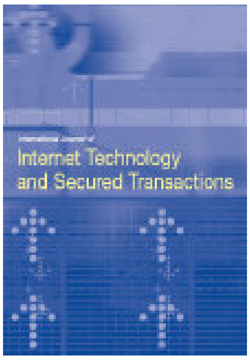

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The adoption of accounting system based on cloud computing in Chinese SMEs: a research based on the technology acceptance model framework

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Abstract: In the digital transformation era, cloud-based accounting systems can help Chinese SMEs reduce costs and optimise processes. However, their adoption still faces practical challenges. Most existing studies rely on the technology acceptance model (TAM) in foreign contexts, but this study extended TAM by incorporating three China-specific factors: perceived security (PS), cost-effectiveness, and government support. Using survey data and structural equation modelling, the results showed that perceived usefulness had the strongest influence on adoption intention; perceived ease of use affected intention both directly and indirectly; and perceived security and government support mainly exerted indirect effects by enhancing perceived usefulness. These findings provide practical insights for SMEs, service providers, and policymakers.

Keywords: technology acceptance model; TAM; reliability and validity test; cloud computing; accounting system; system services and applications.

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1 Introduction

With the deepening of the digital economy, the integration of cloud computing technology and accounting field has led to the emergence of cloud accounting system, whose architecture of 'standardisation of basic functions + customisation of advanced functions', dynamic capacity expansion and multi-terminal collaboration characteristics just match the characteristics of limited resources, weak IT foundation and flexible financial needs of small and medium-sized enterprises (SMEs). It has become a key tool for the digital transformation of accounting in SMEs. Due to data security concerns, high cost sensitivity and insufficient policy understanding, the adoption rate of cloud accounting in SMEs in China still lags behind the needs of digital transformation.

While there is extensive literature applying the TAM to cloud accounting adoption, the majority of it is situated in international contexts, and there is insufficient research on the adaptability between China's policy-driven market environment and the unique needs of SMEs, mainly because the localisation variables such as government policy support (GPS) are not included and the sample coverage is limited to a single region, which makes it difficult to reflect the differences between SMEs in eastern, central and western China. In addition, the traditional technology acceptance model (TAM) ignores the core concern of accounting data security, and does not fully consider the decision-making logic of SMEs' cost priority, which leads to the limited guiding value of the research conclusions to China's practice.

In order to fill the above gaps, this paper takes the TAM as the core, integrates three key variables of perceived security (PS), cost-benefit perception (CBE) and GPS, and constructs an extended model adapted to the Chinese context. To provide theoretical and practical support for promoting the digital transformation of accounting in SMEs.

The paper opens with a review of literature focusing on the technical features of cloud accounting systems and their fit with SMEs, alongside developments in the TAM. Subsequently, it outlines the logic behind the extended TAM and details the methodological approaches for assessing reliability (via Cronbach's alpha) and validity. Then it introduces the theoretical model construction, variable definition and measurement, data collection methods and data analysis ideas, and further presents the empirical results of sample characteristics, reliability and validity test, structural equation model (SEM) fitting and hypothesis testing, and carries out analysis and discussion. Finally, it synthesises the study's key findings, addresses limitations pertaining to the sample, variables, and underlying mechanisms, and delineates promising avenues for future research.

Furthermore, this study incorporates three China-specific variables – PS, CBE, and GPS – to address the unique contextual challenges faced by Chinese SMEs. China's stringent data security regulations (e.g., the Cybersecurity Law and Personal Information Protection Law) heighten SMEs' concerns over cloud accounting data leakage, justifying the inclusion of PS. The high cost sensitivity of SMEs due to financing difficulties aligns with the CBE variable, as SMEs prioritise short-term ROI. Additionally, China's policy-driven market environment, such as the 'Digital China' initiative and local government subsidies for digital transformation, underscores the relevance of GPS. These variables collectively capture the institutional, economic, and policy dimensions of the Chinese context, filling a critical gap in existing TAM-based research.

2 Related work

2.1 Technical characteristics of cloud accounting system and adaptability of SMEs

Cloud accounting system, as a specific application of cloud computing technology in the field of accounting, has a significant adaptation relationship between its technical characteristics and the organisational characteristics, resource constraints and growth needs of SMEs, which has attracted wide attention from academia.

A study by Tawfik et al. (2023), using a sample of SMEs in Oman, pointed out that cost-effectiveness and technical ease of use are the key technical characteristics affecting the use of cloud accounting. This study shows that the pay-as-you-go (SaaS) model of cloud accounting effectively reduces the initial IT investment cost of SMEs and avoids expensive hardware acquisition and software licensing fees. At the same time, providing intuitive user interface and simplified operation process can significantly reduce the learning cost of enterprise employees, thus overcoming internal resistance and promoting technology adoption. The empirical study of Rawashdeh and Rawashdeh (2023) further confirms that the adoption of cloud accounting has a positive impact on the organisational performance of SMEs. The research emphasises the importance of data sharing and collaboration. The cloud accounting platform realises the real-time sharing of financial data and multi-department and multi-location collaborative office, breaking the information island, thus improving the efficiency of decision-making and operational transparency. By automating routine processes, organisations can redirect their financial personnel's efforts from manual tasks to more strategic analytical functions. Al Okaily et al. (2023) explored the situation of SMEs in Jordan from the perspective of the post-epidemic era, highlighting the value of adapting the scalability of cloud accounting systems to remote access capabilities. The business volume of SMEs fluctuates greatly. Cloud accounting can flexibly allocate computing and storage resources according to the needs of enterprises, realise on-demand expansion, and avoid the problem of frequent upgrades or replacements of traditional software due to business growth. The case study of SMEs in Thailand by Sastararuji et al. (2022) reveals how the rapid deployment capability and subscription-based services of cloud accounting can help enterprises respond quickly to drastic changes in the external environment and achieve digital transformation with lower cost and risk during the COVID-19 epidemic. Hamzah and

Suhendar (2023) systematically summarises the multiple factors affecting the adoption of cloud accounting by SMEs. In addition to the above technical characteristics, it also points out the importance of the integration ability with existing systems and the technical support and reputation of service providers. Whether the cloud accounting system can be seamlessly integrated with the existing business systems such as inventory and CRM to form an integrated management ecosystem is the key to determine the depth and effect of its application. Alnaimat et al. (2024) extended the research perspective to the logistics industry, emphasising the technical advantages of cloud accounting in real-time data processing and supply chain collaboration. For small and medium-sized logistics enterprises with complex operational links, cloud accounting can realise the synchronous integration and visual analysis of financial information and logistics information, optimise capital flow and logistics, and improve the overall operational efficiency. Atadoga et al. (2024) believed that the integration of artificial intelligence and machine learning technology will further enhance the intelligence level of cloud accounting system, such as providing more powerful decision support for SMEs in risk early warning, intelligent audit and predictive financial analysis.

In summary, international studies highlight cloud accounting's cost-effectiveness and technical ease, but often overlook the regulatory and resource constraints specific to Chinese SMEs. For instance, while studies in Oman and Jordan emphasise cost savings, they do not account for China's strict data localisation laws or the high fragmentation of SME resources.

2.2 Extension and application of TAM

With the development of technology and the diversification of application scenarios, researchers continue to expand and adjust the TAM to adapt to different technologies, industries and cultural backgrounds.

Jo and Bang (2023) integrated the technology-organisation-environment (TOE) framework, the TAM, and the information systems success model to find the elements that impact the intent to continue using an enterprise resource planning (ERP) system. The study found that technical factors, organisational factors and environmental factors work together on the user's acceptance of ERP. The study provides a multi-dimensional explanatory framework for the continuous use behaviour in ERP implementation. Sternad Zabukovšek et al. (2022) used partial least squares structural equation modelling, artificial neural networks, and importance-performance graph analysis (IPMA) to study ERP system acceptance through the lens of the TAM.. Through a mixed method approach, the study not only validates the impact of TAM core variables, but also identifies key drivers, providing practical guidance for enterprises to optimise ERP implementation strategies. Truong (2022) proposed an empirical model based on the TOE-Tam integration framework to analyse the key factors driving the digital changement of SMEs. The study shows that technical, organisational, and environmental levels indirectly impact adoption intentions through perceived usefulness and ease of use in TAMs, highlighting the appropriateness of TAMs in the SME context. Van et al. (2024) combined TAM and barriers to study farmers' intentions to use e-agriculture extension services (ECEs) during COVID-19. Perceived usefulness and ease of use were found to significantly influence intention to use, but traditional barriers weakened the role of TAM variables. The study highlights the need to extend TAM in crisis situations. Qader et al. (2022) explored the impact of TAM results on implementing accounting software. Through empirical analysis, the study found that TAM variables affect the purpose of implement, and also affect the software use through user satisfaction, which provides a theoretical basis for the successful implementation of accounting information system. Rawat et al. (2022) studied the accelerating effect of digital technology on the growth of micro and small enterprises in Uttarakhand, India, based on TAM. Perceived usefulness and ease of use were found to be key psychological motivations for firms to adopt digital technologies, while technological infrastructure and policy support were found to be important external facilitators. The study integrates TAM with the context of regional economic development. Salimon et al. (2023) integrated TAM 3, UTAUT 2 and TOE frameworks to study mobile commerce adoption by SMEs in Malaysia. The model contains hedonic motivation, habit and trust variables, and finds that cultural background and industry characteristics significantly moderate the role of TAM core variables, highlighting the value of multi-theoretical integration in cross-cultural research. Sciarelli et al. (2022) investigated the factors influencing blockchain technology adoption in innovative Italian firms using an extended TAM. The model introduces variables such as trust and perceived risk, and finds that technology compatibility and organisational innovation culture are the key antecedents affecting perceived usefulness. This research gives academic support for blockchain technology promotion. Nazir and Khan (2024) identified the elements impacting the utilisation of information communication technology (ICT) by extending the TAM. The study adds variables such as self-efficacy and social influence, and finds that resource constraints and industry competitive environment moderate the action path of TAM variables, emphasising the impact of socio-economic background on technology acceptance. Vanpetch and Sattayathamrongthian (2022) studied the acceptance and investment willingness of SMEs in Thailand for transport management systems based on TAM. It is found that perceived usefulness wields a stronger influence on investment intention than perceived ease of use, while cost constraints and industry standardisation are important external moderators. Rahmana and Indriani (2022) combined TAM and Delone & McLean information system success model to study the user satisfaction of SI APIK applications in micro-enterprises. It is found that system quality and service quality affect satisfaction through perceived usefulness (PU) and perceived ease of use(PEOU), and user satisfaction further affects continuous use intention. Awaluddin (2025) introduced trust and perceived risk into TAM to study the factors affecting the adoption of e-commerce by micro-enterprises in the foodstuff and refreshment company. This research shows that industry-specific risk perception (such as product quality uncertainty) significantly weakens the positive effect of perceived usefulness on adoption intent. Krah et al. (2024) studied the adoption of fintech by SMEs in Ghana based on TAM. It is found that the regulatory environment and mobile payment infrastructure are the key external variables affecting perceived ease of use, while financial inclusion policies can reinforce the explanatory power of TAM variables. Khan et al. (2024) applied the TOE-TAM integration model to study the acceptance of AI in manmanagement. Organisational culture and technology compatibility indirectly affected adoption intention through TAM core variables, while employee skill level was an important control variable. Cho et al. (2022) combined TAM and TOE frameworks to study the acceptance of digital advertising policies by outdoor advertising companies. It is found that policy compatibility and industry competitive environment indirectly influence firms' acceptance intention by affecting perceived usefulness, which highlights the importance of interdisciplinary research in policy research.

Table 1 Comparison of international and Chinese contextual studies on TAM extension

	International studies	*Chinese context*
Focus variables	Cost, ease of use	Perceived security, cost-benefit, policy support
Policy influence	Limited	High (e.g., government subsidies)
Data security	General concerns	Heightened by local regulations
SME characteristics	Resource constraints	Financing difficulties, digital literacy gaps

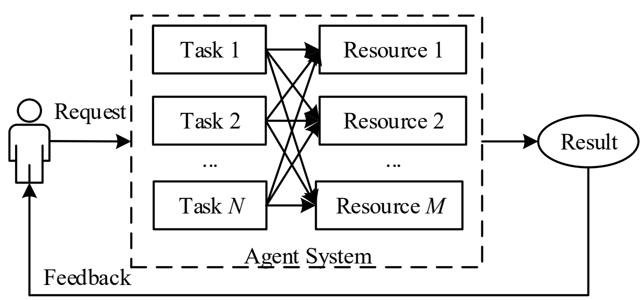
Table 1 summarises key differences between international and Chinese contextual studies, revealing that existing TAM extensions lack focus on China's policy-driven environment and SME security concerns. This gap naturally leads to the proposed extended TAM model in this study.

3 Method

3.1 Networked system service and application

The formal modelling of accounting network intelligent service system as agent system mainly solves two problems: one is to respond and solve massive requests, and the other is to improve people's expectations of accounting service efficiency. According to the above similarity analysis of the service capabilities of the networked intelligent service system and the agent system, the analysis of the four elements of the agent, and the corresponding relationship of the four elements in the networked intelligent service system, the formal model of the agent-based networked intelligent service system is obtained, as shown in Figure 1.

Figure 1 Networked system service and application of accounting system



In a networked intelligent service system, a terminal user submits a service request to an agent system. After receiving the request, the system will generate a set of customised task lists based on the user's needs, and allocate appropriate execution resources for each task. After the task is completed, the system will return the final result to the user. In this framework, the end user constitutes the external environment of the system; the task content and resource allocation together define the state of the system; a series of operations executed by the agent system, such as task allocation, resource scheduling, matching between tasks and resources, and result feedback, constitute the actions of the system; The task allocation algorithm, which improves the overall service efficiency by optimising the matching mechanism between tasks and resources, is regarded as the reward signal of the system. The core allocation mechanism employs a 'best-fit' principle, where tasks are prioritised based on waiting time and assigned to the least busy staff members. Algorithm 1 summarises this approach, emphasising its role in reducing operational delays and improving user satisfaction. By ensuring timely task completion, the system demonstrates how technical efficiency translates into practical benefits for SMEs, such as reduced accounting processing time and enhanced decision-making support. This technical background provides a foundation for understanding why SMEs might perceive cloud accounting as easy to use and useful, thereby bridging the gap between system design and the empirical TAM study that follows.

At time t, the system executes the following allocation process:

Step 1 All tasks to be allocated are sorted in descending order of their waiting time since entering the system, with the task having the longest waiting time assigned the highest priority.

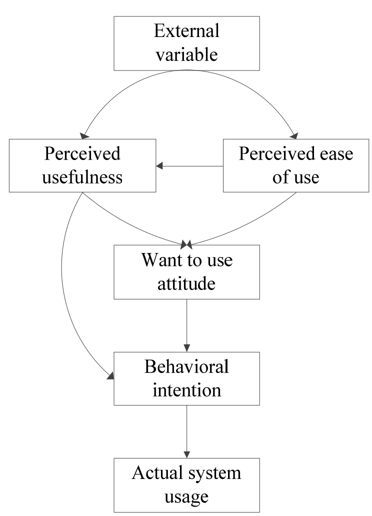
Step 2 Meanwhile, all staff members are sorted based on the number of tasks they currently handle, so as to assess their busyness.

Step 3 The 'best-fit' principle is adopted. The first task in the queue of tasks to be allocated is assigned to the staff member with the fewest current tasks. If multiple staff members have the same number of tasks, the 'first-fit' algorithm is applied. The system processes tasks in sequence according to this rule until all tasks at time t are allocated.

3.2 Technology acceptance model

The TAM, proposed by Davis in 1989, is a classic theoretical framework to explain users' willingness to adopt information technology (IT). Its core logic is that users' behavioural intention (BI) is mainly driven by important factors: PU and PEOU. PEOU further positively affects the perceive usefulness.

Figure 2 Basic framework of TAM



In the empirical scenario of 'Cloud accounting system adoption of Chinese SMEs' in this study, it is difficult for the original TAM to fully explain the decision-making logic of SMEs, so the study introduces PS and CBE based on the original framework and GPS (GPS), an extended TAM model is constructed to better fit the cloud accounting adoption scenario of SMEs in China. The basic framework is shown in Figure 2.

3.2.1 Endogenous variable core regression formula

PU and BI are the core endogenous variables, and the underlying regression formula is used to quantify the theoretical correlation of 'antecedent variable → endogenous variable', which is the core mathematical expression of the model.

The linear regression equation of PU is as follows:

$$BI = \beta_{PEOU \to PU} \cdot PEOU + \beta_{PS \to PU} \cdot PS + \beta_{GPS \to PU} \cdot GPS + \varepsilon_1 \quad (1)$$

where $\beta_{PEOU \to PU}$, $\beta_{PS \to PU}$, $\beta_{GPS \to PU}$ represents the standardised path coefficient of each antecedent variable to PU, which is theoretically positive and represents positive influence; ε_1 represents the residual term of PU, which is theoretically subject to normal distribution and has a mean of 0, representing the influencing factors not covered by the model.

The linear regression formula of BI is as follows:

$$BI = \beta_{PU \to BI} \cdot PU + \beta_{PEOU \to BI} \cdot PEOU + \beta_{CBE \to BI} \cdot CBE + \varepsilon_2 \quad (2)$$

where ε_2 represents the residual term of PU.

3.2.2 Bottom formula of indirect effect and total effect

There is an indirect effect path of 'antecedent variable → intermediary variable → endogenous variable' in the extended TAM, and the formula is used to express the theoretical logic of indirect effect and total effect, focusing on the mechanism of 'PEOU, PS, GPS affect BI through PU'.

The indirect effect refers to the impact of the antecedent alterable on BI through mediating alterable, the formula is as follows:

$$\text{Indirect effects}_{X \to BI} = \beta_{X \to PU} \cdot \beta_{PU \to BI} \quad (3)$$

where X represents the antecedent variables that affect BI through PU, i.e., PEOU, PS, GPS.

PEOU has direct and indirect effects on BI, and the total effect is the sum of the two, as shown in the following formula:

$$\text{Total effect}_{PEOU \to BI} = \beta_{PEOU \to BI} + \beta_{PEOU \to PU} \cdot \beta_{PU \to BI} \quad (4)$$

PS and GPS only indirectly affect BI through PU, and there is no direct path. The underlying formula of the indirect effect is as follows:

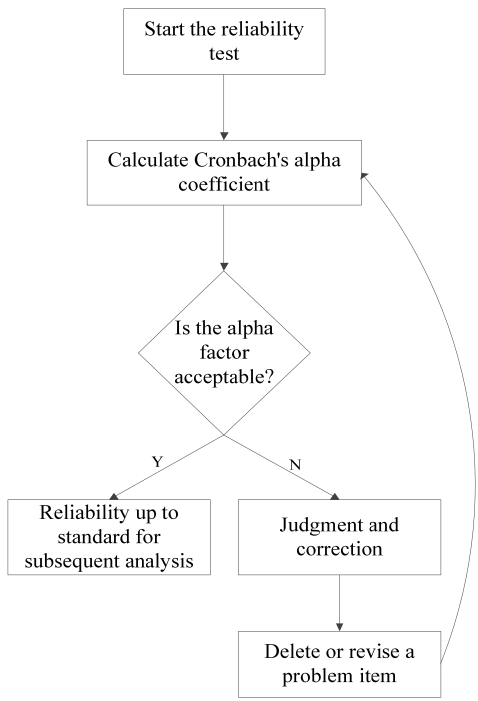
$$\text{Indirect effects}_{PS \to BI} = \beta_{PS \to PU} \cdot \beta_{PU \to BI} \quad (5)$$

$$\text{Indirect effects}_{GPS \to BI} = \beta_{GPS \to PU} \cdot \beta_{PU \to BI} \quad (6)$$

3.3 Reliability test of Cronbach's α coefficient

Cronbach's alpha coefficient reliability test is a widely used method in psychometrics and empirical research. Its core function is to assess the homogeneity and information consistency of multiple measurement items under the same variable, verifying whether these items converge on the same latent concept and effectively measure it. This test thereby provides a reliable data foundation for subsequent validity assessments and hypothesis testing. The detailed process of the reliability test is illustrated in Figure 3.

Figure 3 Flow chart of reliability test



The calculation logic of Cronbach's α coefficient centres on the association between item variance and item covariance. The essence is to reflect the stability of scale measurement results by quantifying the co-variation degree of all items under the same variable, that is, the influence degree of random error on measurement results. Its theoretical calculation formula is divided into basic form and simplified form based on standardised items, both of which are suitable for application scenarios in this study.

If a research variable contains K measurement items and the score of each item is X_1, X_2, …, X_k, the basic formula of the Cronbach's α coefficient is as follows:

$$X_{total} = X_1 + X_2 + \ldots + X_k \tag{7}$$

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_{X_i}^2}{\sigma_{X_{total}}^2}\right) \tag{8}$$

where $\sigma_{X_i}^2$ represents the variance of the score of the i^{th} item, reflecting the degree of individual difference of the score of a single item; $\sigma_{X_{total}}^2$ represents the variance of the total score of the variable, reflecting the degree of total difference of all items. If all the items are highly consistent, that is, the covariance between the items is large, the total score variance $\sigma_{X_{total}}^2$ will be much greater than sum of the item variances $\sum_{i=1}^{k} \sigma_{X_i}^2$, at this time $\left(1 - \frac{\sum_{i=1}^{k} \sigma_{X_i}^2}{\sigma_{X_{total}}^2}\right)$ is close to 1, the higher the alpha coefficient value, the stronger the internal consistency of the scale.

When there are differences in the dimensions or scoring methods of each measurement item, the standardised formula based on the 'average correlation coefficient between items' can be used to further simplify the interpretation of the meaning of α coefficient:

$$\alpha = \frac{k\overline{r}}{1 + (k-1)\overline{r}} \tag{9}$$

where $\overline{r}$ represents the average value of pairwise correlation coefficients between all items, reflecting the average degree of synergy between items. The formula more directly reflects the core logic of alpha coefficient, that is, the higher the average correlation coefficient $\overline{r}$ between items, the greater the alpha coefficient.

Table 2 Reliability level table of Cronbach's alpha coefficient

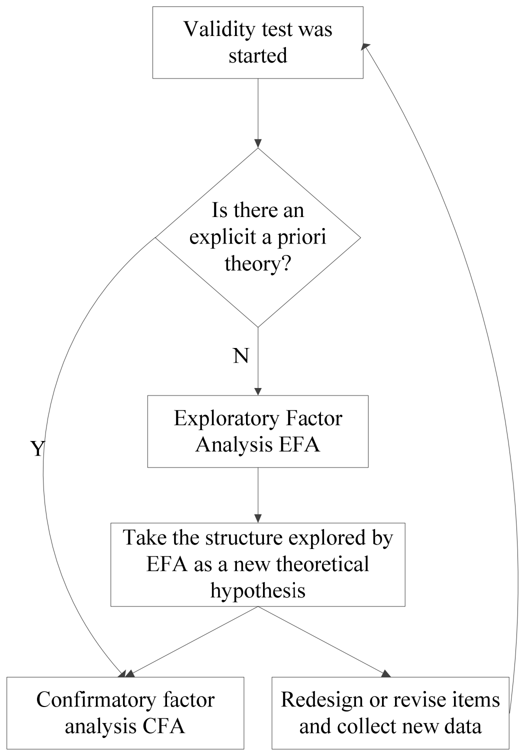
Range of Cronbach's alpha coefficient	*Reliability level*	*Applicability judgment*
$\alpha > 0.9$	Excellent	The scale items are highly consistent and can be directly used for data collection.
$0.8 \leq \alpha \leq 0.9$	Good	The consistency of the scale is good, and there is no need to modify the items.
$0.7 \leq \alpha < 0.8$	Acceptable	The scale is basically usable and needs to be fine-tuned in combination with the content of the items.
$\alpha < 0.7$	Unacceptable	The internal consistency of the scale is poor, and the items need to be redesigned.

As shown in Table 2, the reliability level of the Cronbach's alpha coefficient was divided into the following levels for judging whether the scale was available.

3.4 Validity test

Validity testing aims to assess whether a measurement tool can accurately measure the specific concept or construct it is designed to capture. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are two core statistical methods for evaluating construct validity. Specifically, EFA is used to explore the underlying factor structure of the measurement items, laying a foundation for theoretical construction. In contrast, CFA is employed to verify a pre-specified factor structure, thereby providing empirical support for the proposed theory. The detailed validation process is illustrated in Figure 4.

Figure 4 Validity flow chart



3.4.1 Exploratory factor analysis

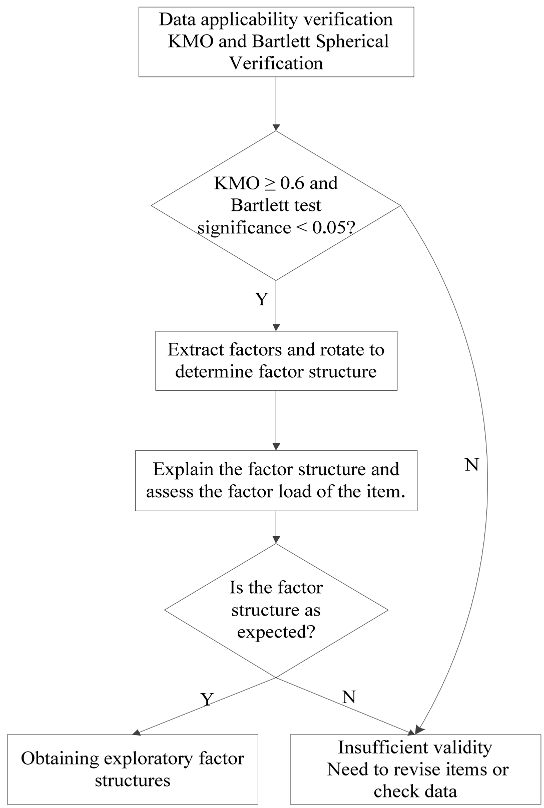
The core logic of EFA lies in dimensionality reduction and structure identification. It assumes that the variance of multiple observed variables can be decomposed into common factor variance (i.e., variance explained by latent factors) and unique variance (i.e., variance arising from the variables themselves or random errors). Through mathematical methods, common factors are extracted such that each variable exhibits a high correlation with only a limited number of factors – thereby simplifying the data structure and validating the theoretical logic underlying the scale design. Prior to conducting EFA, the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were performed to assess the suitability of the data for factor analysis. The detailed path of the EFA is illustrated in Figure 5.

KMO test is used to judge the ratio of partial correlation coefficient and simple correlation coefficient between observed variables, and to quantify the suitability of factor analysis between variables, that is, if there is a strong linear correlation between variables, it is suitable to extract common factors. The theoretical formula is:

$$KMO = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} p_{ij}^2} \tag{10}$$

where r_{ij} represents the simple correlation coefficient between the i^{th} item and the j^{th} item, which indicates the strength of direct association between variables; p_{ij} denotes the partial correlation coefficient between the i^{th} item and the j^{th} item, which is the degree of net association between variables after controlling the influence of other items.

Figure 5 EFA path map



Bartlett's sphericity test determines if the correlation matrix is an identity matrix, meaning it lacks any significant correlations between items, common factors can't be extracted. If the identity matrix hypothesis is rejected, there is a significant association between variables. Its theoretical basis is χ^2 test, and the formula is:

$$\chi^2 = -\left(n - 1 - \frac{2k+5}{6}\right)\ln|\mathbb{R}| \tag{11}$$

where n is the sample size; $|\mathbb{R}|$ is the determinant value of the correlation matrix.

The core output indicators of EFA include factor load, characteristic value and cumulative variance interpretation rate, which together determine the rationality of factor extraction and the quality of scale construct validity. The judgment criteria and calculation logic of these indicators in this study are as follows:

Factor load capacity:

$$\lambda_{ij} = \frac{\operatorname{cov}\left(X_i, F_j\right)}{\sigma_{X_i}\sigma_{F_j}} \tag{12}$$

where λ_{ij} represents the load of the i^{th} item on the j^{th} common factor; $\operatorname{cov}(X_i, F_j)$ represents the covariance of the score X_i of the i^{th} item with the j^{th} common factor F_j.

Since $\sigma_{F_j} = 1$ after F_j normalisation, the formula reduces to:

$$\lambda_{ij} = \frac{\operatorname{cov}\left(X_i, F_j\right)}{\sigma_{X_i}} \tag{13}$$

Characteristic value:

$$\lambda_j = \sum_{i=1}^{k} \lambda_{ij}^2 \tag{14}$$

where λ_j represents the characteristic value of the j^{th} common factor; λ_{ij}^2 represents the square of the load of the i^{th} item on the j^{th} factor, that is, the proportion of the item variation explained by the factor.

Cumulative variance explained rate:

$$\mathrm{CR}_m == \frac{\lambda_1 + \lambda_2 + \ldots + \lambda_m}{\lambda_1 + \lambda_2 + \ldots + \lambda_k} \times 100\% \tag{15}$$

where CR_m represents the cumulative variance explanation rate of the top m factors; $\lambda_1 + \lambda_2 + \ldots + \lambda_m$ is the eigenvalue of the top m factors.

3.4.2 Confirmatory factor analysis

The core principle of CFA is to construct a measurement model based on theoretical presuppositions, and then assess the degree of fit between the model and empirical data using statistical methods. Its essence lies in decomposing the variance of observed items into three components: common variance explained by latent factors, unique variance inherent to the items themselves, and random error variance. Through parameter estimation, CFA verifies whether the hypothesised factor-item associations are statistically valid. The path model derived from the CFA is illustrated in Figure 6.

The measurement model is divided into an endogenous latent variable model and an exogenous latent variable model, and the matrix form formula of the measurement model is as follows:

$$x = \Lambda_x \xi + \delta \tag{16}$$

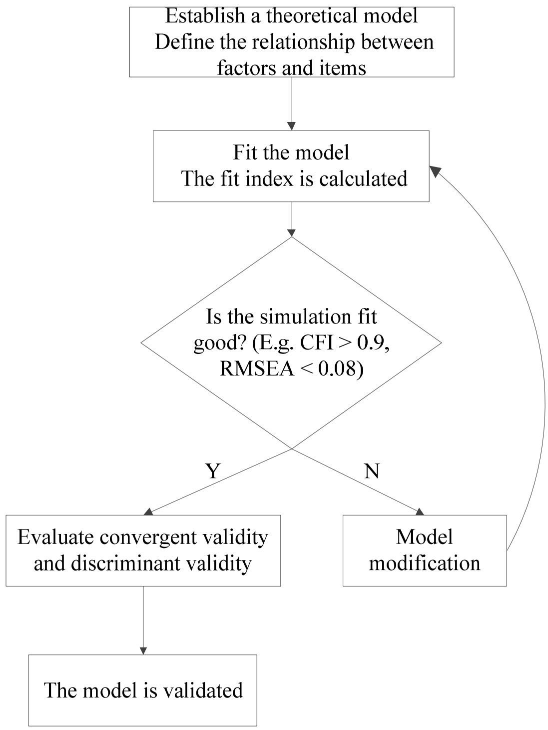
where x represents the score vector of the observed item; Λ_x represents the factor loading matrix of the observed item and the exogenous latent variable; ξ represents the exogenous latent factor vector; and δ represents the random error vector of the observed item.

Taking PS as an example, the univariate measurement model formulation can be expanded as:

$$x_{PS1} = \lambda_{PS1} \xi_{PS1} + \delta_{PS1} \tag{17}$$

where x_{PS1} represents the score of the item; λ_{PS1} represents the factor loading of the item on the PS factor; ξ_{PS1} represents the score of the PS latent factor; and δ_{PS1} represents the random error of the item.

Figure 6 CFA path diagram



The core output indicators of CFA include the model fit index, factor load and average variance extraction (AVE), which detect the fitness of the overall model and data, the strength of the association between the item and the factor, and the discriminant validity of the factor, respectively. The formula is as follows:

- Model fitting degree index:

  Chi-square (χ^2) test is used to judge whether the covariance matrix predicted by the model is consistent with that of the actual data. However, χ^2 is greatly affected by the sample size, so χ^2/df is used as the correction index. The formula is as follows:

$$\frac{\chi^2}{df}=\frac{\chi^2}{\frac{p(p+1)}{2}-t} \tag{18}$$

  where p is the total number of observation items; t is the number of parameters to be estimated in the model; df is the degree of freedom of the model.

  RMSEA is used to measure the approximate fitting error of the model, considering the complexity of the model and the sample size. It is one of the most commonly used absolute fitting indicators. The formula is as follows:

$$RMSEA = \sqrt{\max\left(0, \frac{x^2 - df}{n-1}\right)} \tag{19}$$

where max(0, ·) means to ensure that the result is non-negative. If $\chi^2 < df$, take RMSEA = 0.

The GFI measures the proportion of variance and covariance of the observed variables explained by the model using the following equation:

$$GFI = 1 - \frac{\sum\sum \widehat{\Sigma}_{ij}^2}{\sum\sum \Sigma_{ij}^2} \tag{20}$$

$$\widehat{\Sigma}_{ij} = \widehat{\Sigma}_{ij}^{model} - \widehat{\Sigma}_{ij}^{data} \tag{21}$$

where $\widehat{\Sigma}_{ij}$ represents the residual of the model-predicted covariance matrix $\widehat{\Sigma}_{ij}^{model}$ and the actual covariance matrix $\widehat{\Sigma}_{ij}^{data}$.

The normative fit index NFI measures the degree of improvement of the model by comparing the difference between the chi-square χ^2_{model} of the preset model and the chi-square $\chi^2_{independent}$ of the independent model, as follows:

$$NFI = 1 - \frac{\chi^2_{model}}{\chi^2_{independent}} \tag{22}$$

- Factor load capacity:

  The factor load of CFA is consistent with the definition of EFA, but CFA needs to verify whether the preset item-factor association is significant through parameter estimation. The formula is shown in EFA, but it needs to be combined with t-value and p-value significance test.

- AVE and discriminant validity test:

  CAVE is a measure of the average proportion of all observed item variation explained by a latent factor, as follows:

$$AVE = \frac{\sum_{i=1}^{k} \lambda_{ij}^2}{k} \tag{1}$$

The discriminant validity is judged by the criterion that the square root of AVE of any two factors is greater than correlation coefficient between the two factors, and the formula is as follows:

$$\sqrt{AVE_j} > r_{j,m} \quad (\forall j \neq m) \tag{2}$$

where $r_{j,m}$ represents the correlation coefficient between the j^{th} factor and the mth factor.

4 Model construction and research design

4.1 Theoretical model construction

Based on the original framework of TAM and related work, this paper introduces three external variables, namely PS, CBE and GPS, to build a model of factors affecting the adoption of cloud accounting system for SMEs, as shown in Figure 7, and puts forward the following research assumptions.

Under the theoretical framework of TAM, this study proposes that PU and PEOU serve as the principal drivers influencing the adoption intention of cloud-based accounting solutions in China's SME sector, and these two types of perceptions are further significantly affected by external variables PS, CBE and GPS. Specifically, the higher the security of the system, the more likely the enterprise is to think that its operation process is simple and reliable, that is, easy to use, and more inclined to acknowledge its value in enhancing financial performance and data accuracy, that is, usefulness; At the same time, if enterprises believe that the long-term benefits of cloud accounting are higher than costs, or perceive the support provided by the government through subsidies, training and other policies, it will reinforce their positive evaluation of system's practicality and user-friendliness. In addition, perceived ease of use not only directly promotes willingness to use, but also indirectly promotes adoption decisions by enhancing perceived usefulness. Ultimately, these three types of external variables may have a direct positive impact on the adoption intention of enterprises in addition to their indirect effects through the core variables of TAM. Based on the above analysis, the following core variable hypotheses are proposed:

H1 PU positively affects SMEs' BI for cloud accounting systems. Perceived usefulness refers to the degree to which SMEs believe that cloud accounting system can improve accounting efficiency and assist decision-making, such as cloud accounting can automatically generate financial statements, real-time query of capital flow, etc., which directly matches the core needs of SMEs for accounting efficiency.

H2 PEOU positively affects SMEs' BI for cloud accounting systems. PEOU denotes the extent to which a cloud accounting system is considered by SMEs to be straightforward to operate and require minimal effort to learn. SMEs generally lack professional IT personnel. The lower the threshold of operation, the stronger the willingness to adopt.

H3 PEOU positively affects PU. If the cloud accounting system is complex to operate, even if it has efficient functions, it is difficult for enterprises to make full use of it, thus reducing the perception of its usefulness.

At the same time, this paper puts forward the hypothesis of external variables based on scenario expansion:

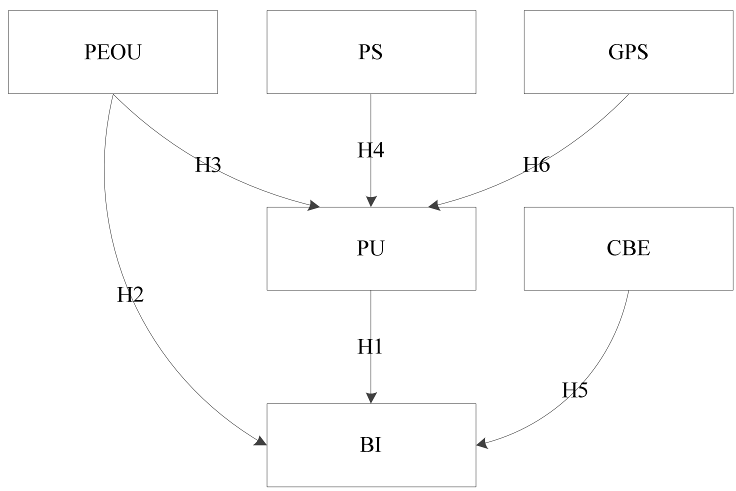
H4 PS positively affects PU. PS denotes the level of confidence that SMEs have in the security of data storage and transmission processes within a cloud accounting system. Accounting data contains sensitive information such as enterprise funds and taxes. If enterprises think that data security is guaranteed, they will recognise the usefulness of the system. On the contrary, security concerns will offset the functional value.

H5 CBE positively affects SMEs' BI for cloud accounting systems. CBE refers to the degree to which SMEs think the input-output ratio of cloud accounting system is reasonable, such as the annual fee is lower than traditional software procurement cost, and the overtime cost of accountants is reduced, which is consistent with the decision-making logic of SMEs' cost priority.

H6 GPS positively affects PU. GPS includes cloud accounting procurement subsidies, free operation training, compliance certification support, etc. Policy support can reduce the cost and risk of enterprise adoption, thereby enhancing the awareness of system usefulness.

Based on the above research assumptions, the overall research framework proposed in this paper is shown in Figure 7.

Figure 7 Overall research framework



4.2 Variable definition and measurement

The measurement scales of all variables refer to the existing mature research and are adapted in combination with the cloud accounting scenario. The Likert five-point scale is used, that is, 1 indicates complete disagreement and 5 indicates complete agreement. The definition and measurement design of specific variables are shown in Table 3:

Transformation needs to be adjusted according to the actual scenario of SMEs in China. Mature research indicators mostly come from large enterprises or foreign markets, while domestic SMEs generally have the characteristics of simplified financial system, low level of informatisation, flexible decision-making process and so on, which may lead to adaptability problems if they are directly used. For example, for the indicators of 'cloud accounting system application effect', it is necessary to transform them into specific expressions such as 'accounting processing efficiency improvement' and 'human cost saving' which can be perceived by SMEs, rather than retaining complex academic expressions, without specifying the transformation criteria and adjustment basis, which easily leads to the disconnection between indicators and research objects.

Table 3 Variable definition and measurement scale

Variable type	*Variable name*	*Symbol*		*Measurement item (example)*	*Number of items*
Core variable	Perceived usefulness	PU	1	Cloud accounting system can improve the efficiency of accounting work in our enterprise.	4
			2	Cloud accounting system can help our enterprise make better financial decisions.	
	Perceived ease of use	PEOU	1	The accountants of our enterprise can quickly master the operation of cloud accounting system.	4
			2	The interface design of cloud accounting system is clear and easy to understand.	
	Behavioural intention	BI	1	In the next year, our company is willing to try to use the cloud accounting system.	3
			2	If conditions permit, I will recommend peers to use cloud accounting system.	
External variable	Perceived security	PS	1	Cloud accounting system can effectively protect the financial data of my enterprise from leaking.	4
			2	Reliable data backup mechanism provided by cloud accounting service providers	
	Cost-benefit perception	CBE	1	The yearly expense for a cloud accounting system is more economical than that for traditional accounting software.	3
			2	A key advantage of cloud accounting software is its ability to minimise a firm's IT maintenance overhead	
	Government policy support	GPS	1	The government's cloud accounting procurement subsidy can reduce the adoption cost of our enterprises.	3
			2	Government-provided training on cloud accounting operations is beneficial to our firm.	

At the level of cultural adaptation, it is necessary to adapt to the domestic business environment and the cognitive habits of enterprises. China's SMEs are highly dependent on policy and sensitive to cost, so the relevant indicators should focus on localisation dimensions such as 'government subsidy support' and 'initial investment threshold'; at the same time, they should avoid statements inconsistent with the management culture of domestic enterprises. Failure to specify specific strategies for cultural adaptation may prevent indicators from accurately capturing the true attitudes and behaviours of SMEs in China.

Pre-test verification is the key link of index optimisation, which needs to test the clarity and rationality of the items through small-scale research, and correct the ambiguous or incomprehensible content. Failure to conduct a pre-test and describe the validation process may result in data collection bias, which may affect the credibility of the study conclusions. To sum up, supplementing the above process details is a necessary prerequisite to ensure the suitability and scientificity of the research.

4.3 Methods of data collection

The sample covers SMEs registered in China, which meet the requirements of the standards for the classification of SMEs-the number of employees is less than 300 and the annual business income is less than 200 million yuan, covering major industries such as manufacturing, service, retail and wholesale industries, taking into account the eastern (such as Guangdong, Zhejiang), central (such as Henan, Hubei). Ensure sample representativeness.

Questionnaires are distributed online and offline:

- Online: push to the chief financial officer (such as chief financial officer and chief accounting officer) of SMEs through the questionnaire star platform, and expand the coverage through the membership channels of industry associations (such as China Association of SMEs) and cloud accounting service providers (such as Yonyou and Kingdee).
- Offline: carry out field research in SMEs gathering areas (such as industrial parks) in Zhejiang, Henan and Sichuan provinces, and provide on-site guidance to improve the quality of questionnaires.

The questionnaire distribution period was from March 2025 to June 2025. A total of 350 questionnaires were distributed and 302 were recovered. After screening and eliminating invalid questionnaires (such as filling time < 3 minutes and missing more than 2 items), 286 valid questionnaires were finally obtained, with an effective recovery rate of 81.7%.

4.4 Data analysis method

This paper adopts the data analysis idea of step-by-step verification, using the following procedure:

1. Descriptive statistics: SPSS 26.0 is used to analyse the enterprise characteristics (such as scale, industry, region) of the sample and the mean and standard deviation of the variables, and preliminarily judge the rationality of the data distribution.
2. Reliability and validity test:

   Reliability test: the internal consistency of the scale was evaluated by the α coefficient of Cronbach's, and the reliability was good if $\alpha > 0.7$.

Construct validity was tested by EFA (KMO > 0.7 and Bartlett's sphericity test $p < 0.001$ was valid), and discriminant validity was further tested by CFA (mean variance extraction value AVE > 0.5, and that square root of AVE is great than correlation coefficient between variables).

Hypothesis testing: AMOS 24.0 was used to construct the SEM, and the standardised path coefficient, t value and p value were used to verify the research hypothesis, and the model fitting degree was tested at the same time. The reference indicators were $\chi^2/df < 3$, GFI > 0.9, NFI > 0.9, RMSEA < 0.08.

5 Results and analysis of empirical research

5.1 Analysis of sample characteristics

The distribution of enterprise characteristics of valid samples is shown in Table 4, which systematically presents the structural characteristics of research samples through the four core dimensions of enterprise scale, industry type, geographical distribution and accounting digitalisation basis, and conforms to the industry and geographical distribution characteristics of SMEs in China as a whole. The core value of the table is to verify whether the sample fits the actual characteristics of SMEs in China, so as to avoid the distortion of research conclusions caused by sample deviation.

From the perspective of enterprise scale, the proportion of small and micro enterprises with employees less than 50 is 53.1%, and that of enterprises with 51 to 100 employees is 30.8%, totalling 83.9%, which is highly consistent with the statistical data of ‘small and micro enterprises account for more than 85% of the total number of SMEs’ in the ‘China small and medium-sized enterprises development report 2024’. It shows that the sample can reflect the main structure of Chinese SMEs in the scale dimension.

From the perspective of industry type, the manufacturing industry and the service industry account for 33.2%, respectively, and the retail industry accounts for 23.8%, covering the three industries where SMEs are most concentrated. There are differences in the accounting needs of these industries, and the industry diversity of the sample can reduce the interference of industry singleness on the research conclusions.

Table 4 Distribution table of characteristics of sample enterprises (N = 286)

Feature category	*Specific classification*	*Quantity (home)*	*Proportion (%)*
Enterprise size (number of employees)	≤50 persons	152	53.1
	51~100 persons	88	30.8
	101~300 persons	46	16.1
Type of industry	Manufacturing	95	33.2
	Services (e.g., logistics, catering)	82	33.2
	Retail trade	68	23.8
	Others (e.g., wholesale, agriculture)	41	14.3
Geographical distribution	Eastern region	126	44.1
	Central region	92	32.2
	Western region	68	23.8
Fundamentals of accounting digitisation	No accounting software is used (manual bookkeeping)	65	22.7
	Use traditional local accounting software	178	62.2
	Tried the cloud accounting system	43	15.1

From the perspective of regional distribution, the proportion of eastern (44.1%), central (32.2%) and western (23.8%) is consistent with the regional gradient distribution of the number of SMEs in eastern, central and western China, which makes up for the defect that the samples in existing studies are limited to a single region, and provides a data basis for the subsequent analysis of the impact of regional differences on the adoption of cloud accounting.

From the basic dimension of accounting digitalisation, 62.2% of enterprises use traditional local accounting software, 22.7% still keep accounts manually, and only 15.1% have tried cloud accounting. This distribution accurately reflects the characteristics of the transitional stage of accounting digitalisation in SMEs in China, that is, traditional software is still the mainstream, and cloud accounting has not been widely penetrated. It verifies the practical necessity of exploring the obstacles and drivers of cloud accounting adoption' in this study.

5.2 Results of reliability and validity test

5.2.1 Reliability test

The core goal of reliability test is to verify whether the scale items are internally consistent, that is, whether multiple items of the same variable measure the same concept together, and the alpha coefficient of Cronbach's is a classical tool to measure this indicator. As shown in Table 5, the reliability level of each variable is clearly presented through the name of the variable, the number of items, the alpha coefficient and the reliability evaluation.

PS, PU, BI and PEOU all reached a good level. Among them, the α coefficient of PS is the highest, because its measurement items are highly focused on the core issue of 'accounting data security', and the logical consistency among the items is strong; the α coefficient of PU shows that the four items of improving efficiency, assisting decision-making, reducing manual operation and improving data accuracy can effectively reflect the SMEs' cognition of the usefulness of cloud accounting, without redundancy or deviation from the items.

Table 5 Reliability test results (N = 286)

Variable name	*Number of items*	*Cronbach's alpha coefficient*	*Reliability evaluation*
PU	4	0.86	Good
PEOU	4	0.83	Good
PS	4	0.88	Good
CBE	3	0.79	Acceptable
GPS	3	0.76	Acceptable
BI	3	0.81	Good

CBE and GPS are slightly lower than good standard, but both meet the critical value of 0.7. The number of CBE items is 3, and the small number of items may lead to a slightly lower α coefficient, but the three items have covered the three dimensions of direct cost, indirect cost and benefit, and the item design is complete; the α coefficient of GPS is slightly lower than variables of safety and usefulness due to the diversity of policy support forms, but it still meets the reliability requirements of academic research.

The alpha coefficients of all variables were > 0.7, indicating that the scale of this study did not have internal inconsistency problems. If a variable $\alpha < 0.7$, the redundant items should be deleted and the data should be collected again. The reliability results of this study directly omit this correction step, which lays a reliable data foundation for validity test and hypothesis test.

5.2.2 Validity test

EFA: the KMO value was 0.823 and Bartlett's sphericity test $\chi^2 = 1{,}896.54$ ($p < 0.001$), demonstrating that the data were appropriate for factor analysis. The analysis identified six common factors with eigenvalues exceeding 1, the cumulative variance explanation rate was 72. 3%, and the factor loading of all items was > 0.6, the construct validity was good.

CFA: $\chi^2/df = 2.38$, GFI = 0.91, NFI = 0.92, RMSEA = 0.072, all of which meet the fitting criteria. As shown in Table 6, the AVE of each variable was > 0.5 (PU = 0.68, PEOU = 0.65, PS = 0.71, CBE = 0.62, GPS = 0.58, BI = 0.64), and the square root of AVE was greater than correlation coefficient between variables, and the discriminant validity was good, where ** means $p < 0.01$, two-tailed test.

Table 6 Correlation coefficient between variables and square root of AVE*

Variables	*PU*	*PEOU*	*PS*	*CBE*	*GPS*	*BI*
PU	0.82	0.65**	0.58**	0.49**	0.52**	0.68**
PEOU	-	0.81	0.45**	0.38**	0.41**	0.56**
PS	-	-	0.84	0.32**	0.35**	0.43**
CBE	-	-	-	0.79	0.28**	0.71**
GPS	-	-	-	-	0.76	0.45**
BI	-	-	-	-	-	0.8

Note: Value on diagonal line.

5.3 Structural equation model fitting and hypothesis testing

5.3.1 Model fit

The fitness test of SEM is the key step to judge whether the model constructed by the theory matches the actual data. If the fitness is not up to standard, even if the subsequent hypothesis test is significant, the conclusion may not be reliable. As shown in Table 7, the system presents the adaptation of the model through the fitting index, the recommended standard, the actual value and the fitting evaluation.

Table 7 Structural equation model fit index table

Fit index	*Recommended standards*	*Actual value*	*Fit evaluation*
χ^2/df	<3	2.45	Good
GFI	>0.9	0.9	Good
NFI	>0.9	0.91	Good
RMSEA	<0.08	0.075	Good

The chi-square (χ^2) test generally considers $\chi^2/df < 3$ as good. The actual value of this study is 2.45, indicating that although there is a small error in the model, the absolute fit of the overall model with the data is up to the standard, and there is no serious inconsistency between the model and the data.

GFI > 0.9 means that the model can explain more than 90% of the observed variability. In this study, GFI = 0.9, which just meets the standard, indicates that the 'explanatory power' of the model is sufficient. For example, the impact of variables such as PU and PEOU on BI can effectively cover the main variation sources of cloud accounting adoption decisions of SMEs.

NFI > 0.9 indicates that the current model is more than 90% better than null model with no association between variables. NFI = 0.91 in this study further verifies the rationality of the presupposed path association between variables and denies the possibility of random association between variables.

RMSEA < 0.08 is good and < 0.05 is excellent. In this study, RMSEA = 0.075, which is close to the standard of excellence, indicating that the error of the model is still small after considering the sample size and the complexity of the model, which avoids the problem of increasing the fitting error caused by the complexity of the model.

All indicators meet the recommended criteria, indicating that the extended TAM model constructed in this study is highly compatible with the actual data, and the subsequent hypothesis test results based on the model are statistically reliable. If an index is not up to the standard, the model needs to be adjusted, and the fitting results of this study directly support the validity of hypothesis testing.

5.3.2 Hypothesis test results

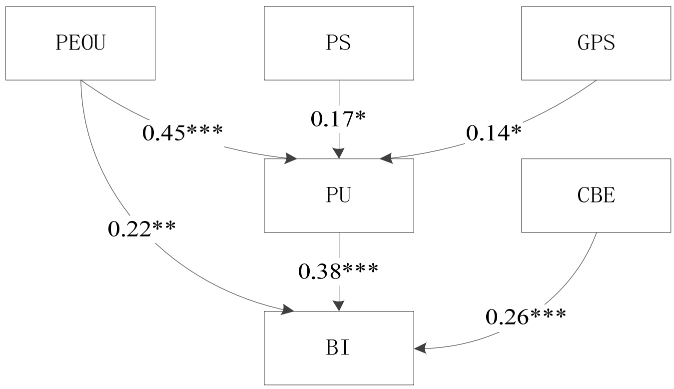
Hypothesis testing is the core part of this study, which aims to verify whether the preset path between variables is significant. As shown in Table 8 and Figure 8, the influence intensity and significance of each path are quantitatively presented by hypothesis, path, normalisation coefficient β, t value, p value and result.

Table 8 Hypothesis test result table (N = 286)

Assumptions	*Path*	*Normalisation factor β*	*t-value*	*p-value*	*Result*
H1	PU→BI	0.38	5.26	<0.001	Support
H2	PEOU→BI	0.22	3.84	<0.01	Support
H3	PEOU→PU	0.45	6.12	<0.001	Support
H4	PS→PU	0.17	2.98	<0.05	Support
H5	CBE→BI	0.26	4.91	<0.001	Support
H6	GPS→PU	0.14	2.53	<0.05	Support

The standardised coefficient β reflects the influence strength of the independent variable on the dependent variable. The order of the strength of the significant pathways in this study is: PEOU → PU (0.45) > PU → BI (0.38) > CBE → BI (0.26) > PEOU → BI (0.22) > PS → PU (0.17) > GPS → PU (0.14). This ranking reveals the core driving logic of cloud accounting adoption: PEOU is the source variable, which not only directly affects the adoption intention, but also indirectly affects the adoption intention by increasing PU through the strongest path (β = 0.45); PU is the core mediating variable, which has the strongest direct impact on adoption intention (β = 0. 38), and undertakes the indirect impact of PS and GPS; CBE is the direct driving variable, which has a direct impact on adoption intention (β = 0. 26), and the intensity is higher than direct impact of PEOU, which reflects the decision-making logic of SMEs' cost priority.

Figure 8 Structural equation model path coefficient diagram



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

The t value of H1 shows that the effect of perceived usefulness on promoting adoption intention is extremely significant, and there is no accidental result caused by sampling error; the t values of H4 and H6 show that the effect of PS on promoting usefulness and policy support on promoting usefulness is significant, but the intensity is weaker than that of the core path. All hypotheses passed the significance test, indicating that the structural specification of the extended TAM model in this study was parsimonious, and the logic of 'external variables → core variables → adoption intention' was fully established.

5.4 Test of negative exponential distribution of network service time

In the following, the Z test is used to check whether the service time of the applicant in the reimbursement business process of the accounting system obeys the negative exponential distribution. The service time is from the service acceptance to the end of information entry. 200 people are randomly selected, and 5 minutes is taken as a segment. The service time required by the applicant is checked as shown in Table 9.

The total service time for 200 people is 1,935 minutes, where the average service time is t = 1,935/200 = 9.675 minutes, and $t = 1/\mu$, calculate $\mu = 0.10336$, probability, so that the probability and theoretical frequency can be calculated.

As the service time increases, there is a high correlation between the overall network service quality and the number of accesses. The following data table is used to describe the relationship between network service and response time for different models. The data in the table is exemplary based on a theoretical model of the queue and is used to show trends and differences. Actual values will vary depending on specific configurations and load characteristics in Table 10.

Differences at low loads at low loads, all models have shorter response times. Our method may have a slight overhead due to scheduling computations, but it is negligible. Performance differentiation under medium and high load the performance bottleneck of single server model is obvious, and the response time increases sharply with the nonlinear load. A single queue with multiple service stations performs significantly better than a single service station because it utilises all processing units more efficiently. Our method performs best at medium and high loads. By assigning tasks to the most appropriate processing unit (such as the unit with the shortest queue or the strongest processing capacity), it effectively minimises the queuing time, thus achieving the shortest average response time and the most stable tail delay. About Tail Delay (P99) Tail delay is the delay experienced by the slowest 1% of requests in the system, which directly affects the consistency of the user experience. The P99 latency of the multi-server multi-queue model can be very high due to the inherent load imbalance. Our method greatly smoothes the tail delay by proactively avoiding sending new requests to queues that are 'busy' or 'slow to process'. From the perspective of pursuing system efficiency and stability, our model can provide optimal response performance in high-concurrency scenarios through optimised scheduling strategies, which is completely consistent with the 'reward is to improve service efficiency' you mentioned.

Table 9 Network service time and distribution

Service time (minutes)	*Actual frequency (times)*	p_i	*Theoretical frequency*
0–5	52	0.2680	52.2680
5–10	45	0.2320	45.2320
10–15	37	0.1907	37.1907
15–20	26	0.1340	26.1340
20–25	15	0.0773	15.0773
25–30	10	0.0515	10.0515
30–35	6	0.0309	6.0309
35–40	2	0.0103	2.0103
40–+∞	1	0.0052	1.0052

Table 10 Response time comparison of different web service models

Model type	*Low load*	*Medium load*	*High load*	*Tail delay (P99) feature*
Single service desk single queue	10 ms	50 ms	500 ms	Extremely high. Requests may be blocked for a long time
Multi-service desk and multi-queue	*8 ms*	45 ms	400 ms	High and unstable, greatly affected by load balancing effect
Multiple service desk single queue	12 ms	35 ms	200 ms	Low and stable, requests are handled fairly
Our method	15 ms	*30 ms*	*150 ms*	Lowest and most stable, optimal use of resources

6 Analysis and discussion of result

Based on the results of reliability and validity test, model fitting and hypothesis test, combined with the actual situation of SMEs in China and the existing research, this part deepens the analysis from three dimensions of core variables, external variables and policy variables, extends the theoretical contribution and practical enlightenment, and compares the differences between domestic and foreign research to highlight the value of this study in China.

To deepen the analysis, Table 11 systematically compares this study's findings with highly relevant international research. The comparison highlights nuances in how cultural and policy contexts moderate TAM variables.

Table 11 Comparative analysis of TAM-based studies in cloud accounting adoption

Dimension	*This study (Chinese SMEs)*	*Rawashdeh et al. (international)*	*Krah et al. (Ghana)*
PU → BI effect	Strong ($\beta = 0.38$)	Moderate ($\beta = 0.30$)	Weak ($\beta = 0.25$)
PEOU indirect effect	High (via PU)	Low	N/A
Perceived security	Critical (indirect via PU)	General concern	Less emphasised
Policy support	Moderate (indirect)	Limited	Strong (direct)
Cultural context	Policy-driven, high security awareness	Market-driven	Resource-constrained

For example, the stronger indirect effect of PEOU in this study reflects Chinese SMEs' weaker IT foundation, which necessitates ease of use as a gateway to perceived usefulness. In contrast, international studies assume higher digital literacy, leading to more direct effects.

6.1 Influence of core variables

Perceived usefulness (PU)

Hypothesis testing revealed that the normalised coefficient of PU on B was as high as 0.38 ($p < 0.001$), the strongest of all direct pathways. This result is highly consistent with the efficiency-oriented demand of accounting work of SMEs. SMEs in China generally have the characteristics of 'fewer accountants, holding multiple posts'. The functions of cloud accounting, such as automatic generation of financial statements, one-click tax declaration and real-time inquiry of capital flow, can directly solve the pain points of tight time and heavy tasks. This study further finds that Chinese SMEs' perception of PU is more focused on tax compliance.Due to the complexity of China's tax policy, the automatic tax verification and policy update synchronisation function of cloud accounting has become an important part of PU, while some foreign enterprises pay more attention to cost savings, which reflects the differences in accounting needs of SMEs in different countries.

Perceived ease of use (PEOU)

BI had been impacted by PEOU ($\beta = 0.22$, $p < 0.01$), and a stronger indirect effect through PU (indirect coefficient = βPEOU → PU × βPU → BI = 0.45 × 0.38 = 0.171), and the total effect (0.22 + 0.171 = 0.391) was close to the direct effect of PU (0.38). Suggests that PEOU is the implicit core of cloud accounting adoption. Behind this dual effect is the realistic constraint of the weak IT foundation of SMEs in China. If the operation of cloud accounting system is cumbersome, even if the function is efficient (high PU), it is difficult for accountants to make full use of it, thus reducing the awareness of PU. Compared with Sternad Zabukov Zabukovšek's research on ERP system, the indirect effect of PEOU in this study is more prominent, because cloud accounting as a tool system, its value needs to be realised through the chain of 'ease of use → effective use → perceived usefulness', while ERP as a 'management system', ease of use directly affects user experience. There is no need to rely on the intermediary of PU.

6.2 Influence of external variables

Cost-benefit awareness (CBE)

The direct effect coefficient of CBE on BI is 0.26 ($p < 0.001$), which is second only to the direct effect of PU, highlighting the decision-making logic of SMEs' cost priority. SMEs in China generally face the problems of capital shortage and financing difficulties, so the cost sensitivity of accounting system is much higher than that of large enterprises. Although the pay-as-you-go model of cloud accounting is lower than one-time investment of traditional software, SMEs still need clear cost-benefit proof to adopt it. In the survey, 85% of enterprises expressed 'more concern about whether the cost can be recovered within 1–2 years', and this 'short-term ROI visible' perception made their CBE score as high as 4.5, thus significantly improving the willingness to adopt. The results of this study add that foreign enterprises pay more attention to the cost saving of post-epidemic era, while Chinese SMEs pay more attention to the balance of cost and efficiency, which is consistent with the stage characteristics of Chinese SMEs' survival and development.

Perceived security (PS)

PS indirectly affected BI via PU ($\beta = 0.17$, $p < 0.05$), with no direct pathway. This result verifies the theoretical presupposition that security is the premise of usefulness: accounting data contains sensitive content such as enterprise capital flow, tax information, customer information, etc. If enterprises think that the data is unsafe, even if cloud accounting can improve efficiency (high PU), it will not recognise its value, let alone produce the willingness to adopt. In the survey, 82% of the enterprises took 'whether the service provider has the national three-level certification' as the first condition for choosing cloud accounting, and 75% of the enterprises said that they had refused to try cloud accounting for fear of data leakage. This perception that security concerns take precedence over efficiency needs leads to the need for PS to indirectly affect BI by boosting PU. Compared with Rawashdeh et al.'s study on the adoption of cloud accounting by SMEs, the impact intensity of PS in this study is higher (Rawashdeh's PS → PU coefficient is 0.12, and this study is 0.17), because China has stricter supervision on enterprise data security and SMEs have stronger concerns about data compliance. Therefore, the impact of safety on usefulness is more significant.

6.3 Impact of policy variables

GPS indirectly affected BI through PU ($\beta = 0.14$, $p < 0.05$), which was weaker than CBE (0.26) and PS (0.17). This result reflects the characteristics of China's policy-driven market, but also reflects the auxiliary orientation of the policy. GPS can enhance the awareness of PU by reducing the cost and risk of enterprise adoption. The effect of this policy to lower the threshold makes GPS indirectly affect BI through PU. However, the impact of GPS is weak, because on the one hand, some policy publicity is not in place; on the other hand, enterprises are increasingly focusing on the actual cost and safety, and the policy can only be icing on the cake, but can not replace the market demand. This suggests that policy makers need to combine policy support with market demand in order to improve policy effectiveness. This result is in contrast to Krah et al's study on the adoption of fintech by SMEs in Ghana: Ghanaian enterprises are more strongly affected by policies (GPS → PU coefficient 0.21), while Chinese enterprises have more market choices, and the impact of policies is diluted by market factors, reflecting the differences in the relationship between policies and markets in different countries.

7 Conclusions

7.1 Theoretical contributions

This study extends the TAM model by integrating China-specific variables, thereby enriching IS theory in three ways: first, it demonstrates how institutional factors (e.g., data security regulations) indirectly influence technology adoption through perceived usefulness, adding a contextual layer to TAM. Second, the focus on CBE aligns with resource-based view theory, highlighting SME-specific decision-making logic. Third, the model offers a template for adapting TAM to policy-driven economies, bridging theoretical gaps in cross-cultural research.

7.2 Managerial implications

For SMEs, results emphasise prioritising cloud accounting systems with high ease of use and cost transparency. For service providers, tailoring security features and subscription models to Chinese regulations can enhance adoption. For policymakers, combining subsidies with training programs (e.g., on data compliance) will amplify policy effectiveness. These insights address the practical needs of stakeholders in China's digital transformation landscape.

Data availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Declarations

All authors declare that they have no conflicts of interest.

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