traditional analytics systems, reliant on on-premises infrastructure, are often prohibitively expensive and lack the scalability required by SMEs. Cloud computing provides a cost-effective alternative. In particular, cloud analytics, delivered through SaaS models, allows SMEs to leverage advanced analytics capabilities without the need for significant upfront investment or extensive IT expertise (Mikalef et al. 2019; Armbrust et al. 2010). This integration of cloud infrastructure and analytics addresses many of the resource and scalability constraints faced by SMEs, presenting a transformative opportunity for data-driven decision-making.

To understand the adoption of cloud analytics in SMEs, this study draws on two theoretical frameworks: the TAM and the TOE framework. TAM, developed by Davis (1986), focuses on individual-level adoption behaviors, positing that behavioral *intention to adopt* a technology is influenced by *perceived usefulness* and *perceived ease of use* (Davis 1989). *Perceived usefulness* refers to the belief that using a system will enhance job performance, while *perceived ease of use* reflects the belief that the system will be free of effort. Technologies perceived as easy to use are often considered more beneficial, strengthening the relationship between *perceived ease of use* and *perceived usefulness* (Schillewaert et al. 2005). TAM has been widely applied to analyze user adoption across various contexts, explaining up to 40 % of the variance in *behavioral intention* (Autry et al. 2010). However, critics argue that TAM oversimplifies complex adoption scenarios, particularly in organizational settings like SMEs, where external and organizational factors also play critical roles (Chen and Tan 2004; Legris et al. 2003).

The TOE framework, proposed by Tornatzky and Fleischer (1990), provides a broader perspective, examining adoption through three dimensions: technological, organizational, and environmental. Technological factors include system complexity, perceived benefits, and compatibility with existing infrastructure (Alamgir Hossain and Quaddus 2011). Organizational factors encompass firm size, leadership support, and resource availability, which influence readiness for adoption (Musawa and Wahab 2012; Intan Salwani et al. 2009). Environmental factors, such as regulatory pressures, competitive dynamics, and vendor support, highlight external influences on adoption decisions (Musawa and Wahab 2012). While TOE offers a comprehensive view of organizational and contextual influences, it has been criticized for its lack of specificity and reliance on context-dependent variables, requiring adaptation to address unique industry or firm-level challenges (Dedrick and West 2003; Zhu et al. 2006).

An alternative framework frequently applied in technology adoption research is the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. 2003), which synthesizes elements from TAM, the theory of reasoned action (TRA; Fishbein and Ajzen 1975), the theory of planned behavior (TPB; Ajzen 1991), and several other acceptance models into a unified predictive framework. While UTAUT and its extension UTAUT2 (Venkatesh et al. 2012) offer strong individual-level predictive power, they do not explicitly account for the organizational and environmental dimensions that are central to understanding adoption in resource-constrained SME contexts. In contrast, the TOE framework captures these contextual layers, including *organizational maturity*, *leadership support*, and *competitive pressure*, which are theoretically and practically critical for an analysis of SMEs. Integrating TAM with TOE therefore offers a more comprehensive analytical lens: TAM captures behavioral determinants such as *perceived usefulness* and *perceived ease of use*, while TOE contextualizes these within the technological, organizational, and external environments that shape SMEs' readiness and capacity to adopt cloud analytics. This integrated approach highlights the interplay between individual user perceptions, organizational constraints, and external pressures. By examining this interplay, the present study aims to offer actionable insights into fostering cloud analytics adoption in SME environments.

2.2 Related works and research gap

The adoption of technology by SMEs has been focus of academic literature for some time, particularly through the lens of frameworks like TOE and TAM. Research applying the TOE framework has highlighted key factors influencing SME technology adoption. Musawa and Wahab (2012) identified external pressure, organizational readiness, and perceived benefits as critical in Nigerian SMEs, while Wen and Chen (2010) emphasized competition intensity and technology readiness in US SMEs. Studies like those by Alshamaila et al. (2013) and Mousa et al. (2024) demonstrated the importance of relative advantage, compatibility, and cost considerations for cloud computing adoption. Zhu and Kraemer (2005) provided a cross-national perspective, noting that economic and regulatory environments significantly shape adoption

dynamics. Ahmad et al. (2023) explored Industry 4.0 readiness in Malaysian SMEs, emphasizing the importance of addressing infrastructure challenges.

TAM has been widely used to analyze technology adoption, often integrated with TOE for a comprehensive view. Awa et al. (2015) showed the impact of socio-technical considerations on e-commerce adoption in SMEs, while Gangwar et al. (2015) highlighted relative advantage and management support as key determinants for cloud computing in Indian organizations. Chatterjee et al. (2021) applied a TAM-TOE model to AI adoption, emphasizing leadership and organizational readiness. Studies like Kamal et al. (2020) and Katebi et al. (2022) underscored the influence of cultural barriers and organizational factors, although not SME-specific.

Research on digital technology adoption in SMEs, such as Ramdani et al. (2009) and Hentschel et al. (2018), has identified factors like organizational readiness, cost efficiency, and management support as critical. Barriers such as GDPR compliance, limited technical expertise, and resource constraints are particularly pronounced in German SMEs (Karunagaran et al. 2017; Stieninger et al. 2014). Fragmented adoption strategies and a focus on short-term solutions further hinder SMEs from leveraging technology's full potential (Justy et al. 2023; Leclerque et al. 2021). Leadership support and alignment with strategic goals remain underexplored despite their critical role in adoption success (Jayeola et al. 2022).

Although existing studies provide valuable insights into SME technology adoption, gaps remain in understanding the specific challenges faced by German SMEs in adopting advanced technologies like cloud analytics. Current TAM and TOE frameworks often overlook critical factors such as regulatory environments (e.g., GDPR) and the interplay between internal readiness and external pressures. The resource and digital maturity constraints of German SMEs, coupled with their risk-averse culture, further complicate adoption processes (Hentschel et al. 2019; Kohn and Hüsig 2006). Existing studies also fail to comprehensively address the alignment of cloud analytics adoption with strategic and operational goals.

2.3 Hypotheses formulation

Hypotheses have been formulated that combine TAM's focus on individual perception with TOE's consideration of organizational and environmental factors. These hypotheses are based on theoretical constructs and previous research. The aim is to test current preconceptions aggregated from existing research on the topic of individual-level cloud analytics adoption in the explicit context of SMEs. While several TOE constructs, such as *organizational maturity*, *leadership support*, and *competitive pressure*, are inherently organizational in nature, this study wants to measure them through individual employee perceptions. This approach is consistent with established practice in PLS-SEM-based adoption research, where individual respondents serve as informants about organizational conditions (Gangwar et al. 2015; Chatterjee et al. 2021). The rationale is that organizational factors influence adoption not directly, but through their effect on individual perceptions and behavioral intention. The hypotheses are therefore formulated as relationships between perceived organizational conditions and individual-level adoption constructs.

Relative advantage, defined by Rogers (2003) as the competitive benefits of the new technology over existing alternatives, plays a crucial role in adoption decisions. In the context of cloud analytics, benefits like reduced fixed costs, better scalability, flexibility, and operational efficiency (Gangwar et al. 2015; Marston et al. 2011) have been shown to be especially pertinent for SMEs with limited financial and human resources (Awa et al. 2015; Jayeola et al. 2022). Based on this and the TAM constructs the following hypotheses are proposed:

H1a *Relative advantage has a positive effect on perceived usefulness.*

H1b *Relative advantage has a positive effect on perceived ease of use.*

Compatibility, reflecting the alignment of cloud analytics with existing workflows, strategies, and cultural practices (Calisir et al. 2009; Peng et al. 2012), is another critical factor. When technology integrates seamlessly with organizational processes, friction is reduced and adoption becomes more likely (Jain 2024; Rogers 2003). Thereby, multiple studies have demonstrated that compatibility significantly influences *perceived ease of use* and *perceived usefulness* (e.g., Abdekhoda et al. 2019; Gholami et al. 2018). Accordingly, our hypotheses are:

H2a *Compatibility has a positive effect on perceived usefulness.*

H2b *Compatibility has a positive effect on perceived ease of use.*

Complexity, or the perceived difficulty of understanding a system, likely acts as a significant barrier to adoption, particularly for SMEs with limited technical expertise (Gholami et al. 2018; Liu et al. 2020). Systems perceived as complex are less likely to be considered useful or easy to use (Idris 2015; Liu et al. 2020). Thus, the hypotheses for cloud analytics adoption in SMEs are:

H3a *Complexity has a negative effect on perceived usefulness.*

H3b *Complexity has a negative effect on perceived ease of use.*

Training is pivotal for adoption success. It is defined as the degree to which a company educates its employees in terms of quality and quantity when using new technologies (Schillewaert et al. 2005). Adequate training helps reduce employees' anxiety and stress around complex systems like cloud analytics, and equips employees to use new systems effectively. It has been shown to enhance both *perceived ease of use* and *perceived usefulness* (Venkatesh and Davis 2000; Gangwar et al. 2015). Regarding cloud analytics, we therefore hypothesize:

H4a *Training has a positive effect on perceived usefulness.*

H4b *Training has a positive effect on perceived ease of use.*

Maturity, encompassing well-defined processes, innovation management, and cultural readiness, positively influences adoption by enabling firms to leverage technology effectively (Wang et al. 2022; Gangwar et al. 2015). In the context of adoption research, organizational maturity has been shown to significantly influence employees' perceptions of a system's usefulness and ease of use (Kamal et al. 2020; Chatterjee et al. 2021). This leads us to hypothesize:

H5a *Maturity has a positive effect on perceived usefulness.*

H5b *Maturity has a positive effect on perceived ease of use.*

Leadership support, encompassing active involvement and resource commitment from managers (or owners), fosters a supportive environment for technology adoption (Wu et al. 2007; Kowitlawakul 2011). Leadership support can mitigate resistance and enhances perceptions of usefulness and ease of use (Chatterjee et al. 2021). For cloud analytics in SMEs, this leads to the hypotheses:

H6a *Leadership support has a positive effect on perceived usefulness.*

H6b *Leadership support has a positive effect on perceived ease of use.*

Competitive pressure, representing the influence of market forces on technology adoption (Zhu et al. 2006; Lin and Lin 2008), drives firms to adopt technologies to remain competitive. It acts as a direct motivator for technology adoption, with firms pressured to prioritize the need to adopt over concerns about individual perceptions of *perceived ease of use* or *perceived usefulness* (Elbeltagi et al. 2016). Therefore, we hypothesize for cloud analytics in SMEs:

H7 *Competitive pressure has a positive effect on intention to adopt.*

Partner support, including technical assistance and data security provided by cloud vendors (Hentschel et al. 2018; Zhu and Kraemer 2005), addresses adoption challenges and facilitates smoother transitions. Zhu and Kraemer (2005) highlight that trading partners, including service providers, are instrumental in driving technology adoption by offering consistent, reliable services. The resulting hypothesis is:

H8 *Partner support has a positive effect on intention to adopt.*

Finally, consistent with the original TAM (Davis et al. 1989), *perceived ease of use* and *perceived usefulness* are often shown to be central determinants of adoption intention. Additionally, *perceived ease of use* has been shown to influence *perceived usefulness* by reducing cognitive load (Venkatesh and Davis 2000). Therefore we hypothesize:

H9a *Perceived usefulness has a positive effect on intention to adopt.*

H9b *Perceived ease of use has a positive effect on intention to adopt.*

H9c *Perceived ease of use has a positive effect on perceived usefulness.*

All hypotheses, informed by foundational models and empirical studies, form the basis for analyzing the specific dynamics of cloud analytics adoption in SMEs. The subsequent methodology section will further outline the integration of these relationships into a composite model, paving the way for a comprehensive investigation of adoption drivers and barriers.

3 Method

3.1 Research model

The TAM and TOE frameworks complement each other in addressing the limitations of their individual predictive capabilities. TAM, while significant in explaining user acceptance through the constructs *perceived ease of use* and *perceived usefulness*, is often criticized as a partial model with undefined external variables that vary by context (Legris et al. 2003). Conversely, the TOE framework, while broad and applicable across industries, lacks clarity in its major constructs and specificity in its application (Riyadh et al. 2009; Wang et al. 2010). By integrating TAM with TOE, the strengths of each framework can address the other's weaknesses, offering a richer theoretical basis that measures individual perception and consequently, how this interacts on the organizational level affecting technology adoption (Gangwar et al. 2014). This combined approach has been advocated for because of its ability to provide a holistic understanding of adoption behaviors, particularly in diverse and complex contexts like organizations (Riyadh et al. 2009; Gangwar et al. 2015; Lifen Zhao et al. 2010). In the specific case of cloud analytics adoption in SMEs the composite model allows to take into account the organization context of small business and its influence on individual-level adoption. The model and respective hypotheses (cf., Section 2.3) are shown in Figure 1.

Constructs and measurement items were designed based on related research in line with the argumentation of the hypotheses and the TAM and TOE model. The sources on which the items were based are shown in the Table 1. The constructs and corresponding questions are displayed in Table 11 in the online appendix. All model construct consists of three to four measurement items each.

3.2 Data collection and sample

An online survey was selected to collect the quantitative data to assess the model. A questionnaire was implemented using the SoSciSurvey platform, which is widely recognized in academic research and complies with GDPR (Leiner 2019). The questionnaire was divided into three main sections designed to comprehensively explore the determinants of cloud analytics adoption among SMEs.

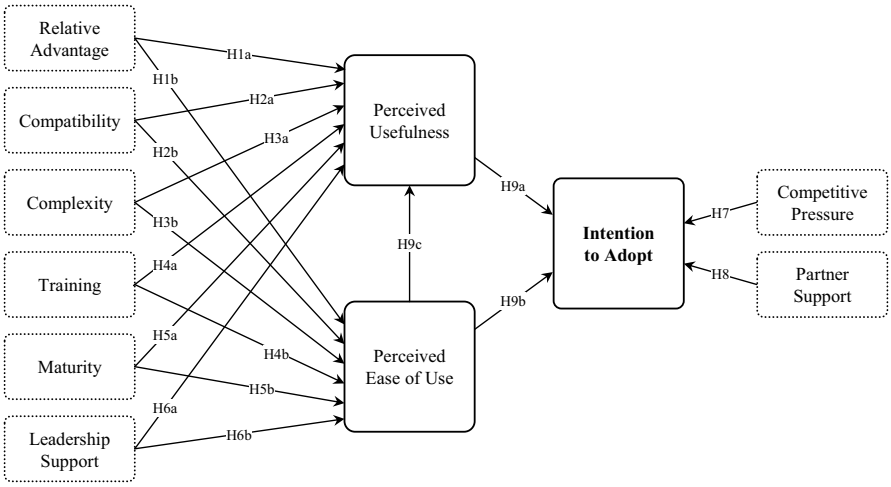


Fig. 1 Research model and hypotheses

Table 1 Construct overview with referenced sources

Framework	Constructs	References
TOE	Relative advantage	Abdekhoda et al. (2019)
TOE	Compatibility	Géczy et al. (2012), Gholami et al. (2018)
TOE	Complexity	Idris (2015), Parveen and Sulaiman (2008), Sonnenwald et al. (2001)
TOE	Leadership support	Gangwar et al. (2015), Tan et al. (2007), Wang et al. (2010)
TOE	Training	Aboelmaged (2014), Idris (2015)
TOE	Maturity	Chatterjee et al. (2021), Gangwar et al. (2015), Maduka et al. (2018)
TOE	Competitive pressure	Chatterjee et al. (2021), Rogers (2003), Yang et al. (2015)
TOE	Partner support	Chatterjee et al. (2021), Haans et al. (2015), Zheng and Yang (2015)
TAM	Perceived ease of use	Chatterjee et al. (2021), Yousafzai et al. (2007)
TAM	Perceived usefulness	Davis (1989), Lee et al. (2003)
TAM	Intention to adopt	Gangwar et al. (2015), Yousafzai et al. (2007)

The initial section served to engage participants and provide a foundational understanding of the research. Participants are introduced to the study's objectives and the importance of their contributions. To establish a shared context, a detailed scenario is presented, describing a hypothetical cloud analytics provider tailored to the needs of SMEs. This scenario offers a concrete example of how cloud analytics could be implemented within an SME setting and address specific barriers in SME technology adoption.

The central part of the questionnaire was then organized around the theoretical constructs outlined in Section 3.1. Each construct category is presented separately following the structure: TAM constructs, technology constructs, organization constructs, and environment constructs. This layout supports a clear and organized flow, guiding participants systematically through each category. All items are measured

using a 7-point Likert-scale as per previous research, ensuring both reliability and validity of the data (Tornatzky and Fleischer 1990; Venkatesh and Bala 2008).

The third and final section includes an instructional manipulation check (IMC), in the form of a blue dot test. This test helps identify and filter out inattentive respondents by requiring them to follow simple instructions unrelated to the survey content (Oppenheimer et al. 2009). Additionally, a page gathered demographic information on the companies, including industry, number of employees or full-time equivalents (FTE), and balance sheet totals aligned with the SME classification criteria to enable filtering based on company characteristics.

Given that all variables were collected from the same respondent in a single cross-sectional survey, common method bias (CMB) is a potential concern (Podsakoff et al. 2003). To mitigate this risk, several procedural remedies were implemented during the survey design: construct categories were presented on separate questionnaire pages to reduce priming effects, items were randomized within each category, and respondents were assured of anonymity.

To ensure the clarity and relevance of the questionnaire, a pretest was conducted with ten individuals from the authors' academic and professional network. The pretest focused on evaluating the content appropriateness of the questions as well as the clarity of wording and layout (Bryman 2016). Based on the feedback received, minor revisions were implemented before the main survey was launched.

The target population comprised employees within German SMEs, with each response reflecting individual perceptions of firm-level conditions and practices. Data were collected between September and November 2024 using a one-time cross-sectional design (Bryman 2016), a common approach in technology adoption research that captures a snapshot of organizational practices at a specific point in time (Chatterjee et al. 2021; Gangwar et al. 2015). Participants were recruited through a purposive sampling strategy (Etikan 2016), contacting 100,000 firms listed in the Orbis database (Moody's Analytics 2024) that met the official SME criteria (Eurostat 2023). Data collection was prompted through cold-call email invitations via general business e-mail addresses to comply with GDPR. Recipients therefore had no prior relationship with the researchers. This ensured broad sectoral coverage and minimized sampling bias toward pre-existing networks, but it also typically results in lower response rates due to limited personalization and the high volume of unsolicited business emails.

In total, 2,343 individuals accessed the survey, with 330 partially completed and 586 fully completed questionnaires meeting the initial inclusion criteria. After filtering based on the SME revenue and FTE thresholds (Eurostat 2023), as well as the IMC check, the final dataset comprised n = 368 valid observations. The demographic composition of the sample is presented in Table 2.

The majority of respondents in this study come from the industry and manufacturing sector (n = 92), followed by services (n = 77), construction and real estate (n = 65), and IT and telecommunications (n = 42). Together, these sectors constitute the core of the sample and provide insights from central areas of SME activity. Other sectors, including retail and consumer goods, energy and environment, health and social services, and transportation and logistics, are represented to a lesser extent.

Table 2 Demographic sample profile

Variable *(n = 368)*	Quantity	(Proportion)
Revenue		
< 2 mn EUR	135	(36.7%)
> 2 & < 10 mn EUR	181	(49.2%)
> 10 & < 50 mn EUR	52	(14.1%)
FTE		
1-10	166	(45.1%)
11-50	164	(44.6%)
51-250	38	(10.3%)
Sector		
Industry and manufacturing	92	(25.0%)
Services	77	(20.9%)
Construction and real estate	65	(17.7%)
IT and telecommunication	42	(11.4%)
Retail and consumer goods	26	(7.1%)
Energy and environment	21	(5.7%)
Health and social services	18	(4.9%)
Transportation and logistics	13	(3.5%)
Hotel and catering	9	(2.4%)
Public sector and education	5	(1.4%)

To assess the representativeness of the sample, the distributions of firm size and sector were compared with national SME statistics from Institut fur Mittelstandsforschung Bonn (2023). Goodness-of-fit tests were conducted across firm size, turnover, and sector categories, and Cramér's V was calculated to quantify deviations between the sample and the population (Field 2018). Following benchmarks of Cohen (1988), values smaller than 0.10, 0.30, and 0.50 are typically interpreted as small, medium, and large deviation effects, respectively.

The results indicate that the sample reflects the overall SME population in Germany with small to medium deviations (Cramér's V between 0.26 and 0.43). Slight overrepresentation is observed in IT, construction, and real estate sectors, industries that tend to be more digitally active, while health, social services, and retail are somewhat underrepresented. In terms of firm size, medium-sized enterprises (51-250 employees) are slightly underrepresented compared to small and micro enterprises and the expected prevalence. Overall, the differences are deemed within acceptable limits for exploratory analyses.

3.3 Data analysis

The collected data was analyzed using PLS-SEM. This method is well-suited for complex models and smaller sample sizes (Hair et al. 2022). PLS-SEM is a powerful multivariate analysis technique that enables the simultaneous examination of multiple direct and indirect cause-effect relationships between latent variables. Given the use of a 7-point Likert-scale for all measurements, which often leads to non-normally distributed data, PLS-SEM is preferred (Henseler et al. 2016). Unlike covariance-based structural equation modeling (CB-SEM), PLS-SEM does not require strict

assumptions of multivariate normality (Henseler et al. 2016). This makes it a more robust and reliable method for testing the hypotheses in this study.

The software SmartPLS (Ringle et al. 2024) was used for the computations. Descriptive statistics were computed to provide a comprehensive overview of the sample (Hair et al. 2022). Correlation matrices examined bi-variate relationships among variables supported by the variance inflation factor. The reliability and validity of the measurement instruments were assessed for convergent validity. Discriminant validity was evaluated and model fit was assessed, ensuring a comprehensive evaluation of the research model. This also included statistical assessment for potential CMB (Kock 2015). The hypotheses were tested based on the estimated path coefficients (β) and their significance (Hair et al. 2022). To assess the significance of the relationships between constructs, bootstrapping was employed to calculate respective p-values (Henseler et al. 2016).

4 Results

4.1 Model quality

4.1.1 Composite validity

The assessment of composite validity is a critical aspect of evaluating the internal consistency of measured items, and it ensures that the constructs are measured accurately and consistently. This section describes Cronbach's alpha (α) and composite reliability (ρ_c) for each variable in the model.

Cronbach's alpha is a widely used measure of internal consistency, providing insight into how closely related the items within a construct are. Generally, an α -value above 0.7 is considered acceptable, indicating adequate reliability, while values above 0.8 are deemed good, and values above 0.9 are excellent but may indicate redundancies (Hair et al. 2022; Hanafiah 2020). In this model, α-values for *relative advantage* (0.877) and *compatibility* (0.935) indicate strong internal consistency, demonstrating that these items reliably measure their intended constructs. In contrast, *complexity* presents a lower α of 0.588, which could suggest issues with item alignment. This lower value may partly stem from the inclusion of an inverted item within this construct, which could have been misunderstood by respondents, leading to an inconsistent interpretation on the Likert scale. This could indicate a potential design issue within the questionnaire, where the inverted item might not align well with the other indicators, affecting overall reliability. Constructs like *perceived ease of use* (0.773) and *training* (0.735) meet acceptable reliability thresholds, supporting their internal consistency (Table 3).

Composite Reliability (ρ_c) is frequently used in PLS-SEM as an alternative to Cronbach's alpha, as it accounts for the varying loadings of individual items, offering a more accurate measure of internal consistency. Like α-values, ρ_c-values above 0.7 are considered acceptable, while values above 0.8 are good. ρ_c is an additional measure to PLS-SEM, which accommodates different indicator loadings and is more reflective of the construct's true reliability compared to α (Hair et al. 2022; Becker

Table 3 Composite validity tests

Construct	α	ρ_c	*AVE*
Relative advantage	0.877	0.924	0.802
Compatibility	0.935	0.953	0.836
Complexity	0.588	0.742	0.537
Training	0.735	0.842	0.642
Maturity	0.828	0.895	0.741
Leadership support	0.822	0.883	0.715
Competitive pressure	0.818	0.891	0.736
Partner support	0.901	0.931	0.773
Perceived usefulness	0.932	0.956	0.880
Perceived ease of use	0.773	0.868	0.688
Intention to adopt	0.942	0.963	0.896

et al. 2022). For our model, the ρ_c-values reinforce the insights from Cronbach's alpha. *Relative advantage* and *compatibility* show high Composite Reliability values of 0.924 and 0.953, respectively, confirming their robust internal consistency. The *complexity* construct, however, presents a ρ_c of 0.742, which, while acceptable, is lower relative to other constructs. This aligns with Cronbach's alpha results, supporting the notion that *complexity* may need refinement.

In addition to Cronbach's alpha and composite reliability, we examined the average variance extracted (*AVE*) to assess the convergent validity of each construct. *AVE*-values indicate the proportion of variance in the indicators explained by the latent construct and should ideally be 0.5 or higher. Values above this threshold suggest that the construct explains a sufficient portion of the variance in its indicators, supporting convergent validity (Hair et al. 2022). In this study, *relative advantage* (0.802), *compatibility* (0.836), *perceived usefulness* (0.880), and *intention to adopt* (0.896) demonstrate strong *AVE*-values, indicating that these constructs capture substantial variance from their indicators. However, *complexity* shows a low *AVE*-value of 0.537, close to the commonly accepted threshold, which could suggest issues with item alignment or potentially misunderstood items within this construct. This aligns with our previous observation of lower reliability metrics for *complexity*, likely influenced by an inverted item that may have caused inconsistent responses. Other constructs fall within acceptable ranges, reinforcing their convergent validity.

To assess the robustness of the complexity construct, we re-estimated the model after removing the reverse-coded item (CX2) that exhibited low loading. Removing CX2 increases Cronbach's alpha from 0.588 to 0.715 and *AVE* from 0.537 to 0.778. The structural model results remain substantively unchanged: the paths from complexity to perceived usefulness and perceived ease of use retain their direction and significance levels. These supplementary results confirm that the instability in the complexity construct is localized to the reverse-coded item and does not materially affect the substantive conclusions.

Together, Cronbach's alpha, composite reliability, and average variance extracted provide a comprehensive assessment of each construct's internal consistency and validity. While most constructs meet the necessary thresholds, *complexity* appears to require further refinement to enhance alignment across its items.

4.1.2 Discriminant validity

Discriminant validity testing is an essential step to ensure that the latent variables in the PLS-SEM model are distinguishable from each other. Several approaches were used for this purpose: the analysis of correlations, the variance inflation factor (*VIF*), the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations (*HTMT*).

The correlations between the latent variables were analyzed to obtain initial indications of possible correlations between the constructs. The correlations range from 0.041 (between *maturity* and *competitive pressure*) to 0.857 (between *perceived usefulness* and *intention to adopt*). High correlations, such as between *perceived usefulness* and *intention to adopt* (0.857), indicate a strong relationship and can theoretically be explained by the close connection between the concepts. However, such a high correlation may also indicate a lack of discriminant validity. Part of the close proximity between perceived usefulness and intention to adopt may be attributable to item wording: ITA1 ("a cloud analytics solution is advantageous for our firm") is phrased in advantage terms that overlap conceptually with perceived usefulness and relative advantage. We therefore treat the magnitude of the relationship as partly reflecting this overlap and flag item refinement as a priority for replication. In contrast, the very low correlation of 0.041 between *maturity* and *competitive pressure* shows that these variables act independently of each other and describe different aspects of technology acceptance (Table 4).

The remaining correlations are mostly in a moderate range, such as the relationship between *compatibility* and *perceived ease of use* (0.749) or between *relative advantage* and *perceived usefulness* (0.736). These values reflect the theoretical

Table 4 Correlation matrix

	RA	CB	CX	TR	MA	LS	CP	PS	PU	PEOU	ITA
Relative advantage (RA)	1.000										
Compatibility (CB)	0.742	1.000									
Complexity (CX)	0.440	0.555	1.000								
Training (TR)	0.379	0.462	0.586	1.000							
Maturity (MA)	0.204	0.387	0.455	0.492	1.000						
Leadership support (LS)	0.562	0.716	0.502	0.521	0.392	1.000					
Competitive pressure (CP)	0.430	0.333	0.227	0.226	0.041	0.300	1.000				
Partner support (PS)	0.708	0.720	0.399	0.430	0.336	0.571	0.361	1.000			
Perceived usefulness (PU)	0.736	0.769	0.434	0.343	0.234	0.570	0.397	0.731	1.000		
Perceived ease of use (PEOU)	0.626	0.749	0.584	0.534	0.446	0.584	0.311	0.587	0.683	1.000	
Intention to adopt (ITA)	0.773	0.825	0.462	0.385	0.254	0.607	0.411	0.750	0.857	0.695	1.000

assumptions that perceived advantages and compatibility are central influencing factors on the intention to use and ease of use, without, however, indicating an overlap between the constructs. As provided in Table 12 of the online appendix, the *VIF* quantifies multicollinearity among predictors, with values below 5 (preferably below 3) indicating acceptable levels (Hair et al. 2019). The *VIF*-values are predominantly below the threshold of 3. One construct, *compatibility* (to *perceived usefulness* 4.019; to *perceived ease of use* 3.425), exceeds the threshold of 3, but remains below the critical threshold of 5, indicating that these constructs remain sufficiently independent. The *VIF*-analysis confirms that all constructs meet the PLS-SEM criteria for discriminant validity, additionally suggesting that CMB is unlikely to substantively bias the results.

The Fornell-Larcker criterion was applied to assess the discriminant validity of the constructs in the model. This criterion compares the square root of the average variance extracted (*AVE*) for each construct with the pairwise correlations between constructs (Fornell and Larcker 1981). The analysis confirmed that all constructs satisfy the criterion, as the square roots of their *AVE*-values are greater than their highest inter-construct correlations. These results demonstrate that the measurement model achieves satisfactory discriminant validity. The evaluation is presented in Table 5, derived from the Fornell-Larcker criterion matrix provided in Table 13 of the online appendix.

Analyzing the *HTMT*-values also shows that most variables do not exceed the recommended threshold of 0.90 (Henseler et al. 2014). An exception is again the relationship between *perceived usefulness* and *intention to adopt*, where an *HTMT*-value of 0.913 was calculated. This study accepts this value since it relies on standard approach for TAM validated in several studies and a standard questionnaire (Davis 1989; Gangwar et al. 2015; Lee et al. 2003; Yousafzai et al. 2007). However, it demonstrates a need for further item refinement in the presented context (Table 6).

In summary, the measurement model demonstrates adequate psychometric properties for an exploratory study. Convergent validity is confirmed for most constructs, with *AVE* values exceeding the 0.5 threshold (Hair et al. 2022). The *complexity* construct represents a notable exception, with lower Cronbach's alpha (0.588) and *AVE*

Table 5 Fornell-Larcker criterion evaluation

Construct	Square root of *AVE*	Max. corr	To construct	Passed?
Relative advantage (RA)	0.896	0.773	ITA	Yes
Compatibility (CB)	0.914	0.825	ITA	Yes
Complexity (CX)	0.733	0.586	TR	Yes
Training (TR)	0.801	0.586	CX	Yes
Maturity (MA)	0.861	0.492	TR	Yes
Leadership support (LS)	0.846	0.716	CB	Yes
Competitive pressure (CP)	0.858	0.750	ITA	Yes
Partner support (PS)	0.879	0.430	RA	Yes
Perceived usefulness (PU)	0.938	0.857	ITA	Yes
Perceived ease of use (PEOU)	0.829	0.749	CB	Yes
Intention to adopt (ITA)	0.947	0.857	PU	Yes

Table 6 Heterotrait-monotrait ratio matrix

	RA	CB	CX	TR	MA	LS	CP	PS	PU	PEOU	ITA
Relative advantage (RA)											
Compatibility (CB)	0.814										
Complexity (CX)	0.595	0.639									
Training (TR)	0.412	0.526	0.756								
Maturity (MA)	0.225	0.424	0.576	0.636							
Leadership support (LS)	0.568	0.732	0.557	0.691	0.447						
Competitive pressure (CP)	0.478	0.353	0.344	0.252	0.087	0.324					
Partner support (PS)	0.810	0.804	0.545	0.520	0.421	0.587	0.398				
Perceived usefulness (PU)	0.807	0.821	0.522	0.359	0.252	0.557	0.425	0.810			
Perceived ease of use (PEOU)	0.754	0.876	0.739	0.678	0.533	0.673	0.373	0.729	0.795		
Intention to adopt (ITA)	0.842	0.876	0.542	0.405	0.271	0.588	0.438	0.824	0.913	0.809	

(0.537), likely attributable to the inclusion of a reverse-coded item that may have introduced response inconsistencies. While *complexity* is retained in the model to preserve theoretical completeness, the results for hypotheses involving this construct should be interpreted with appropriate caution. Discriminant validity is broadly established through the Fornell-Larcker criterion, *VIF* analysis, and *HTMT* ratios. However, the high *HTMT* value between *perceived usefulness* and *intention to adopt* (0.913) warrants careful consideration. This overlap is consistent with prior TAM research where these constructs are closely related (Davis 1989; Venkatesh and Davis 2000), and the *VIF* values remain below the critical threshold of 5, suggesting that multicollinearity does not undermine the structural model. Nonetheless, this proximity limits the degree to which the extended TOE variables can be said to add explanatory power beyond the TAM core, and we address this point explicitly in the discussion.

4.1.3 Model fit

This section evaluates the quality of the model by analyzing its ability to explain variance in the dependent variables, examining the effect sizes of predictors, and assessing overall model fit.

The study employs the cross-validated predictive ability test (CVPAT) due to its focus on predictive performance (Liengaard et al. 2020). CVPAT not only evaluates predictive relevance through repeated cross-validation but also includes statistical significance tests to confirm whether the PLS-SEM model delivers better predictions

Table 7 PLS-SEM compared to indicator averages

Construct	PLS loss	IA loss	Avg. loss diff	t-value	p-value
Perceived usefulness	1.249	2.847	−1.598	9.330	0.000
Perceived ease of use	1.446	2.515	−1.069	8.836	0.000
Intention to adopt	1.002	3.003	−2.001	12.829	0.000
Overall	1.232	2.788	−1.556	11.933	0.000

Table 8 PLS-SEM vs. linear model

Construct	PLS loss	LM loss	Avg. loss diff	t-value	p-value
Perceived usefulness	1.249	1.147	0.102	1.776	0.077
Perceived ease of use	1.446	1.461	−0.015	0.426	0.670
Intention to adopt	1.002	0.937	0.064	1.691	0.092
Overall	1.232	1.182	0.050	1.690	0.092

Table 9 Adjusted R-squared

Construct	Adjusted R^2
Perceived usefulness	0.670
Perceived ease of use	0.632
Intention to adopt	0.782

than benchmarks like indicator averages or simple linear models (Liengaard et al. 2020; Becker et al. 2022). This ensures robust and practically relevant results. The predictive losses for all constructs and the overall model are consistently lower for PLS-SEM compared to indicator averages (cf. Table 7), with the differences confirmed as statistically significant. This finding underscores the predictive accuracy of PLS-SEM, making it a more reliable approach when assessing the practical implications of cloud analytics adoption in SMEs.

When compared with the linear model, PLS-SEM shows similar predictive performance (cf., Table 8). The differences in predictive losses between the two methods are minimal and statistically insignificant, indicating that both approaches perform comparably in terms of predictive accuracy. However, PLS-SEM's ability to significantly outperform indicator averages suggests that it offers unique advantages in modeling complex relationships while maintaining predictive robustness. This affirms the robustness and suitability of PLS-SEM for this analysis (Liengaard et al. 2020).

R-squared (R^2) indicates the proportion of variance explained by the predictors for each dependent variable, providing insight into the model's explanatory power (Hair et al. 2021). The adjusted R^2-value was utilized to assess the explanatory power of the model while accounting for the number of predictors, ensuring a more accurate evaluation of the model's fit and reduced risk of overfitting (Hair et al. 2021) (Table 9).

While, *perceived usefulness* and *perceived ease of use* show moderate R^2-values above the threshold of 0.5, the *intention to adopt* on the other hand demonstrates an R^2-values with substantial explanatory power above the threshold of 0.75 (Hair et al. 2021; Ozili 2022). Effect size (f^2) assesses the individual impact of each predictor on the dependent variables, with f^2-values of 0.02, 0.15, and 0.35 considered small, medium, and large, respectively (Hair et al. 2021). *Relative advantage* has a moderate effect size of 0.133 on *perceived usefulness* and a small effect size of 0.030 on *perceived ease of use*, suggesting a notable influence on *perceived usefulness*. *Compatibility* demonstrates moderate to large effects on both *perceived usefulness* (0.112) and *perceived ease of use* (0.174), confirming its significant role in influencing these constructs. *Competitive pressure* exerts a small effect size of 0.104 on *intention to adopt*, indicating a modest contribution. Notably, the relationship between *perceived usefulness* and *intention to adopt* has the largest effect size (0.515).

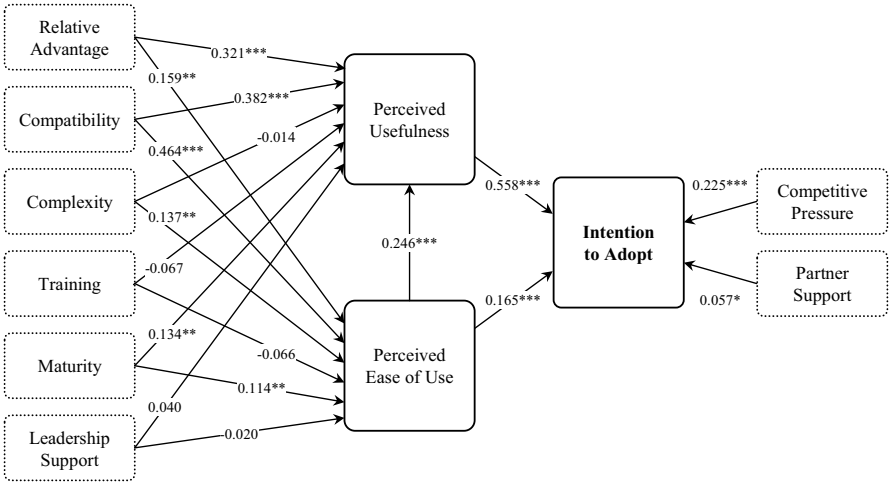
Other predictors, such as *partner support* (0.013 on *intention to adopt*) and *maturity* (0.024 on *perceived ease of use*), have minimal effects, highlighting *perceived usefulness* and *compatibility* as particularly impactful factors within the model. Furthermore, *complexity* (on *perceived usefulness* 0.000), Leadership Support (on *perceived usefulness* 0.002, on *perceived ease of use* 0.001) demonstrate no notable effect size. A detailed overview with significance levels is displayed in Table 14 of the online appendix. The model's overall fit is additionally evaluated through the standardized root mean square residual (*SRMR*), which indicates good fit when values are below 0.08 (Hair et al. 2019, 2021). The values of 0.086 for the saturated model and 0.088 for the estimated model imply acceptable fit for the explorative model (Kenny 2024; Hu and Bentler 1999) (Table 15).

In summary, the model demonstrates high explanatory power, as evidenced by the strong R^2 values, particularly for *intention to adopt*. Effect sizes highlight the practical significance of predictors like *perceived usefulness* and *compatibility*, which show the largest influences on key outcomes. Model fit indices, including *SRMR* and discrepancy measures, indicate an acceptable fit with the observed data. The path coefficients validate several theoretical relationships, with *relative advantage*, *compatibility*, and *perceived usefulness* emerging as influential constructs. Collectively, these evaluations confirm the robustness and predictive capability of the model, supporting its reliability for interpreting adoption intentions within this context.

4.2 Hypotheses testing

For evaluating the structural model, the path coefficients were analyzed for significance. Bootstrapping was used to calculate confidence intervals and p-values. Significant path coefficients demonstrate the strength of the relationships between constructs. As shown in Figure 2, most path coefficients were significant, further supporting the strength of the proposed relationships.

In H1, *relative advantage* was hypothesized to have a positive effect on both *perceived usefulness* and *perceived ease of use*. The results show a significant positive



Note: *p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001

Fig. 2 Research model and path coefficients with related p-values

effect of *relative advantage* on *perceived usefulness* ($\beta = 0.321$, $p < 0.001$), supporting H1a. Similarly, *relative advantage* also shows a positive and significant effect on *perceived ease of use* ($\beta = 0.159$, $p = 0.002$), supporting H1b.

The second hypothesis H2 proposed *compatibility* to positively influence both *perceived usefulness* and *perceived ease of use*. The results indicate a strong positive relationship between *compatibility* and *perceived usefulness* ($\beta = 0.382$, $p < 0.001$), leading to the acceptance of H2a. Additionally, *compatibility* has a substantial positive effect on *perceived ease of use* ($\beta = 0.464$, $p < 0.001$), supporting H2b.

Complexity was expected to have a negative impact on *perceived usefulness* and *perceived ease of use*. However, the data show no significant relationship between *complexity* and *perceived usefulness* ($\beta = -0.014$, $p = 0.764$), leading to the rejection of H3a. Interestingly, *complexity* shows a small but positive effect on PEOU ($\beta = 0.137$, $p = 0.006$), contradicting the hypothesized direction and resulting in the rejection of H3b. These results are in line with the effect sizes f^2.

In H4, *training* was hypothesized to positively influence *perceived usefulness* and *perceived ease of use*. The results reveal no significant effect of *training* on *perceived usefulness* ($\beta = -0.067$, $p = 0.114$), leading to the rejection of H4a. In contrast, *training* has a significant positive effect on *perceived ease of use* ($\beta = 0.134$, $p = 0.003$), supporting H4b.

Maturity was hypothesized to positively affect *perceived usefulness* and *perceived ease of use*. The results show no significant relationship between *maturity* and *perceived usefulness* ($\beta = -0.066$, $p = 0.099$), leading to the rejection of H5a. However, *maturity* does have a significant positive effect on *perceived ease of use* ($\beta = 0.114$, $p = 0.004$), supporting H5b.

Leadership support was expected to positively impact *perceived usefulness* and *perceived ease of use*. However, the data indicate no significant effect of *leadership support* on *perceived usefulness* ($\beta = 0.040$, $p = 0.407$), resulting in the rejection of H6a. Similarly, *leadership support* shows no significant influence on *perceived ease of use* ($\beta = -0.020$, $p = 0.678$), leading to the rejection of H6b. Both are in line with the effect sizes f^2.

Competitive pressure was hypothesized to have a positive effect on *intention to adopt*. The results support this hypothesis, as *competitive pressure* shows a small but significant positive effect on *intention to adopt* ($\beta = 0.225$, $p < 0.001$), leading to the acceptance of H7.

Partner support was expected to positively influence *intention to adopt*. The results confirm this hypothesis, as *partner support* has a significant positive effect on *intention to adopt* ($\beta = 0.057$, $p < 0.05$), providing evidence for the support of H8.

The core constructs of the TAM, *perceived usefulness* and *perceived ease of use*, were hypothesized to positively influence *intention to adopt* and each other. The results indicate a strong positive effect of *perceived usefulness* on *intention to adopt* ($\beta = 0.558$, $p < 0.001$), supporting H9a and highlighting *perceived usefulness* as a key determinant of adoption intentions. *Perceived ease of use* also has a significant positive effect on *intention to adopt* ($\beta = 0.165$, $p < 0.001$), confirming H9b and suggesting that ease of use enhances the intention to adopt cloud analytics. Additionally, *perceived ease of use* positively affects *perceived usefulness* ($\beta = 0.246$, $p < 0.001$), supporting H9c.

The following Table 10 shows the discussed hypotheses in an aggregated form. Most hypotheses were supported by the data, particularly those related to *relative advantage*, *compatibility*, *training*, *maturity*, *competitive pressure*, *partner support*, and the core constructs of *perceived usefulness* and *perceived ease of use* as they influence the *intention to adopt*. However, mainly *leadership support* and a set of factors on *perceived usefulness*–namely *complexity*, *training*, and *maturity*–did not show a significant effect as hypothesized, suggesting that these may play a limited role in determining usefulness and ease of use of SMEs' cloud analytics adoption.

5 Discussion

5.1 Contextualized key findings

Compatibility emerged as the strongest predictor of both *perceived usefulness* ($\beta = 0.382$, $p < 0.001$) and *perceived ease of use* ($\beta = 0.464$, $p < 0.001$), highlighting the importance of aligning new technologies with existing workflows, organizational culture, and business models. Such alignment minimizes operational disruptions and resistance to change, thereby facilitating smoother adoption processes. This finding is consistent with prior research emphasizing compatibility as a critical enabler for technological innovations in resource-constrained contexts (Gholami et al. 2018; Chat-

Table 10 Hypotheses evaluation

Hypothesis	Path	Path coeff	t-value	p-value	Evidence
H1a	Relative advantage $\xrightarrow{+}$ Perceived usefulness	0.321	5.705	0.000	Supported
H1b	Relative advantage $\xrightarrow{+}$ Perceived ease of use	0.159	3.122	0.002	Supported
H2a	Compatibility $\xrightarrow{+}$ Perceived usefulness	0.382	5.366	0.000	Supported
H2b	Compatibility $\xrightarrow{+}$ Perceived ease of use	0.464	8.346	0.000	Supported
H3a	Complexity $\xrightarrow{-}$ Perceived usefulness	−0.014	0.300	0.764	Not supported
H3b	Complexity $\xrightarrow{-}$ Perceived ease of use	0.137	2.761	0.006	Not supported
H4a	Training $\xrightarrow{+}$ Perceived usefulness	−0.067	1.583	0.114	Not supported
H4b	Training $\xrightarrow{+}$ Perceived ease of use	0.134	3.019	0.003	Supported
H5a	Maturity $\xrightarrow{+}$ Perceived usefulness	−0.066	1.652	0.099	Not supported
H5b	Maturity $\xrightarrow{+}$ Perceived ease of use	0.114	2.847	0.004	Supported
H6a	Leadership support $\xrightarrow{+}$ Perceived usefulness	0.040	0.829	0.407	Not supported
H6b	Leadership support $\xrightarrow{+}$ Perceived ease of use	−0.020	0.416	0.678	Not supported
H7	Competitive pressure $\xrightarrow{+}$ Intention to adopt	0.225	4.841	0.000	Supported
H8	Partner support $\xrightarrow{+}$ Intention to adopt	0.057	2.369	0.018	Supported
H9a	Perceived usefulness $\xrightarrow{+}$ Intention to adopt	0.558	9.939	0.000	Supported
H9b	Perceived ease of use $\xrightarrow{+}$ Intention to adopt	0.165	4.243	0.000	Supported
H9c	Perceived ease of use $\xrightarrow{+}$ Perceived usefulness	0.246	3.990	0.000	Supported

terjee et al. 2021). For German SMEs specifically, Kohn and Hüsig (2006) emphasize that compatibility not only streamlines integration but also reinforces acceptance by ensuring that employees can readily adapt to new systems. The finding that compatibility outperforms all other TOE predictors suggests that in SME contexts, the critical contingency for technology adoption is not resource availability or top-down commitment, but rather the degree to which the technology aligns with established work practices. This extends contingency-theoretic accounts of IT adoption by specifying

workflow alignment as a primary mechanism through which organizational context shapes individual perception in resource-constrained settings.

Relative advantage also demonstrated a significant impact on both *perceived usefulness* ($\beta = 0.321$, $p < 0.001$) and perceived ease of use ($\beta = 0.159$, $p < 0.01$), underscoring SMEs' preference for solutions that bring tangible operational benefits. This aligns with Rogers' diffusion of innovations theory, which identifies functional advantages-such as cost-efficiency-as key adoption drivers (Sahin 2006).

In the German context, Karunagaran et al. (2017) noted similar trends, where perceived advantages such as improved scalability and data-driven decision-making led SMEs to adopt cloud-based tools despite concerns about regulations like GDPR. Early adopters often seek first-mover advantages, while more cautious firms await proof of these benefits.

Competitive pressure ($\beta = 0.225$, $p < 0.001$) significantly influenced the *intention to adopt*, reflecting the interplay between external market forces and organizational decision-making. Rapid digitalization in manufacturing and retail markets may intensify such pressure for German SMEs (Hentschel et al. 2019). Yet, studies in more stable environments have found that competitive pressure plays a lesser role in adoption (Alshamaila et al. 2013), highlighting how regional and sector-specific factors can alter technology uptake. Service partner support, though small ($\beta = 0.057$, $p = 0.018$), suggests that trusted external expertise still matters, especially when SMEs lack internal capacity to handle complex technologies. These external partners may indirectly influence other constructs (e.g., reducing integration barriers or addressing skill gaps) rather than exerting a strong direct effect on intention (Alshamaila et al. 2013).

Complexity, *training*, and *maturity* each showed a modest but significant positive effect on *perceived ease of use*. *Complexity* ($\beta = 0.137, p < 0.01$) unexpectedly displayed a positive relationship, indicating that SMEs may view complexity as surmountable if the perceived long-term benefits are compelling and adequate support is available (Abdekhoda et al. 2019). This suggests that advanced features do not necessarily deter adoption, provided the firm anticipates improvements in efficiency, scalability, or competitive positioning. Likewise, *training* ($\beta = 0.134, p < 0.01$) underscores the role of skilled employees in reducing perceived difficulty (Gangwar et al. 2015), while *maturity* ($\beta = 0.114, p < 0.01$) points to how adaptive cultures and robust IT infrastructures facilitate smoother integration (Hentschel et al. 2019). Even so, rigid hierarchies or limited digital leadership may undermine these benefits in some SMEs, emphasizing that organizational attributes are critical to user-friendly adoption.

Because two of the three complexity items tap compatibility and resource readiness rather than difficulty, the positive association between"complexity"and perceived ease of use should be read as a likely measurement artefact rather than as evidence that greater task difficulty improves ease of use; we refrain from a strong substantive interpretation of this path.

The TAM constructs further clarified adoption pathways: *Perceived usefulness* was a much stronger predictor of *intention to adopt* ($\beta = 0.558, p < 0.001$) than *perceived ease of use* ($\beta = 0.165, p < 0.001$). This underscores an outcome-oriented mindset in which expected gains outweigh initial usability concerns (Gangwar et al. 2015). Nonetheless, *perceived ease of use* still positively influences *perceived usefulness* ($\beta = 0.246, p < 0.001$), indicating that ease-of-use perceptions reinforce usefulness beliefs, a classic TAM relationship also observed in other organizational contexts (Venkatesh et al. 2012). In many German SMEs, strong emphasis on compliance and operational efficiency may intensify the importance of perceived utility over ease-of-use (Alshamaila et al. 2013).

Certain findings were non-significant, particularly the effects of *leadership support*, *complexity*, *training*, and *maturity* on *perceived usefulness*. *Leadership support* did not directly affect *perceived usefulness* or *perceived ease of use* ($\beta = 0.040$ and $\beta = -0.020$, both $p > 0.05$), possibly because many technical decisions and user perceptions form at operational levels or through external collaborations (Gangwar et al. 2015). The non-significance of leadership support on both perceived usefulness and perceived ease of use is a notable departure from prior TOE research, which consistently identifies management support as a key adoption enabler (Gangwar et al. 2015; Chatterjee et al. 2021). In the SME context, this finding may reflect the structural reality that leadership in small firms shapes adoption through indirect channels like resource allocation, culture setting, and vendor selection rather than through direct influence on individual technology perceptions. This distinction has implications for how leadership constructs should be modeled in future SME adoption research.

Complexity did not significantly influence *perceived usefulness* ($\beta = -0.014, p > 0.05$), suggesting SMEs assume that modern SaaS tools inherently deliver value if they are adopted (Abdekhoda et al. 2019). Similarly, *training* ($\beta = -0.067, p > 0.05$) and *maturity* ($\beta = -0.066, p > 0.05$) may be overshadowed by the role of external service providers or the prioritization of strategic objectives (Alshamaila et al. 2013; Hentschel et al. 2019). Future research could examine how these constructs interact with sector-specific pressures, external partnerships, or leadership styles to uncover indirect pathways influencing *perceived usefulness* and overall adoption decisions.

5.2 Theoretical contribution

This study's contribution lies less in proposing a new adoption theory than in showing precisely how established TAM-TOE mechanisms operate in the specific context of cloud analytics adoption in SMEs. Within this context, the study clarifies which mechanisms matter most and where common assumptions do not hold, in three respects.

First, the findings challenge the prevalent assumption in prior TOE research (Gangwar et al. 2015; Chatterjee et al. 2021) that *leadership support* is a universal enabler of technology adoption. In the present study, *leadership support* showed no

significant effect on either *perceived usefulness* ($\beta = 0.040$, p = 0.407) or *perceived ease of use* ($\beta = -0.020$, p = 0.678). This suggests that in SME contexts, where organizational hierarchies are flat and decision-making is often informal, leadership may shape adoption indirectly, e.g., through resource allocation, vendor selection, or culture setting, rather than through direct influence on individual technology perceptions. Future research on SME adoption should therefore consider modeling leadership as a moderating factor rather than a direct antecedent of perception.

Second, the unexpected positive effect of *complexity* on perceived ease of use ($\beta = 0.137$, p = 0.006) warrants theoretical attention, though this finding should be interpreted cautiously given the construct's lower reliability ($\alpha = 0.588$). If substantive, this result would suggest that SME employees do not perceive *complexity* as an unconditional barrier; rather, when a technology offers clear *relative advantage* and *compatibility* with existing workflows, users may accept or even expect a degree of *complexity* as inherent to a capable tool. This nuances the conventional negative framing of *complexity* in adoption models (Gholami et al. 2018; Liu et al. 2020) and points toward interaction effects between TOE constructs that linear models may not fully capture.

Third, a candid assessment of the model's explanatory structure is warranted. The high correlation between *perceived usefulness* and *intention to adopt* (corr. = 0.857, HTMT = 0.913) and the dominant effect size of the path from *perceived usefulness* to *intention to adopt* ($f^2 = 0.515$) indicate that a substantial share of the model's explanatory power is driven by the familiar TAM core. This is not unexpected, as TAM's predictive strength for adoption intention is well established (Davis 1989). The value of the extended model lies not in rivaling this core relationship but in illuminating the antecedent conditions that shape perceived usefulness and perceived ease of use. *Compatibility* emerged as the strongest TOE predictor on both mediators ($\beta = 0.382$ / 0.464), followed by relative advantage ($\beta = 0.321$ / 0.159), demonstrating that organizational and technological context factors operate upstream of the TAM constructs. The integrated model thus provides a richer understanding of why employees in SMEs perceive cloud analytics as useful (e.g., because of alignment with existing workflows and tangible operational benefits) rather than merely confirming that perceived usefulness drives intention. Taken together, these contributions specify which TOE mechanisms matter most in SME settings and how they interact with established TAM relationships.

5.3 Practical implications

The findings of this study provide actionable insights for three key stakeholder groups: SMEs, cloud service providers, and policymakers. Each group has distinct responsibilities and opportunities to address adoption challenges and promote the effective use of cloud analytics.

SMEs should prioritize cloud solutions offering strong relative advantage and compatibility, ensuring seamless integration with existing workflows and clear operational benefits. To manage complexity, SMEs can adopt incremental strategies (e.g., pilot projects, minimum viable products), testing solutions in controlled environments before broader roll-outs (Barata et al. 2018; Cornejo Fandos 2023). Given that

compatibility emerged as the strongest predictor of both perceived usefulness (β = 0.382) and perceived ease of use (β = 0.464), SMEs should prioritize cloud solutions that integrate seamlessly with their existing workflows, tools, and organizational culture rather than pursuing feature-rich platforms that require substantial process redesign. Although leadership support did not directly shape perceptions in our data, its likely role is indirect: by allocating resources, selecting suitable vendors, and setting an open, adoption-friendly culture, leadership can create the conditions under which compatibility and relative advantage are realized (Nielson 2024; Strawser 2023; Venkatesh et al. 2012). Recommendations for leaders should therefore target these enabling levers rather than assume a direct effect on how employees perceive the technology. By championing a clear vision and leveraging external expertise, they can address skill gaps, strengthen employee confidence, and ensure successful integration (Creasey 2025).

Cloud service providers should offer intuitive, modular, and scalable solutions that emphasize *relative advantage* and *compatibility* with SME operations. Simplifying onboarding processes tackles complexity and builds trust (Alshamaila et al. 2013; Hentschel et al. 2019). Transparency in compliance and data governance is key for regulated environments like Germany (Fraunhofer 2021). Comprehensive security measures and customer-centric support can strengthen trust-based relationships and encourage adoption (Justy et al. 2023). Given that *relative advantage* significantly influences *perceived usefulness* (β = 0.321), providers should clearly communicate tangible operational benefits, such as cost savings, scalability, and time efficiency, rather than emphasizing technical sophistication. Moreover, adapted offering options might have the ability to mitigate concerns about vendor lock-in, data sovereignty, and varying compliance standards, aligning cloud solutions with SMEs' operational and regulatory contexts (Chatterjee et al. 2021; Gangwar et al. 2015).

Although *partner support* showed a modest direct effect on *intention to adopt* (β = 0.057, p = 0.018), its significance suggests that external expertise remains a relevant enabler for SMEs that lack internal capacity to evaluate and implement cloud analytics. Policymakers can leverage this by facilitating structured intermediary programs, such as subsidized consulting services, regional competence centers, or industry-academia partnerships, that connect SMEs with trusted technical partners. Financial incentives such as grants or tax credits can further lower the initial cost barrier for budget-limited SMEs (Kohn and Hüsig 2006). Additionally, clear and actionable guidelines on GDPR and data protection help small firms navigate legal complexities that our data show do not deter adoption when compatibility and relative advantage are perceived as strong, but that may discourage less digitally mature SMEs from exploring cloud solutions in the first place (Fraunhofer 2021; Hentschel et al. 2018; Justy et al. 2023).

5.4 Limitations and future research

Although this study provides valuable insights into cloud analytics adoption in German SMEs, several methodological, conceptual, and contextual limitations merit consideration.

Methodologically, the construct *complexity* showed inconsistencies, suggesting it may not be strictly unidimensional (Abdekhoda et al. 2019). Modern SaaS tools appear to reduce the perceived burden of complexity (Venkatesh and Davis 2000), indicating a need to distinguish between technical, organizational, and cognitive facets. Discriminant validity challenges arose between *perceived usefulness* and *intention to adopt* (*HTMT* = 0.913), and *compatibility* displayed high VIF values, implying potential overlap among constructs (Hair et al. 2019; Henseler et al. 2014). Employing moderation or mediation analysis could further clarify these relationships. More broadly, several constructs (complexity, training, and intention to adopt) contain items whose wording spans adjacent concepts (compatibility, resource readiness, perceived advantage). While this does not alter the direction of the main findings, the paths involving these constructs should be interpreted with corresponding caution, and future work should refine these instruments before drawing strong conclusions. Additionally, using PLS-SEM has confirmatory power limitations (Sarstedt et al. 2014). Comparing PLS-SEM results with covariance-based approaches may increase overall robustness. Further methodological limitations arise from the data collection process. The GDPR-compliant cold-call email approach, while enabling broad coverage of SMEs, inherently led to a low response rate and a risk of self-selection among digitally engaged respondents. Minor sampling biases were observed, with small firms and digitally oriented sectors slightly overrepresented and medium-sized as well as retail and health firms somewhat underrepresented. Although these deviations were small to moderate according to Cramér's V, they constrain the generalizability of the findings and point to the need for more balanced or sector-specific studies (Gangwar et al. 2014).

Despite the procedural and statistical CMB safeguards reported in Sections 3.3 and 4.1, and the presence of both significant and non-significant paths in the structural model, the single-source design remains an inherent limitation. Future research should consider multi-informant designs or longitudinal approaches to further strengthen causal inference.

Conceptually, although combining TAM and TOE provided a broad view (Gangwar et al. 2015), the fixed structure limited exploration of potential interactions, such as direct TOE influences on *intention to adopt* (Chatterjee et al. 2021; Kamal et al. 2020; Katebi et al. 2022). A purely perception-based approach can overlook real-world complexities, so mixed methods may capture operational nuances more effectively (Venkatesh et al. 2003). Evolving technologies and user perceptions also imply that *complexity* may become less salient over time (Venkatesh and Davis 2000), warranting ongoing reevaluation.

Contextually, focusing solely on German SMEs means the regulatory environment (e.g., GDPR) heavily shapes the findings (Brodin 2019; Gangwar et al. 2015). Cross-regional comparisons could uncover how different legal frameworks affect adoption. Cloud analytics' unique features, such as scalability and real-time capabilities, further limit direct extrapolation to other technologies. Additionally, sectoral specificity remains largely unaddressed; industries like manufacturing or finance may exhibit distinct adoption drivers (Chatterjee et al. 2021; Jamwal et al. 2023; Venkatesh et al.

2003). Future research should adopt a more granular, industry-focused lens and consider moderating or mediating variables (e.g., leadership style, external support) to deepen understanding of technology adoption. By addressing these limitations, subsequent studies can refine theoretical models and offer more nuanced, context-sensitive guidance for SMEs.

6 Conclusion and recommendations

This study highlights three primary drivers of cloud analytics adoption among German SMEs–*relative advantage*, *compatibility*, and *competitive pressure*–while also revealing how individual perceptions hinge on *complexity*, *training*, and *maturity*. *Relative advantage* reflects tangible benefits (e.g., cost management, scalability), whereas *compatibility* underscores the importance of aligning with established workflows and culture. Together, these factors motivate SMEs to integrate cloud solutions, especially in competitive markets that demand technological agility. Interestingly, SMEs appear willing to tolerate higher complexity when *relative advantage* and *compatibility* are strong. This suggests that perceived benefits can mitigate concerns about intricate technologies, provided that organizational structures and training resources are in place to ease adoption challenges.

Leadership's role emerges primarily as an enabler: By cultivating readiness, aligning strategies, and fostering an engaged workforce, executives may only indirectly shape successful adoption on an individual level. Investment in structured training and purposeful alignment can boost readiness, with initiatives like pilot programs, feedback loops, and cross-functional collaboration laying a foundation for smoother transitions. Service providers, for their part, can lower adoption barriers by offering SME-centric solutions that complement existing processes, presenting clear advantages, and delivering comprehensive training tailored to varying levels of digital maturity. Policymakers can further drive widespread uptake through targeted incentives, funding mechanisms, and transparent regulatory guidelines-a particularly pressing need in highly regulated environments.

Although these findings offer actionable insights, the reliance on self-reported data and potential sampling biases limit generalizability. Future research could address these limitations by exploring longitudinal trends, underrepresented SME sectors, and strategies for mitigating bias. Ultimately, close collaboration among SMEs, service providers, and policymakers is essential to overcoming hurdles like digital literacy gaps and resource constraints. By working in tandem, stakeholders can harness the full potential of cloud analytics, thereby enhancing SME resilience and competitiveness in an ever-evolving digital landscape.

Appendix A: Complementary tables and data

See Tables 11, 12, 13, 14 and 15.

Table 11 Measurement items and factor loadings

Constructs & related measurement items	Factor loading
Relative advantage (RA)	
RA1: A cloud analytics tool would allow our organization to scale its resources efficiently based on our needs	0.906
RA2: Paying for only the resources we use with this cloud analytics tool helps us manage our budget more effectively	0.868
RA3: The integration capabilities of a cloud analytics tool would streamline our data workflows and enhance efficiency	0.912
Compatibility (CB)	
CB1: Cloud analytics aligns with our strategy	0.931
CB2: Cloud analytics is compatible with our operational needs	0.939
CB3: The use of cloud analytics would be completely compatible with our current business operations	0.883
CB4: Using Cloud analytics would fit our organizational culture	0.903
Complexity (CX)	
CX1: Cloud analytics tools would be compatible with our existing technological architecture	0.890
CX2: The integration with our existing legacy system and connecting to our data is a difficult task for our organization. (reversed)	0.234
CX3: We have sufficient resources to support the implementation of a cloud analytics tool	0.874
Partner support (PS)	
PS1: I believe that Support from the cloud analytics partner is essential during its implementation process	0.894
PS2: Excellent partner support makes things easier to adopt	0.930
PS3: Partner support is essential for solving any technical issue quickly	0.898
PS4: I believe that support from partners is cost effective for our organization	0.788
Competitive pressure (CP)	
CP1: I understand that my company will have a competitive advantage by using a cloud analytics tool	0.931
CP2: I believe that cloud analytics is necessary for sustaining our industry	0.944
CP3: I am aware that a cloud analytics Tool is being implemented by a few of our competitors	0.671
Leadership support (LS)	
LS1: Our management promotes a culture of enterprise-wide information sharing	0.827
LS2: Our management provides strong leadership and actively engages in the adoption of new technologies	0.826
LS3: Our management is likely to view the adoption of cloud analytics as strategically important and would take the associated risks	0.882
Training (TR)	
TR1: The shown cloud analytics tool and its implementation are easily understandable to me	0.887

Table 11 (continued)

Constructs & related measurement items	Factor loading
TR2: I have all the resources needed to learn about analytics technology in my firm	0.815
TR3: Our company offers various training methods (e.g., virtual, in-person) within our organization	0.689
Maturity (MA)	
MA1: Our company has highly specialized or knowledgeable personnel in the area of analytics	0.918
MA2: Our company already has established structures, processes, and roles for analytics	0.918
MA3: We have a dedicated department or Center of Excellence within our organization for analytics	0.733
Perceived usefulness (PU)	
PU1: I agree that using a cloud analytics tool makes our firm more efficient	0.958
PU2: I believe that the use of cloud analytics increases productivity in our organization	0.963
PU3: I could achieve decisions in a quicker way using cloud analytics	0.920
Perceived ease of use (PEOU)	
PEOU1: It is easy for our organization to operate a cloud analytics to support our decision making process	0.950
PEOU2: I would be able to use the cloud analytics tool in our organization	0.952
PEOU3: I agree that all the related employees can quickly learn about the usage of cloud analytics	0.911
Intention to adopt (ITA) ($\alpha = 0.885$)	
ITA1: I think that a cloud analytics solution is advantageous for our firm	0.948
ITA2: I am in favor of a cloud analytics solution	0.963
ITA3: I would like to use a cloud analytics solution to its full potential	0.929

Table 12 Variance inflation factors

	PU	PEOU	ITA
Relative advantage	2.389	2.319	
Compatibility	4.019	3.425	
Complexity	1.920	1.869	
Training	1.889	1.839	
Maturity	1.511	1.475	
Leadership support	2.289	2.287	
Competitive pressure			1.204
Partner support			2.241
Perceived usefulness (PU)			2.804
Perceived ease of use (PEOU)	2.762		1.937
Intention to adopt (ITA)			

Table 13 Fornell-Larcker criterion matrix

	RA	CB	CX	TR	MA	LS	CP	PS	PU	PEOU	ITA
Relative advantage (RA)	0.896										
Compatibility (CB)	0.742	0.914									
Complexity (CX)	0.440	0.555	0.733								
Training (TR)	0.379	0.462	0.586	0.801							
Maturity (MA)	0.204	0.387	0.455	0.492	0.861						
Leadership support (LS)	0.562	0.716	0.502	0.521	0.392	0.846					
Competitive pressure (CP)	0.430	0.333	0.227	0.226	0.041	0.300	0.879				
Partner support (PS)	0.708	0.720	0.399	0.430	0.336	0.571	0.361	0.858			
Perceived usefulness (PU)	0.736	0.769	0.434	0.343	0.234	0.570	0.397	0.731	0.938		
Perceived ease of use (PEOU)	0.626	0.749	0.584	0.534	0.446	0.584	0.311	0.587	0.683	0.829	
Intention to adopt (ITA)	0.773	0.825	0.462	0.385	0.254	0.607	0.411	0.750	0.857	0.695	0.947

Table 14 Effect sizes f^2

Hypothesis	Path	Original sample (O)	Sample mean (M)	Std. dev. (STDEV)	t-value (|O/STDEV|)	p-value
H1a	Relative advantage $\xrightarrow{+}$ Perceived usefulness	0.133	0.140	0.051	2.584	0.010
H1b	Relative advantage $\xrightarrow{+}$ Perceived ease of use	0.030	0.033	0.020	1.495	0.135
H2a	Compatibility $\xrightarrow{+}$ Perceived usefulness	0.112	0.119	0.049	2.314	0.021
H2b	Compatibility $\xrightarrow{+}$ Perceived ease of use	0.174	0.179	0.052	3.346	0.001
H3a	Complexity $\xrightarrow{-}$ Perceived usefulness	0.000	0.004	0.005	0.057	0.955
H3b	Complexity $\xrightarrow{-}$ Perceived ease of use	0.028	0.033	0.022	1.246	0.213
H4a	Training $\xrightarrow{+}$ Perceived usefulness	0.007	0.010	0.010	0.699	0.484
H4b	Training $\xrightarrow{+}$ Perceived ease of use	0.027	0.031	0.019	1.407	0.160
H5a	Maturity $\xrightarrow{+}$ Perceived usefulness	0.009	0.012	0.012	0.763	0.445
H5b	Maturity $\xrightarrow{+}$ Perceived ease of use	0.024	0.027	0.018	1.360	0.174
H6a	Leadership support $\xrightarrow{+}$ Perceived usefulness	0.002	0.005	0.007	0.306	0.759
H6b	Leadership support $\xrightarrow{+}$ Perceived ease of use	0.001	0.003	0.005	0.102	0.918
H7	Competitive pressure $\xrightarrow{+}$ Intention to adopt	0.104	0.110	0.044	2.366	0.018
H8	Partner support $\xrightarrow{+}$ Intention to adopt	0.013	0.015	0.011	1.155	0.248
H9a	Perceived usefulness $\xrightarrow{+}$ Intention to adopt	0.515	0.528	0.127	4.051	0.000
H9b	Perceived ease of use $\xrightarrow{+}$ Intention to adopt	0.065	0.069	0.032	2.020	0.043
H9c	Perceived ease of use $\xrightarrow{+}$ Perceived usefulness	0.067	0.071	0.034	1.964	0.050

Table 15 SRMR

	Original sample (O)	Sample mean (M)	95 %	99 %
Saturated model	0.086	0.038	0.042	0.044
Estimated model	0.088	0.039	0.043	0.045

Author contributions B.L. supervised the study and wrote the main manuscript text. A.F. conducted the data collection and analysis. Both authors conceptualized the study and reviewed the manuscript.

Funding This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability No datasets were generated or analysed during the current study.

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