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RESEARCH ARTICLE

Sri Lankan SMEs' Performance Through Cloud Computing Adoption: An SEM-ANN Analysis

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ABSTRACT This study identifies the determinants of cloud computing adoption and its effect on the performance of Sri Lankan small and medium-sized enterprises (SMEs). The Technology-Organization-Environment (TOE) framework, Technology Acceptance Model (TAM), and individual context were used to derive the study variables. This quantitative cross-sectional study adopted items from previous validated studies. Google Form was employed to collect data, and 418 responses were received from Sri Lankan SMEs. Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4 and Artificial Neural Network (ANN) analysis via IBM SPSS 29 were used for data analysis. Based on the results, all hypotheses are confirmed except for one, and SME performance is significantly affected by cloud computing adoption. This study adds to the existing empirical evidence on cloud computing adoption by introducing an all-inclusive model that integrates the TOE, TAM, and individual factors. This demonstrates the effectiveness of the PLS-SEM/ANN hybrid methodology in analysing the determinants of cloud computing adoption. The significance of top management as a factor is highlighted by providing training and education to employees. Managers can benefit from this result by improving cloud computing adoption among SMEs in Sri Lanka. This is the first study of its kind in Sri Lanka, integrating the TOE, TAM, and individual variables and using a hybrid methodology combining PLS-SEM and ANN.

INDEX TERMS Cloud computing, neural network, PLS-SEM, SMEs, performance, Sri Lanka.

I. INTRODUCTION

Businesses targeting the improvement of efficacy through digital transformation must adopt and integrate valuable technologies [1]. With the development of information technology (IT), numerous software, platforms, and infrastructure have been transformed into a new service called cloud computing [2], which can be scaled up or down according to Internet-driven resources. Mell and Grance [3] defined cloud computing as the basis for facilitating rapid access to shared resources, thus allowing for the release and leasing of those resources whenever needed [4].

Cloud computing solves common system problems by integrating distributed, grid, and parallel computing into one system [5]. This allows SMEs to adjust their need for technical resources accordingly [6]. It also transforms business processes, allowing SMEs to be more productive, flexible, and agile [7]. SMEs are the economic backbone of nations and make up many businesses worldwide [8]. Owing to the abundance of SMEs, competition among them is fierce, exacerbated by an unsupportive business landscape, poor infrastructure, inadequate financial resources, and lack of technological support, including Enterprise Resource Planning (ERP) [9]. SMEs make up 75% of all businesses in Sri Lanka, contributing 52% to the nation's GDP and 45% to its employment sector. SMEs in Sri Lanka have been identified as hindered by insufficient financial resources [10], as well as poor information and communication technology (ICT) capabilities; only 28% have computers, 91% rely on mobile phones instead of proper business landlines, and only 40% use the Internet and social media [11].

Current research on cloud computing benefits remains incomplete because it fails to include comprehensive models analysing the complete influence of technological,

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organizational, and environmental factors together with individual attributes. Recent studies maintain isolated analyses with either TAM or TOE theoretical models or they exclusively focus on urbanised countries. Researchers have yet to extensively integrate these viewpoints about cloud computing adoption in Sri Lankan SMEs. Predictive modelling techniques remain underutilised in most research because most scholars focus solely on linear analytical techniques.

Despite demonstrating rapid growth and its proven economic significance [8], cloud computing adoption among Sri Lankan SMEs remains sluggish [9], [12].This study fills these gaps through the integrating of TAM, TOE and individual context constructs into a single adoption framework and using PLS-SEM together with ANN for dual-stage analysis which improves model prediction as well as explanation. The study of Sri Lankan SMEs provides contextually grounded insights that build present-day technology adoption theories while adding value to the digital transformation literature for emerging economies. Despite the transformative potential of cloud computing, its adoption among SMEs in developing countries like Sri Lanka remains limited. This poses a significant challenge in achieving digital transformation goals and enhancing SME performance. Existing literature predominantly investigates technology adoption in developed economies or focuses on isolated theoretical models such as TAM or TOE. Furthermore, most studies employ linear statistical techniques, lacking predictive analytics capabilities.

This study addresses these gaps by integrating the TOE framework, TAM constructs, and individual-level factors to develop a comprehensive cloud computing adoption model tailored to the SME context in Sri Lanka. By applying a dual-stage analytical approach using PLS-SEM and ANN, the study offers both explanatory and predictive insights. This contributes theoretically by extending existing adoption models with individual cognition and practically by informing policymakers, SME managers, and IT service providers on the key drivers of cloud adoption and performance.

The research opens multiple avenues that future researchers can pursue. New endeavours should include a longitudinal research design with the involvement of cloud service providers and operational-level staff and an analysis of sector-based or country-level differences. Extending the analysis with relevant additional factors such as data security and firm location as well as infrastructure elements would enhance knowledge of cloud adoption patterns in SMEs.

II. LITERATURE REVIEW

ICTs have adopted by various businesses to improve their operations and increase their value amidst fierce market competition and the ever-changing business landscape [13]. To meet their business goals and objectives, for-profit and non-profit bodies must have a high capacity to adapt to business and IT changes. The aim of businesses today is to fulfil customer needs and stand out among the competition [14]. In this regard, cloud computing can facilitate business performance improvement, cost reduction, scalability and flexibility enhancement, and technological usage optimisation [15]. Cloud storage, network access, and processing at the required capacity and free of human interference can be fulfilled by cloud service providers [5]. This technology can also aid the development of new business models [16] and serve as a crucial innovation for performance improvement [17].

In contrast to large firms, SMEs do not have the financial resource backing needed to adopt and invest in technology [18]. This causes them to be highly cautious in hindering them from developing their own ICT support [19]. Thus, SMEs often rely on external resources. With cloud computing, SMEs can provide technical support through a low-cost rental payment system [6]. Its sophistication improves SMEs' management capability, performance, and competitive edge [20]. Even so, SMEs, in general, are still hesitant to adopt them [13], indicating many underlying issues that require proper investigation [21].

A review of empirical research on cloud computing adoption within SMEs has allowed researchers to understand the current state of research. The research reviewed many articles, out of which 18 main studies that published between 2019 up to 2024 are summarised in Table 1. Research studies from various contexts both developing and developed countries investigate numerous determinants at technological, organizational and environmental and individual levels.

The summaries in Table 1 identify many common findings among studies that include key variables such as top management support, technical readiness, along with cost considerations. Several studies have examined adoption factors through constructs derived from TAM, TOE, and DOI models and supplementary variables regarding COVID-19 risks, server locations, and data security considerations. Many studies including the works of Anbuudayasankar et al. [36] and Khayer et al. [37] investigated trust together with self-efficacy and absorptive capacity. However, despite this growing body of work, a few critical research gaps remain. A majority of studies select one theoretical framework such as TAM or TOE for investigation resulting in reduced comprehension of complete cloud adoption drivers for SMEs. Research on cloud adoption factors in SMEs shows limited recognition of characteristics possessed by individuals such as their resistance to change and their self-efficacy. SEM-based techniques appear frequently in research, but studies rarely employ hybrid methods such as SEM-ANN that could provide better explanative and predictive strength to results. The majority of existing digitalisation research investigates well-developed countries, as many underdeveloped countries such as Sri Lanka remain unstudied. Hence, this study develops an integrated model based on TOE framework alongside TAM adoption constructs and contextual elements and investigates the impact of such adoption using PLS-SEM and ANN at its analytical stages. The proposed model intends to deliver an expanded and predictive analysis of cloud computing acceptance by Sri Lankan SMEs.

TABLE 1. Summary of recent studies on cloud computing adoption in SMEs.

Authors	Year	Key Findings
Teh et al. [22]	(2024)	It was found that support from top management significantly mediates the adoption of cloud computing. The novel attributes of DOI theory and the components of the TOE framework positively impact the adoption of cloud computing.
Mousa et al. [23]	(2024)	The SEM analysis results indicated that perceived usefulness, facilitating conditions, server location, perceived cost, and top management support were positively correlated with cloud computing adoption among SMEs in Palestine.
Kumar and Gupta [24]	(2023)	This study aimed to identify the barriers to cloud computing adoption in Indian SMEs using an extensive literature review and expert insights.
Alasady et al. [25]	(2023)	Cloud computing improves the operational efficiency of Iraqi SMEs. Organisational factors including top management support and technological preparedness, significantly influence the intention to use cloud computing and enhance firm performance.
Al-Sharafi et al. [26]	(2023)	The adoption of cloud computing in SMEs is substantially affected by relative advantage, complexity, compatibility, top management support, cost reduction, and governmental support.
Chen et al. [27]	(2023)	The findings indicate that security, managerial backing, employee IT proficiency, competitive pressure faced by the organisation, and assistance from trading partners about the utilisation of a cloud service provider are influential factors in the decision-making process for SMEs to embrace cloud computing.
Ali et al. [28]	(2023)	The research found that cost reductions, organisational size, top management support, and regulatory backing to the significant factors of cloud computing adoption. Conversely, considerations such as security concerns and competitive pressure do not prevail in the adoption of new technology by SMEs in Somalia.
Shetty and Panda [29]	(2023)	The results revealed that perceived usefulness, perceived ease of use, technological readiness, top management support, and trust were the primary factors influencing cloud adoption in SMEs in India, while compatibility and competitive pressure were not significant .
Hamidinava et al. [30]	(2023)	A mixed-methods approach employing expert interviews found six principal components, 24 subfactors, and 24 identifiers. The six fundamental components are drivers, facilitators, competences, critical success elements, attributes of SMEs, and adoption.
Al-Okaily et al. [31]	(2022)	This study found that Performance expectancy, social influence, COVID-19 risk, and trust strongly influenced users' attitude towards Cloud-based accounting information system. Effort expectancy and perceived security did not have influence.
Majengo and Mbise [32]	(2022)	Eight variables significantly affect the adoption of SaaS by SMEs in Tanzania: relative advantage, compatibility, awareness, cost, perceived security and privacy risk, reliability and availability, top management support, and assistance from trading partners.
Saad et al. [33]	(2022)	The relative advantage, security concerns, top management support, organisational readiness, competitive pressure, and the influence of trading partners significantly impacted intention of Jordanian SMEs to adopt cloud accounting.
Gui et al. [34]	(2021)	The primary determinants affecting cloud computing adoption in Indonesian SMEs within the creative industry encompass cloud flexibility, perceived worries, privacy, relative advantage, perceived cost-benefit, service quality, and senior management support.
Khayer et al. [35]	(2020)	SEM findings demonstrate that relative advantage, service quality, perceived risks top management support, facilitating conditions, the influence of cloud providers, server location, computer self-efficacy, and resistance to change greatly affect the adoption of cloud computing.
Anbuudayasankar et al. [36]	(2020)	This study employed Importance-Performance Analysis to pinpoint areas for enhancement in cloud computing service providers and their effectiveness.
Khayer, et al. [37]	(2020)	It was found that Performance expectancy, effort expectancy, absorptive capacity, data security, privacy, and perceived trust affect the adoption of cloud computing by SMEs.
Fernando et al. [38]	(2019)	The article concludes that perceived usefulness, compatibility, security and privacy, management support, and competitive pressure greatly influence the adoption of cloud computing in Indonesia's creative sectors, hence enhancing business competitiveness.
Asiaei and Rahim [39]	(2019)	The primary determinants influencing cloud computing adoption in Malaysian SMEs include data security, technological preparedness, managerial support, competitive pressure, and innovativeness.

III. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The conceptual model developed in this study was based on the TOE framework [40]. As its name suggests, the three components of the framework impact decision-making in relation to innovation adoption [41]. The literature review revealed that the determinants of cloud computing adoption among SMEs have not been extensively studied, particularly in Sri Lanka, with even less research focusing on human-related factors. The comprehensiveness of the framework provides a theoretical foundation for investigating the acceptance and dissemination of innovation. It has been employed in numerous studies on corporate technology adoption (e.g., [41], [42], [43], [44]. Considering how fast ICT develops, none of the determinants of technology adoption can be captured by a single model.

The acceptance of new IT is commonly investigated using the TOE framework and the TAM developed by Davis [45]. Both models have been extensively used in technology adoption studies. With TAM, external variables can be selected more freely, enabling insight into individual acceptance behaviours. TOE focuses on how technical, organisational, and environmental factors determine corporate adoption behaviour. With the combination of both frameworks and by leveraging their respective capacities, adoption behaviours can be captured at numerous levels. Gangwar [2], for instance, combined the two frameworks in investigating organisational-level cloud adoption. Qin et al. [46] also combined both models to examine the adoption of building information modelling by construction players. Likewise, TOE-TAM integration was used to identify the determinants of AI adoption [47] and cloud computing adoption [2].

A. TECHNOLOGICAL FACTORS

New Internet-enabled IT delivery is the mainstay of cloud computing. Thus, its adoption requires technological support. The TOE model highlights both internal and external technology requirements for this purpose, with the specific factors of Relative Advantage, Compatibility, and Complexity

1) RELATIVE ADVANTAGE

A given technology must demonstrate a relative advantage over its counterparts to be adopted. Relative advantage is "the extent to which using innovation is perceived to make one better off than they would be otherwise" [48]. In the context of SMEs, technology must be perceived as beneficial for improving their performance and, hence, their revenue. This element has been found to be highly significant in driving the adoption of cloud-based ERP systems among SMEs and large firms [42]. Relative advantages in the form of cost savings and security assurance have been indicated to impact firms' revenue, organisational reliability, and total performance [49], [50]. In the context of cloud computing, the relative advantage is cost effectiveness, that is, the ability to reduce infrastructural and maintenance expenses [44]. SMEs are driven to adopt cloud computing once they are informed of its relative advantages [5]. A personal computer is not required when using the cloud technology. As this technology enables resource sharing, SME employees can access their resources in an omnipresent manner, making them cost- and time-effective. Based on all the above, these hypotheses are developed:

H1a: Relative Advantage positively affects PU.

H1b: Relative Advantage positively affects PEOU.

2) COMPATIBILITY

Compatibility is defined by Rogers [51] as "the extent to which potential adopters perceive an innovation to be consistent with their existing values, past experiences, and needs". This dimension determines whether the employee and organisational beliefs, experiences, and behavioural patterns are well-matched to the innovation in question [52]. This innovation must be easily implementable and in line with the organisation's culture and objectives [41]. This element also entails the organisation's internal demands and how innovation can add to or enhance its existing processes. Peng [52], among others, has proven the significance of compatibility in driving the aspects of perceived usefulness (PU) and perceived ease of use (PEOU). The prompt adoption of an innovation transpires once the business acknowledges its compatibility with its prevailing systems [14]. A business is more likely to adopt cloud computing and reduce employee uncertainty regarding its usage when it perceives that the cloud platform is compatible with the Internet platform [53]. In the context of this study, it is pertinent to ensure that cloud computing is aligned with SMEs' current technology infrastructure. Based on all the above, these hypotheses are developed:

H2a: Compatibility positively affects PU.

H2b: Compatibility positively affects PEOU.

3) COMPLEXITY

The level of complexity of a new technology often influences the decision of a business to adopt it. This element is delineated as "the degree to which an innovation is perceived to be relatively difficult to understand" [54]. An innovation is deemed complex when there is confusion among technology providers and IT users regarding its implementation [42]. Businesses tend to steer clear of seemingly complex technologies [41] because technical challenges disrupt their operations [55]. The decision to adopt cloud technology is often based on how long it takes to complete certain tasks, its ability to be integrated with existing applications, how it improves data transfer, how well its system functions, and how its interface is designed. Essentially, this element is closely associated with the aspects of PU and PEOU, which are assumed to be two separate constructs in many previous studies. Innovation adoption is negatively affected by the perceived complexity of understanding, using, and managing it [56]. Based on all the above, these hypotheses are developed:

H3a: Complexity negatively affects PU.

H3b: Complexity negatively affects PEOU.

B. ORGANISATIONAL FACTORS

Organisational factors comprise the qualities and resources that the firm has to facilitate the implementation of the technology. Successful cloud implementation leads to organisational and technical shifts. This means that organisational factors significantly affect the decision to adopt cloud technology. In this study, these factors include Organisational Readiness, Top Management Support, and Training and Education.

1) ORGANISATIONAL READINESS

This factor refers to an organisation's capacity to embrace innovation. Specifically, it refers to the level of knowledge, resources, commitment, and governance that the organisation has, which would facilitate its adoption of a new technology [57]. Such readiness has been shown to affect innovation adoption [58]. Technology usage in an organisation can be boosted when there is sufficient ICT infrastructure, technical expertise, and financial backing [59]. Based on all the above, these hypotheses are developed:

H4a: Organisational Readiness positively affects PU.

H4b: Organisational Readiness positively affects PEOU.

2) TOP MANAGEMENT SUPPORT

This factor refers to top management's attitude and behaviour regarding technology usage towards producing corporate value [60]. With such support, the organisation would be able to develop a long-term vision, reinforce its values, commit its resources, ensure the best management of its resources, cultivate a positive organisational setting, create better self-efficacy assessments, develop better mitigation practices, and overcome change resistance [61]. Management support has been shown to have a significant effect on innovation adoption [62]. Top executives have the power to define the organisation's vision and mobilise its staff to support it. As it takes a lot to convince top managers to accept a new technology, their eventual support is of great significance [63]. The strategic significance of technology, as emphasised by top management, drives the momentum of related projects [41]. Top management support has often been highlighted in management and IT adoption literature as a driver of innovation adoption and deployment. It has also been proven to be correlated with the PU and PEOU of various technologies [2]. Based on all the above, these hypotheses are developed:

H5a: Top Management Support positively affects PU.

H5b: Top Management Support positively affects PEOU.

3) TRAINING AND EDUCATION

This factor refers to the degree to which employees have been trained to use the adopted technology [64]. Prior to cloud technology deployment, employees must be trained to use it. This alleviates apprehension and improves confidence in innovation. It also reduces uncertainties, facilitates knowledge attainment, and improves PU and PEOU [2]. Hence, these hypotheses are proposed:

H6a: Training and Education positively affect PU.

H6b: Training and Education positively affect PEOU.

C. PERCEIVED USEFULNESS (PU)

This factor is delineated as "the extent to which an individual believes that employing a particular system would improve his or her job performance" [45]. Essentially, it is the belief that cloud adoption improves an organisation's performance. Behavioural intention research highlights it as a key predictor [65] with a direct effect on behavioural intention [66]. This suggests that the perception of performance-boosting capacity drives the use of new technology. The significant effect of PU on usage intention has been extensively proven [65]. In short, the intention to adopt cloud technology can be predicted by user perceptions of its usefulness. Thus, we propose the following hypothesis:

H7: PU positively affects Intention to Adopt Cloud Computing.

D. PERCEIVED EASE OF USE (PEOU)

As asserted by Venkatesh and Davis [67], behavioural intention can also be predicted by PEOU, which refers to "the extent to which a person believes that utilising a specific system would be effortless" [45]. Essentially, it refers to SMEs' belief in how easy it is to adopt, learn, and implement cloud technology. Technology acceptance is often determined by perceived usability. Al-Gahtani [68] and Faqih and Jaradat [69] agree that PEOU significantly determines behavioural intention. This means that SMEs have a higher likelihood of adopting cloud technology if they perceive it to be user-friendly. Hence, PEOU is expected to affect SMEs' behavioural intention to adopt cloud technology [70], [71]. Based on the above, the following hypothesis is proposed:

H8: PEOU positively affects Intention to Adopt Cloud Computing.

In turn, cloud adoption intention has a favourable effect on adoption decisions. Hence, we propose the following hypothesis:

H9: Intention to Adopt Cloud Computing positively affects the Adoption of Cloud Computing.

E. ENVIRONMENTAL FACTORS

These factors represent SMEs' existing operational landscape and determine their capacity to adopt new technology. These determinants include Competitive Pressure and Trading Partner Support.

1) COMPETITIVE PRESSURE

This factor has been proven to strongly predict innovation adoption [72]. It entails the gravity of competition faced by the organisation as exerted by its counterparts in the industry [73]. This factor has a positive effect on technology adoption, particularly when rivalry is involved. To remain a top market contender, innovation adoption is pertinent [74], as it can facilitate the organisation in boosting its competitiveness, strengthening its structure, and outperforming its competitors [75]. This means that early cloud adopters have a significant competitive advantage and survivability rate. Based on the above, the following hypothesis is proposed:

H10: Competitive Pressure positively affects Adoption of Cloud Computing.

2) TRADING PARTNER SUPPORT

One of the mainstays of service providers is their ability to ensure constant data availability. Failure in this aspect raises doubts regarding their efficacy. This underscores the necessity for cloud service providers to have reliable trading partners, that is, those who facilitate technical assistance and maintain cloud infrastructure [41]. The total data availability is guaranteed by the adoption of an established platform with a high-availability architecture [76]. The availability of support cannot be compromised when it comes to on-premise cloud computing, as cloud service providers are paid to guarantee this aspect. This means that cloud service providers must have well-trained support personnel in place [77]. Based on the above, the following hypothesis is proposed:

H11: Trading Partner Support positively affects the Adoption of Cloud Computing.

F. INDIVIDUAL CONTEXT

Individual determinants have also been shown to significantly affect behavioural intentions [78]. Due to the centralised nature of SMEs, managers and owners have a significant say in businesses' strategic corporate decisions [19].

1) SELF-EFFICACY

This factor refers to the extent to which one believes that he/she can complete a given task [79]. Someone who believes that they are highly efficient has no issues in learning about new technologies [80], [81]. Yang and Lin [82] proved that self-efficacy boosts perceptions about cloud technology. In the context of this study, the focus is on the self-efficacy of the SMEs' chief executive officers (CEOs) in deciding about cloud technology adoption [83]. CEOs who are highly knowledgeable about technology would naturally have high levels of self-efficacy, which in turn drives their decision to adopt cloud computing for the business. Based on this, the hypothesis below is developed:

H12: Self-efficacy positively impacts the Adoption of Cloud Computing.

2) SOCIAL INFLUENCE (SI)

A person's behavioural intention to adopt an innovation is influenced by the people close to them. Venkatesh, Thong, and Xu [84] delineate this factor as "the degree to which an individual perceives that important others believe that he or she should use the new technology". Social influence has been proven to affect one's intention to utilise Internet-based services [85]. This effect is even more significant under voluntary conditions [86]. When decision-makers' interaction with others leads to behavioural changes, there is a good chance that SMEs will adopt cloud technology. Based on this, the hypothesis below is developed:

H13: Social Influence positively affects the Adoption of Cloud Computing.

3) RESISTANCE TO CHANGE

A willingness to change is necessary when it comes to innovation adoption. Unfavourable attitudes towards a proposed shift are delineated as resistance to change [87]. This factor determines the success rate of new technology implementation [87]. Hoque and Sorwar [88] demonstrated a negative effect of this factor on m-health adoption. As decision-makers in SMEs have different characteristics, the idea of adopting cloud computing is met with varying levels of acceptance, as this would mean significant adjustments to the organisations' current structures, activities, procedures, and systems. Managing such changes would require a lot from decision makers, leading to apprehensions and various concerns.

H14: Resistance to Change negatively affects the Adoption of Cloud Computing.

G. CLOUD COMPUTING ADOPTION AND FIRM PERFORMANCE

Strategic organisational decisions are expected to result in better organisational performance. Core capacity and performance have been shown to improve by successful IT adoption and orientation [89]. In the context of cloud technology, performance refers to the capability of a cloud provider to boost an organisation's procedures and operations. The adoption and usage of cloud technology have been proven to positively impact the non-financial performance of organisations [90]. Cloud technology allows SMEs to focus on their core capabilities, leading to improved productivity, operational performance, and ultimately, financial performance. Garrison et al. [91] agree that effective cloud implementation has a positive impact on cloud-related performance. Hence, the following hypothesis is developed:

H15: The Adoption of Cloud Computing positively influences Firm Performance.

Figure 1 on next page presents the model developed based on the proposed hypotheses.

IV. METHODOLOGY

This study was conducted deductively to determine the technological, organisational, environmental, and individual drivers of cloud computing adoption intention and actual adoption, as well as the effect of adoption on SMEs' performance.

A. SAMPLE SIZE AND SAMPLING METHOD

The targeted decision makers worked for SMEs across all nine Sri Lankan provinces within 25 districts. The people in charge of making choices included owners and CEOs alongside IT managers and executives who were responsible for

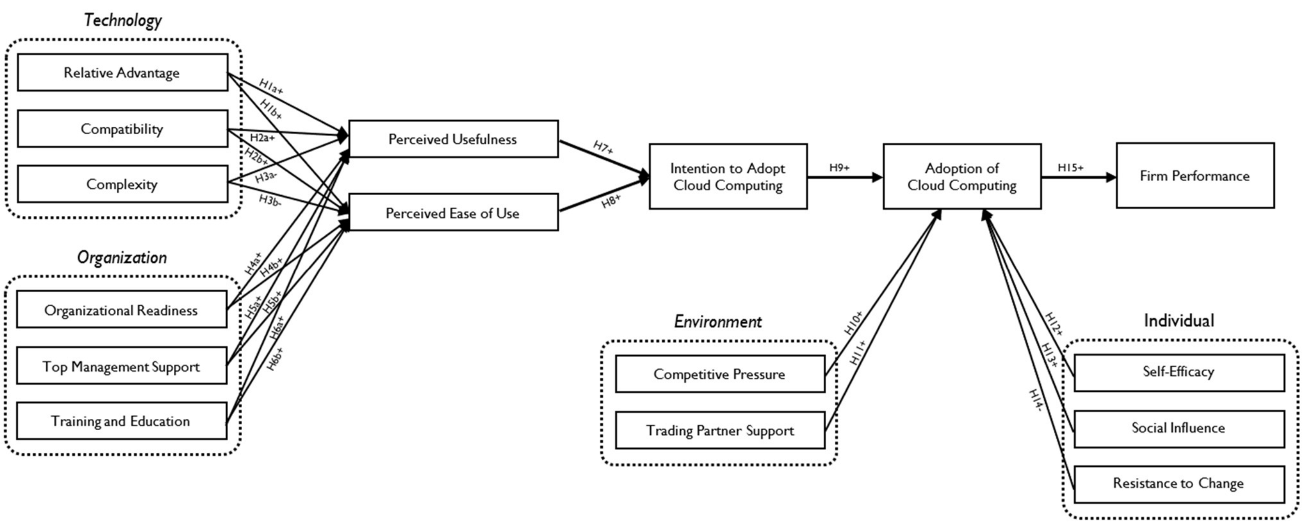

FIGURE 1. **Proposed research model.**

technological innovation assessment, implementation, and management. The researchers selected participants through purposive sampling because they demonstrated sufficient knowledge and experience in IT decision processes with a focus on cloud computing adoption. The chosen method fits well for organizational investigations focusing on innovation adoption, because it taps into the expertise of knowledgeable participants. The study used Thorndike's [92] multivariate analysis formula ($N \geq 100 + 8m$) to establish the minimum sample requirement by counting the number of model predictors as m. Hence, at least 356 participants with 16 independent variables were required for this study. A total of 418 respondents who completed valid responses through Google Forms helped enhance statistical power while ensuring representative inclusion of different sectors and geographical regions. The sample size fulfils the PLS-SEM standards by transcending the recommended thresholds, thus validating its robustness for structural modelling.

B. INSTRUMENT DEVELOPMENT

The components of the TOE and TAM models and individual factors were considered when developing the study's questionnaire, with the adoption of items from prevailing instruments.

C. DATA ANALYSIS

Data collected via Google Forms were exported to Microsoft Excel. After omitting all incomplete and missing data, the main analysis was performed using the remaining data. The research design combined PLS-SEM at its initial stage and subsequently used an ANN analysis. The research team chose PLS-SEM implemented with SmartPLS 4.0 since the model analysis software provides excellent functionality for complex surveys and sample sizes and predictive research design. This technique allows users to measure multiple dependent relationships at once and it demonstrates resistance against non-normal data distribution. The ANN within SPSS version 29 combines with SEM by capturing nonlinear analysis while providing a ranking system for predictor significance. The dual-stage examination (SEM-ANN) provides improved explanatory power and prediction capabilities to the study according to existing literature [90] that find application in technology adoption research.

V. DATA ANALYSIS AND FINDINGS

A. DATA PREPARATION AND DESCRIPTIVE STATISTICS

Before proceeding to the analysis stage, the data must first be screened, checked for missing values, coded, cleaned, evaluated for missing data, identified as outliers, and tested for multivariate assumptions [93]. Using statistical methods, a large amount of data can be summarised concisely, utilising a small number of values. Descriptive statistics describe the characteristics of the sample, such as their Mean value (central tendency) and Standard Deviation (variability).

B. UNENGAGED RESPONSES AND MISSING DATA

There were 19 unengaged responses in the dataset that were subsequently omitted [94]. The online survey requires all items to be answered completely to enable the measurement of latent variables. As expected, there were no missing data.

C. DEMOGRAPHY OF THE RESPONDENTS

The demographic data gathered included the respondents' gender, age, education level, current work tenure, cloud computing experience, position at present, and role in IT decision-making. Table 2 tabulates the information gathered, enabling a comprehensive analysis of cloud computing acceptance in SMEs and its impact on their performance.

Most respondents were male (341, 81.6%), while the remaining respondents were female (77, 18.4%). Most of

TABLE 2. **Demographic details of the respondents.**

Variable	Measurement	Frequency	Percentage
Gender	Male	341	81.60%
	Female	77	0.184
Age	Below 30 years old	28	0.067
	31 – 40 years old	112	0.268
	41 – 50 years old	236	0.565
	Over 51 years old	42	0.1
Education level	No Formal Education	7	0.017
	GCE (O /L)	14	0.033
	GCE (A /L)	51	0.122
	Bachelor / Professional Qualification (CA, CIMA, ACCA, etc.)	315	0.754
	Master's / PhD	31	0.074
Are you familiar with Cloud Computing?	Yes	418	1
	No	0	0
What is your position?	Owner	6	0.014
	CEO	17	0.041
	IT Manager	204	0.488
	IT Executive	138	0.33
	Others (please specify)	53	0.127

Source: Data Collected for this study

them were middle-aged, that is, between 41 and 50 years (236 or 56.5%). The rest were between 31 and 40 (112, 26.8%), 30 and below (28, 6.7%), and 51 and above (42, 10.0%). Most of them were also highly educated, holding either a bachelor's degree or professional certificate (315 or 75.4%), a GCE (A/L) (51 or 12.2%), and a master 's or PhD (31 or 7.4%). The remaining held a GCE (O/L) (14 or 3.3%), while a small portion claimed to be non-formally educated (7 or 1.7%). In terms of job position, most were IT Managers (204 or 48.8%). The rest were IT Executives (138, 33.0%), CEOs (17, 4.1%), and owners (6, 1.4%). The category Others comprised 53 respondents (12.7 %).

D. 5.4 DESCRIPTIVE STATISTICS OF THE LATENT VARIABLES

Table 3 presents the descriptive statistics for the 418 SMEs. Adoption (ADO) is slightly negatively skewed, with an average value of 4.880, suggesting a high cloud adoption rate among most SMEs, with scores leaning to the scale's higher end.

There was a positive attitude towards cloud adoption, as shown by the mean values for Compatibility (that is, 4.340), and PU (that is, 4.192). Based on their standard deviations and skewness, variability was observed in these factors. Meanwhile, the mean values for Complexity and Competitive Pressure were greater than five, suggesting that these factors significantly affect cloud adoption.

Next, there was significant heterogeneity and skewness for Firm Performance, Intention to Adopt, and Organisational Readiness, suggesting variability in the responses. Social Influence and Training and Education were significant predictors of adoption based on their high mean scores and negative skewness, with most of the responses leaning toward the scale's higher end. Slightly peaked and flat distributions with no notable deviations were demonstrated by kurtosis values. Statistically, the results showed a positive attitude towards cloud adoption. However, perceptions of complexity and ease of use, as well as external pressure, vary.

TABLE 3. **Descriptive statistics (n = 418).**

Variable	Mean	Std. Deviation	Skewness	Kurtosis
ADO	4.880	0.889	-0.069	-0.197
COMPAT	4.340	0.850	-0.078	0.377
COMPLX	5.026	1.137	-0.130	-0.527
FP	4.395	1.259	-0.186	-0.368
INT	3.654	1.165	-0.161	-0.432
ORR	4.152	1.275	-0.050	-0.261
PEOU	4.322	1.163	-0.294	-0.276
PRES	4.941	1.011	-0.077	-0.525
PU	4.192	1.209	-0.114	-0.214
RA	4.692	1.060	-0.246	-0.468
RE	4.685	1.136	-0.230	-0.556
SE	4.426	0.975	0.070	-0.216
SI	4.906	1.092	-0.335	-0.324
TE	4.890	1.170	-0.248	-0.371
TMS	4.428	1.129	-0.023	-0.532
TPS	4.168	1.118	-0.071	-0.052

Source: SPSS 29 Output

Note: *RA – Relative Advantage; COMPAT – Compatibility; COMPLX – Complexity; OR – Organisational Readiness; TMS – Top Management Support; TE – Training and Education; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; INT – Intention to Adopt; PRES – Competitive Pressure; TPS – Trading Partner Support; SE – Self-Efficacy; SI – Social Influence; RE – Resistance to Change; ADO – Cloud Computing Adoption; FP – Firm Performance.*

E. NORMALITY TEST

Skewness and kurtosis were evaluated to determine the normality [93]. Table 3 presents the results, indicating generally

TABLE 4. Outer loadings of items.

Items	Outer Loadings	Items	Outer Loadings
ADO1	0.939	RA1	0.856
ADO2	0.751	RA2	0.852
ADO3	0.926	RA3	0.833
COMPAT1	0.813	RA4	0.825
COMPAT2	0.848	RA5	0.828
COMPAT3	0.785	RE1	0.866
COMPAT4	0.880	RE2	0.901
COMPLX1	0.972	SE1	0.837
COMPLX2	0.953	SE2	0.869
COMPLX3	0.912	SE3	0.755
COMPLX4	0.955	SE4	0.729
FP1	0.915	SI1	0.774
FP2	0.822	SI3	0.886
FP3	0.944	SI4	0.897
INT1	0.903	TE1	0.872
INT2	0.864	TE2	0.942
INT3	0.903	TE3	0.845
INT4	0.916	TE4	0.787
OR1	0.909	TE5	0.914
OR2	0.859	TMS1	0.914
OR3	0.939	TMS2	0.934
PEOU1	0.911	TMS3	0.904
PEOU2	0.906	TPS1	0.926
PEOU3	0.937	TPS2	0.910
PEOU4	0.932	TPS3	0.941
PEOU5	0.909	TPS4	0.868
PRES1	0.885		
PRES2	0.854		
PRES3	0.939		
PRES4	0.855		
PU1	0.903		
PU2	0.748		
PU3	0.868		
PU4	0.937		
PU5	0.908		

Source: SmartPLS 4 Output

acceptable ranges for skewness of ±3 and kurtosis of ±10 [95].

F. STRUCTURAL EQUATION MODELLING (SEM)

1) 5.6.1 ANALYSIS OF MEASUREMENT MODEL

The first step in assessing PLS-SEM results is to evaluate the measurement model to determine how the observed and latent variables are related [96]. SmartPLS 4.0 was employed for this purpose.

Indicator Reliability

The outer loading matrix was examined to determine the indicator reliability. According to Hair et al. [93], loading should preferably range between 0.5 and 0.7. FP4 had a factor loading of 0.665, and its removal increased the Average Variance Extracted (AVE) from 0.743 to 0.801.

Meanwhile, RE3 had a loading of 0.653 and its omission increased the AVE of RE from 0.650 to 0.781. Based on Table 4 and Figure 2, all indicators had loading values higher than the cut-off value.

Internal Consistency

Internal consistency was assessed using Jöreskog's [97] composite reliability rho_c, and the results are shown in Table 5. All the rho_c values for the latent variables were

TABLE 5. Reliability and validity measures.

Latent Variables	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
ADO	0.848	0.891	0.908	0.768
COMPAT	0.852	0.858	0.900	0.693
COMPLX	0.963	0.967	0.973	0.899
FP	0.876	0.902	0.923	0.801
INT	0.918	0.920	0.942	0.803
OR	0.886	0.893	0.930	0.816
PEOU	0.954	0.955	0.965	0.845
PRES	0.906	0.913	0.934	0.781
PU	0.922	0.934	0.942	0.766
RA	0.895	0.896	0.922	0.704
RE	0.720	0.730	0.877	0.781
SE	0.812	0.834	0.876	0.639
SI	0.813	0.827	0.890	0.730
TE	0.922	0.932	0.941	0.763
TMS	0.906	0.910	0.941	0.841
TPS	0.932	0.937	0.952	0.831

Source: SmartPLS 4 Output

greater than 0.7 [97], with Cronbach's alpha values greater than 0.7, thus fulfilling the cut-off. Composite Reliability was assessed using rho_a and rho_c.

Table 5 shows that rho_a values were greater than 0.7. Hence, all constructs had adequate internal consistency and reliability.

Convergent Validity

According to Hair et al. [96], convergent validity can be confirmed, with a minimum AVE value of 0.50. Table 5 shows that all AVE values were between 0.639 (SE) and 0.899 (complexity), suggesting that the measurement model had adequate convergent validity.

Discriminant Validity

In this study, discriminant validity was established using the Fornell–Larcker criterion [98] and Heterotrait-Monotrait (HTMT) ratio [99]. Table 6 presents the outputs, indicating that the square root of each construct correlates more with that construct than with the other constructs.

As shown in Table 6, all variables had HTMT values lower than the 0.85 cut-off. However, there was a slight increase for the SE <-> RA variable (0.947), even though no issues were indicated by the outer loadings and Fornell-Larcker criterion. Bootstrapping (complete) was performed using SmartPLS 4, whereby the RE <-> RA variable exhibited a 1.00 difference. Thus, it can be concluded that the measurement model had adequate discriminant validity.

2) 5.6.2 ANALYSIS OF STRUCTURAL MODEL

The subsequent stage entailed a structural model assessment.

Significance and Relevance of the Structural Model Relationships. Table 7 and Figure 3 present the results of the PLS algorithm and bootstrapping resampling. A total of 21 hypotheses were developed, with three proposed negative correlations. All hypotheses showed statistical significance, except for Hypothesis H3b-. Thus, 20 hypotheses were confirmed.

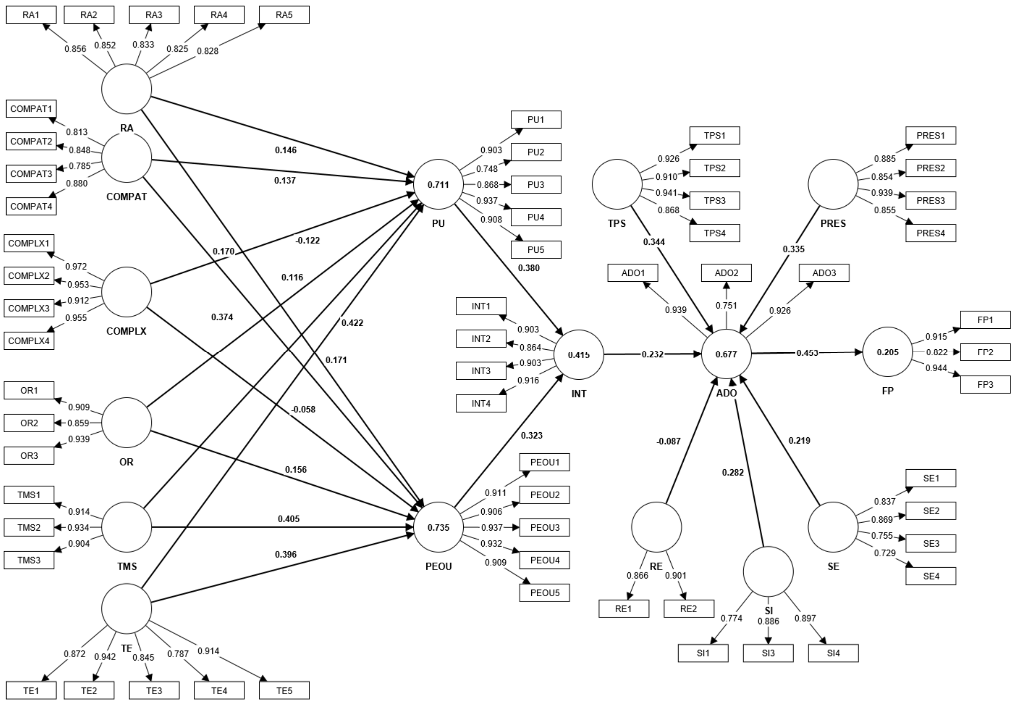

FIGURE 2. Output of measurement model assessment (Source: SmartPLS 4 Output).

TABLE 6. Fornell-larcker criterion and heterotrait-monotrait ratio (HTMT).

Fornell-Larcker Criterion

Latent Construct	ADO	COMPAT	COMPLX	FP	INT	OR	PEOU	PRES	PU	RA	RE	SE	SI	TE	TMS	TPS
ADO	0.877															
COMPAT	-0.022	0.833														
COMPLX	-0.292	-0.397	0.948													
FP	0.453	0.040	-0.368	0.895												
INT	0.432	0.191	-0.558	-0.021	0.896											
OR	0.088	0.147	-0.439	-0.013	0.414	0.903										
PEOU	0.075	0.507	-0.579	-0.055	0.580	0.486	0.919									
PRES	0.461	-0.034	-0.006	0.457	0.024	0.003	0.003	0.884								
PU	0.078	0.479	-0.608	-0.005	0.599	0.457	0.678	0.024	0.875							
RA	0.077	0.584	-0.421	0.112	0.271	0.328	0.476	0.049	0.435	0.839						
RE	0.046	0.505	-0.288	0.065	0.172	0.271	0.384	-0.001	0.355	0.763	0.884					
SE	0.512	0.130	-0.057	0.180	0.227	0.144	0.137	0.279	0.142	0.103	0.115	0.799				
SI	0.479	0.068	-0.315	0.280	0.201	0.090	-0.009	0.188	-0.012	0.041	0.052	0.169	0.854			
TE	0.069	0.268	-0.534	-0.027	0.418	0.242	0.551	0.008	0.589	0.018	-0.023	0.116	-0.026	0.874		
TMS	0.118	0.210	-0.252	-0.029	0.412	0.315	0.593	0.058	0.553	0.302	0.242	0.199	0.042	0.094	0.917	
TPS	0.519	0.171	-0.179	-0.015	0.289	0.171	0.317	0.017	0.283	0.193	0.154	0.319	0.160	0.261	0.335	0.912

Heterotrait-monotrait ratio (HTMT)

Latent Construct	ADO	COMPAT	COMPLX	FP	INT	OR	PEOU	PRES	PU	RA	RE	SE	SI	TE	TMS	TPS
ADO																
COMPAT	0.056															
COMPLX	0.315	0.435														
FP	0.505	0.052	0.400													
INT	0.482	0.215	0.592	0.026												
OR	0.106	0.169	0.472	0.026	0.457											
PEOU	0.079	0.561	0.602	0.063	0.619	0.527										
PRES	0.515	0.040	0.032	0.503	0.035	0.023	0.034									
PU	0.089	0.537	0.642	0.042	0.645	0.502	0.720	0.049								
RA	0.088	0.668	0.452	0.121	0.298	0.365	0.513	0.060	0.473							
RE	0.066	0.641	0.341	0.093	0.211	0.336	0.461	0.038	0.427	0.947						
SE	0.604	0.161	0.063	0.211	0.261	0.164	0.158	0.320	0.175	0.123	0.156					
SI	0.572	0.086	0.355	0.331	0.231	0.104	0.039	0.216	0.042	0.055	0.073	0.194				
TE	0.076	0.298	0.562	0.051	0.450	0.266	0.584	0.031	0.633	0.050	0.032	0.137	0.057			
TMS	0.131	0.238	0.269	0.045	0.451	0.351	0.636	0.062	0.601	0.333	0.296	0.236	0.046	0.104		
TPS	0.572	0.193	0.187	0.036	0.311	0.185	0.336	0.025	0.304	0.210	0.186	0.366	0.182	0.277	0.365	

Source: SmartPLS 4 Output

Coefficient of Determination (R^2)

Each endogenous variable's R^2 value, along with its interpretation are presented in Table 8. The variance in PU was 71% which was explained by the variables of Relative Advantage, Compatibility, Complexity (negative impact), Organisational readiness, top management support,

TABLE 7. Results of the bootstrapping procedure (path coefficients, significance levels) and decision.

Hypotheses	Relationships	Path Coefficient (β)	Std. Dev	T statistics	P values	Decision
H1a	RA -> PU	0.146	0.041	3.573	0.000	Accepted
H1b	RA -> PEOU	0.171	0.036	4.760	0.000	Accepted
H2a	COMPAT -> PU	0.137	0.034	3.974	0.000	Accepted
H2b	COMPAT -> PEOU	0.170	0.035	4.868	0.000	Accepted
H3a-	COMPLX -> PU	-0.122	0.036	3.436	0.001	Accepted
H3b-	COMPLX -> PEOU	-0.058	0.035	1.652	0.099	Rejected
H4a	OR -> PU	0.116	0.031	3.708	0.000	Accepted
H4b	OR -> PEOU	0.156	0.030	5.196	0.000	Accepted
H5a	TMS -> PU	0.374	0.031	12.213	0.000	Accepted
H5b	TMS -> PEOU	0.405	0.028	14.470	0.000	Accepted
H6a	TE -> PU	0.422	0.034	12.480	0.000	Accepted
H6b	TE -> PEOU	0.396	0.032	12.241	0.000	Accepted
H7	PU -> INT	0.380	0.050	7.643	0.000	Accepted
H8	PEOU -> INT	0.323	0.050	6.410	0.000	Accepted
H9	INT -> ADO	0.232	0.027	8.548	0.000	Accepted
H10	PRES -> ADO	0.335	0.033	10.092	0.000	Accepted
H11	TPS -> ADO	0.344	0.032	10.859	0.000	Accepted
H12	SE -> ADO	0.219	0.032	6.937	0.000	Accepted
H13	SI -> ADO	0.282	0.028	10.117	0.000	Accepted
H14-	RE -> ADO	-0.087	0.038	2.285	0.023	Accepted
H15	ADO -> FP	0.453	0.038	11.820	0.000	Accepted

Source: SmartPLS 4 Output

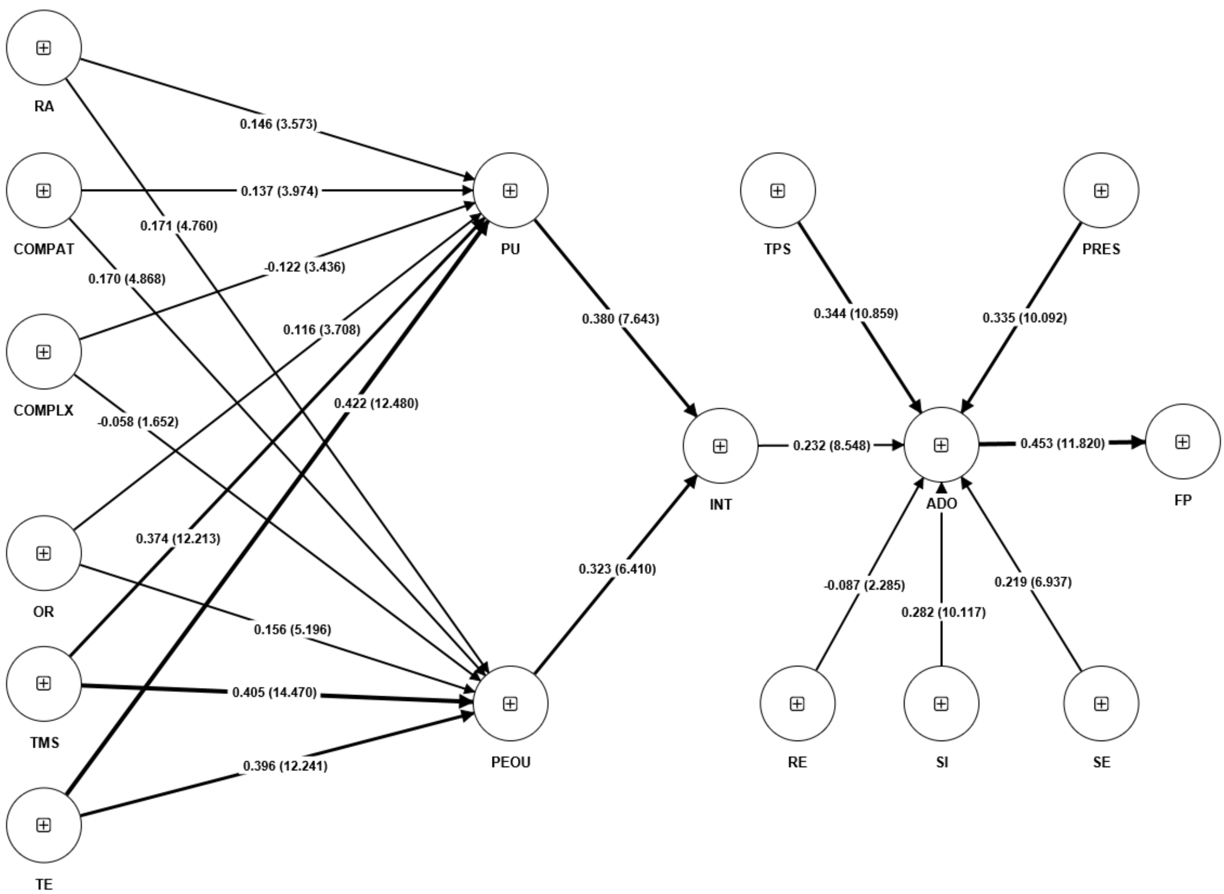

FIGURE 3. Output of structural model assessment (Source: SmartPLS 4 Output).

and training and education. Save for Complexity, all of the aforementioned variables justify 73% of PEOU's variance. PU and PEOU both explain 42% of the variance in Adoption Intention, based on their R^2 value of 0.421. Adoption justifies 68% of the variance in Intention to Adopt, Trading Partner Support, Competitive Pressure, Resistance to Change, Social

TABLE 8. R^2 **of the endogenous latent variable.**

Variable	R-square	R-square adjusted	Interpretation
PU	0.711	0.707	*Moderate*
PEOU	0.735	0.731	*Moderate*
INT	0.415	0.412	*Weak*
ADO	0.677	0.672	*Moderate*
FP	0.205	0.203	*Acceptable*

Source: SmartPLS 4 Output

TABLE 9. **Effect sizes (f^2).**

Relationships	f-square	Effect Size
RA -> PU	0.037	*Small*
COMPAT -> PU	0.037	*Small*
COMPLX -> PU	0.026	*Small*
OR -> PU	0.034	*Small*
TMS -> PU	0.412	*Large*
TE -> PU	0.379	*Large*
RA -> PEOU	0.055	*Small*
COMPAT -> PEOU	0.063	*Small*
COMPLX -> PEOU	0.006	*None*
OR -> PEOU	0.067	*Small*
TMS -> PEOU	0.525	*Large*
TE -> PEOU	0.363	*Large*
PU -> INT	0.133	*Small*
PEOU -> INT	0.096	*Small*
INT -> ADO	0.144	*Small*
PRES -> ADO	0.309	*Medium*
TPS -> ADO	0.304	*Medium*
SE -> ADO	0.118	*Small*
SI -> ADO	0.224	*Medium*
RE -> ADO	0.022	*Small*
ADO -> FP	0.258	*Medium*

Source: SmartPLS 4 Output

Influence, and Self-Efficacy, based on its R^2 value of 0.677. Lastly, with an R^2 value of 0.206, adoption justifies 20% of the variance in Firm Performance.

Effect Size (f^2)

An endogenous construct's R^2 value can also be determined by the impact of the omission of a predictor construct, referred to as the effect size (f^2), shown in Table 9

Of the 21 proposed correlations (COMPLX > PEOU), only one was found to be ineffective. The path coefficient was initially determined to be statistically nonsignificant. Four correlations had large impacts, three had medium impacts, and the rest had small impacts.

Predictive Power of the Model

The R^2 does not indicate the predictive power of the model. This out-of-sample predictive power [100] is a measure of a model's ability to predict future observations. To address this issue, the PLSPredict was developed by Shmueli et al. [101] and was used in this study to determine the predictive power of the proposed model, and the results are presented in Table 10.

This study used five dependent variables and 20 indicators. By comparing the indicators' PLS-RMSE values and the LM RMSE values, 14 were found to have lower PLS-RMSE values than the LM RMSE values. Hence, the model was concluded to have a Medium Predictive Power [101].

TABLE 10. **PLSPredict values.**

Indicators of Dependent Variables	PLS-SEM_RMSE	LM_RMSE
ADO1	*0.626*	0.545
ADO2	1.050	1.063
ADO3	*0.634*	0.580
FP1	*1.337*	1.139
FP2	*1.516*	1.400
FP3	*1.195*	0.969
INT1	1.074	1.088
INT2	1.191	1.206
INT3	*1.102*	1.102
INT4	1.037	1.054
PEOU1	0.811	0.863
PEOU2	0.823	0.856
PEOU3	0.729	0.763
PEOU4	0.750	0.785
PEOU5	0.831	0.870
PU1	0.892	0.920
PU2	1.354	1.408
PU3	0.986	1.027
PU4	0.734	0.736
PU5	0.807	0.834

Source: SmartPLS 4 Output

G. ARTIFICIAL NEURAL NETWORK (ANN) ANALYSIS

IBM SPSS 29 was used for ANN analysis. Table 11 shows the importance of the independent variables. The Multilayer Perceptron (MLP) model was trained by using 418 sample cases. Machine learning typically uses training and testing datasets to determine the model effectiveness.

Table 11 shows that in Model ANN1 (for predicting PU), the most important variable was training and education (100%) with a score of 0.336, followed by top management support (83.7%) with a score of 0.281. Relative advantage (34.1%) and compatibility (29.9%) were less important with scores of 0.115 and 0.101, respectively. The least impactful variables for PU were organisational readiness (25.8%) and complexity (23.9%).

In Model ANN2 (for predicting PEOU), trading partner support was the most important variable (100%) with a score of 0.293. Next is training and education, with 94.5% importance. Relative advantage (52.8 %) and compatibility (45.9 %) were less significant. The least impactful variables on PEOU were organisational readiness (27.8%) and complexity (20.1%).

In Model ANN3 (for predicting intention to adopt), the most important variable was PU (100%) with a score of 0.520. Next, PEOU had 92.4% predictive power. Finally, in Model ANN4 (for predicting cloud computing adoption), the most important variable was trading partner support (100%) with a score of 0.302. This was followed by competitive pressure (66.5%), and social influence (54.5%). The least influential variables for cloud computing adoption were self-efficacy (37.7%) and resistance to change (28.6%). Notably, intention to adopt moderately affected cloud computing adoption with a predictive power of 43.8%.

VI. DISCUSSION

In this study, several variables were identified as critical to the PU and PEOU of cloud computing: Relative advantage,

TABLE 11. Independent variable importance.

Dependent	Independent	Importance	Normalised Importance
PU (ANN1)	TE	0.336	1.000
	TMS	0.281	0.837
	RA	0.115	0.341
	COMP	0.101	0.299
	OR	0.087	0.258
	COMPLX	0.080	0.239
PEOU (ANN2)	TPS	0.293	1.000
	TE	0.277	0.945
	RA	0.155	0.528
	COMP	0.135	0.459
	OR	0.081	0.278
	COMPLX	0.059	0.201
INT (ANN3)	PU	0.520	1.000
	PEOU	0.480	0.924
ADO (ANN4)	INT	0.132	0.438
	TPS	0.302	1.000
	PRES	0.201	0.665
	SI	0.165	0.545
	SE	0.114	0.377
	RE	0.086	0.286

Source: SPSS 29 Output

compatibility, complexity, organisational readiness, top management support, and training and education. Cloud adoption is also determined by competitive pressure, trading partner support, self-efficacy, social influence, and resistance to change. The adoption of cloud technology has also been found to affect SMEs' performance.

Relative advantage was found to have a significant effect on PU (H1a: $\beta = 0.146$; t-value = 3.573; p = 0.000) and PEOU (H1b: $\beta = 0.171$; t-value = 4.760; p = 0.000). Cloud technology adoption by SMEs is driven by the relative advantages that the system offers, as perceived by users, such as productivity enhancement and user-friendliness. Compatibility also had a significant effect on PU (H2a: $\beta = 0.137$; t-value = 3.974; p-value = 0.000) and PEOU (H2b: $\beta = 0.170$; t-value = 4.868; p = 0.000). When SMEs perceive that cloud technology is compatible with their existing technology architecture, programs, formats, interfaces, and structural data, they regard it as a practical system. Hence, management should ensure that the companies' current processes and infrastructure are compatible with the cloud system. Complexity was found to have a significant negative effect on PU (H3a: $\beta = 0.122$; t-value = 3.436; p-value = 0.001) but no statistically significant effect on PEOU (H3b: $\beta = 0.058$; t-value = 1.652; p-value = 0.099). With the accessibility and short learning curve offered by cloud technology, SME employees can accomplish tasks more efficiently. Cloud developers should design cloud solutions that are more intuitive for users and customised to their work-related needs.

One possible explanation is that, while SME decision-makers may acknowledge complexity in cloud technologies, this complexity does not necessarily translate into perceptions of difficulty in using the system. This could be attributed to increased familiarity with mobile and internet-based services, improved interface design by cloud vendors, or outsourcing of complex technical configurations to service providers. Additionally, respondents in this study were predominantly IT professionals (IT managers and executives made up over 80%), who are more likely to perceive cloud systems as manageable despite their underlying technical complexity. This demographic may inherently associate cloud computing with ease of use due to their technical background, thus weakening the perceived impact of complexity on ease of use.

Organisational readiness was found to have a notable effect on both PU (H4a: $\beta = 0.116$, t-value = 3.708, p-value = 0.000) and PEOU (H4b: $\beta = 0.156$, t-value = 5.196, p-value = 0.000). The organisation's existing technology infrastructure and know-how significantly determine how effective and convenient it is to use cloud technology. Policymakers and managers must focus on resource allocation, both financial and technological, encompassing the physical infrastructure, IT expertise, and intangible knowledge. The hypotheses claim that top management support has a significant effect on PU and PEOU, which is confirmed by the analysis results (H5a: $\beta = 0.374$, t-value = 12.213, p-value = 0.000; H5b: $\beta = 0.405$, t-value = 14.470, p-value = 0.000). Top management can significantly persuade and inspire employees with regard to their work behaviour, that is, via the provision of continuous facilitation and the creation of a positive work environment that supports the usage of cloud technology. Employee training helps staff gain functional and technical knowledge and skills related to cloud technology (H6a: $\beta = 0.422$, t-value = 12.480, p-value = 0.000; H6b: $\beta = 0.396$, t-value = 12.241, p-value = 0.000). Employees would be able to properly use cloud technology if they had the right training, knowledge, skills, understanding, and sense of accountability. Management is responsible for developing effective training programs to achieve this aim.

Hypothesis H7 was also confirmed based on the results ($\beta = 0.380$; t-value = 7.643; p-value = 0.000), which show that PU and Behavioural Intention have a significant and positive relationship. Users' perception of the technology's usefulness in improving performance and productivity significantly affects their behavioural intention to use it. In the context of cloud technology, the cloud services offered would strongly increase SMEs' perceptions of their usefulness. The more acquainted they are with the benefits of cloud technology, the more willing they are to adopt it. Therefore, it is necessary to raise awareness about cloud technology among SMEs, especially regarding its productivity and performance enhancement capacities. These results were confirmed in previous studies [102], [103].

PEOU refers to users' perception of how effortlessly it is to understand and use cloud computing. The results show that PEOU has a significant and positive effect on SMEs' behavioural intention to use cloud technology (H8: $\beta = 0.323$, t-value = 6.410, p-value = 0.000). This result aligns with previous studies [68], [69], [104].

The results showed that intention was a significant predictor of actual cloud adoption (H9: $\beta = 0.232$; t-value = 8.548; p-value = 0.000). This significant relationship indicates that the intention to use cloud technology strongly leads to its actual usage, a finding that has been validated in previous research (for example, [105]). With a strong Behavioural Intention to use cloud computing, SMEs are projected to adopt this technology soon. To this end, a supportive environment that drives the actual implementation of cloud computing should be established.

Competitive pressure was found to have a significant effect on cloud technology adoption (H10: $\beta = 0.335$, t-value = 10.092, p-value = 0.000). Previous research has also found the same result (see [106], [107], [108], [109]. This positive relationship indicates that a firm experiences a strong sense of competition when its rivals strategically decide to adopt the cloud technology. Meanwhile, trading partner support was also found to have a significant effect on cloud technology adoption (H9: $\beta = 0.344$; t-value = 10.859; p-value = 0.000) due to the fact that the involved parties (business partners) must be synchronised and collaborating to ensure successful cloud implementation. This relationship has also been demonstrated in previous studies [1], [110], [111]. Constant data availability must be guaranteed by cloud providers via the utilisation of multiple network providers such that when one network fails, another network is still up and running.

Self-efficacy was also proven to significantly affect cloud technology adoption (H12: $\beta = 0.323$; t-value = 6.410; p-value = 0.000). As indicated by previous research [37], [82], self-efficacy in using computers has a substantial effect on innovation adoption based on the situation. The results suggest that people with strong conviction in their technical competence have a higher likelihood of adopting cloud computing. Resistance to change was found to obstruct cloud adoption (H14-: $\beta = -0.087$; t-value = 2.285; p-value = 0.023). This refers to situations in which decision-makers have doubts about accepting changes in the organisation. Some previous studies have highlighted the same finding (e.g. [88]), whereas others have found the opposite (e.g. [37]). Meanwhile, social influence significantly affects cloud technology adoption (H13: $\beta = 0.282$; t-value = 10.117; p-value = 0.000), suggesting the weight of others' opinions on SMEs' decision to adopt this innovation.

Finally, the adoption of cloud computing was found to strongly and positively improve the performance of SMEs (H15: $\beta = -0.453$; t-value = 11.820; p-value = 0.000), as indicated by previous research (e.g. [35], [90], [91]). This result is expected because the shift to cloud technology is meant to reduce expenditure and improve organisational performance. Based on the results, it can be said that the effective adoption of cloud computing would allow SMEs in Sri Lanka to attain numerous operational and strategic benefits, in addition to gaining access to trailblazing information technology resources. Their IT capacity can be boosted by utilising the vendor's IT know-how and adherence to the industry's best practices.

VII. IMPLICATIONS

A. THEORETICAL IMPLICATIONS

The findings of this study further expand the existing empirical evidence on information systems and technology adoption theory, especially in the context of cloud computing adoption. This study develops and verifies a unified research structure that brings together prominent frameworks including the TOE, TAM, and individual context components. The study uses combined theoretical approaches to create comprehensive insights about cloud computing adoption specifically in SMEs which traditional information system adoption research has neglected. This study empirically proves that the fundamental constructs of PU and PEOU from TAM significantly shape firm-level decisions regarding the adoption of new technologies. These findings strengthen the use of TAM in organizational domains and show its importance among SMEs because they rely on individual strategic decision makers for IT decisions.

This study provides a micro-foundational perspective on technology decision-making at the firm level through the incorporation of cognitive traits including Self-Efficacy and Resistance to Change into the organizational adoption framework. This theoretical alignment fills the knowledge gap between the behavioural patterns observed in individuals and organisations regarding information systems. This study presents significant contextual value by proving the TOE-TAM–individual integrated model within the developing setting of Sri Lanka. This study adds research validity through empirical evidence to the existing literature, which primarily consists of studies within developed economies which enhance the cross-cultural adaptability of information system adoption models. The research adopts dual-stage analytical method which includes PLS-SEM analysis and ANN. SEM allows for the hypothesis testing of causal effects, but ANN delivers both nonlinear predictive forecasting capabilities and variable importance significance calculations. The proposed framework responds to information system research requirements by providing an enhanced predictive analytics system for digital transformations.

B. PRACTICAL IMPLICATIONS

In addition to extending the study to new dimensions, it provides several actionable insights for SME decision-makers, policymakers, IT service providers, and development agencies. This study argues that three aspects–Training and Education, Top Management Support, and Organizational Readiness–are drivers to promote cloud adoption. To expedite digital transformation, leaders must invest in developing employees' skills and creating an innovation-friendly organizational culture. For cloud service providers and IT consultants, PU, PEOU, and the importance of Trading Partner Support are major determinants of adoption. While the offerings are replete with SME needs, they are not crafted for SME needs, interfaces are not simple enough, and continuous technical and relationship support is required to help build trust and long-term engagement. For policymakers and government agencies, Competitive Pressure has been critical to the mobilisation of clouds, suggesting the deployment of specific policies and incentives to incentivise the adoption of clouds by SMEs.

Subsidies, training programs, tax incentives, and digital transformation roadmaps can be shaped in the SME sector. This study supports that whether Self-Efficacy or Resistance to Change is more important for adoption can be seen in the high correlation. The results indicate that external stakeholders should concentrate on confidence building programmes, mentorship, and change management workshops to help SME leaders surmount the cognitive barriers to innovation. Evidence shows that the adoption of cloud computing enhances the performance of an organisation, offering a strong reason for SMEs to consider cloud technology not as a mere IT notion, but as a growth, scalability, and competitive tool in the digital economy.

VIII. CONCLUSION

This study evaluated both the adoption factors for cloud computing among Sri Lankan SMEs and the relationship between adoption and firm performance. Digital transformation initiatives are essential for SMEs because they contribute to the generation of employment and increase productivity in developing economies. Limited cloud computing adoption has occurred among Sri Lankan SMEs because of weak top management support and insufficient awareness, along with inadequate training and education. This study integrated different adoption models with individual-level constructs and applied a dual-stage analytical approach through PLS-SEM and ANN. The analysis revealed that all hypotheses were supported, except one, which examined how the complexity level affects perceived ease of use. The results confirmed that cloud computing adoption improves SMEs' performance, and that management support, supplemented by proper training and education, serves as a key factor in adoption. This study demonstrated how the constructs of relative advantage, compatibility, organizational readiness, self-efficacy, and trading partner support determine users' perceptions of value and ease of use in cloud solutions.

The PLS-SEM–ANN hybrid approach enhanced the analysis by validating theoretical relationships through PLS-SEM and generating a strong predictive ranking of important variables using ANN. Using this combined SEM-ANN methodology improved both the theoretical understanding and practical value of the model, offering more insights into SMEs' cloud adoption behaviours. The findings demonstrate that SMEs can improve their performance by adopting cloud computing as a strategic initiative. This study made both methodological and theoretical contributions by using PLS-SEM and ANN to combine different adoption factors, and showed how such integration strengthened predictive outcomes. Future studies could expand this study by focusing on moderating effects, especially industry type and firm size, and incorporating longitudinal models and additional analyses of emerging technology platforms across multiple geographical locations.

IX. LIMITATIONS AND FUTURE DIRECTION

The limitations of this study can be leveraged as a basis for future enquiries. First, in maintaining parsimony, this study focuses solely on variables from the TOE, TAM, and other individual factors. Various other variables, such as location and security, are available for examination. Second, this study used one-time cross-sectional data, owing to limited time and resources. Future studies should focus on longitudinal data. Third, this study only considers the perspectives of SME owners, top personnel, and IT managers. The views of cloud providers and operational-level staff remain open to further investigation. Fourth, as this study takes a holistic view of organisational performance, future enquiries may want to investigate the impact of cloud adoption on specific units/departments. Fifth, this study examines SMEs in general with no specific focus on the type of business. Hence, future enquiries may concentrate on certain types of businesses or industries. Finally, this study primarily focuses on Sri Lankan SMEs. This scope could be expanded to encompass larger nations such as India, so that comparisons can be drawn with the results of the current study.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study can be obtained by contacting the corresponding author.

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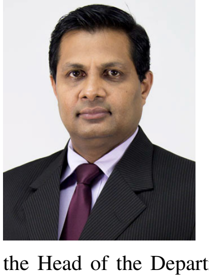

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