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The Impact of Cloud Computing Adoption on Firm Performance Among SMEs in Palestine:
A Machine Learning Approach

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ABSTRACT

This study seeks to identify the driving factors of cloud computing adoption (CCA) among SMEs, and examines the extent to which CCA shape SME performance. Data was gathered from 212 Halal SMEs in Palestine. This study uses a two-phase investigative method to test the research model through integrating structural equation modeling (SEM) and machine learning. SEM findings show that perceived benefit, facilitating states, server location, perceived cost, upper management support, perceived quality, and cloud providers' support significantly affect CCA. Besides, the article verifies that CCA positively shapes SMEs' performance. Machine learning findings unravel perceived benefit as the strongest determinant of CCA. This study is an initial attempt to develop a conceptual framework that hypothesizes the links between technological-organizational-environmental (TOE) factors and SMEs' intent for CCA in Palestine and provides empirical evidence regarding these links.

KEYWORDS

Artificial Neural Network, Cloud Computing, Firm Performance, Machine Learning, Palestine, SMEs, Technology Adoption

INTRODUCTION

Digital transformation is a vital determinant of the achievement and permanence of industries (Sumarliah & Al-hakeem, 2023; Sumarliah et al., 2023b). Radically transforming industrial situation and fantastic business race have pushed small and medium-sized enterprises (SMEs) to implement many high-tech innovations like artificial intelligence and internet of things (Hansen and Bøgh, 2021), blockchain (Hamdan et al., 2022a; Sumarliah et al., 2022a; 2023a), advanced robotics,

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cybersecurity, big data, and especially cloud computing (Somohano-Rodríguez and Madrid-Guijarro, 2022). Nowadays, the Coronavirus disease (COVID-19) pandemic has powerfully altered the global trends (Sumarliah et al., 2021a; 2021e), such as the rapid growth of e-commerce industry (Sumarliah et al., 2021b; 2022b; 2022c), making the cloud-empowered e-commerce platforms more favored to traditional system as they will reduce operational and maintenance costs, capital budgets, and resource usage (Al-Shourbaji and Zogaan, 2021). SMEs in industrial sector growingly face digital transition challenges and a swift to cloud-enable resolutions (Kaymakci et al., 2022). Public and private sectors have become more aware of cloud computing (CC) because of the highly regarded joint networks linking individuals and organizations across the globe (Neicu et al., 2020). CC delivers a state-of-the-art industrial framework for the on-demand, prevalent, and convenient entree to the virtual and allocated means like services, networks, applications, storage, and servers (Daniel and Momoh, 2021). CC service technology encompasses (i) Infrastructure as a Service with computing and storage as its emphasis, (ii) Software as a Service with software application as its core; and (iii) Platform as a Service, which supplies the devices to build and accommodate web applications (Tsai, 2021).

CC enhances firms' capability by delivering facilities on a pay-per-usage base, which enables companies to support the frequency of using technological supplies in line with the existing requests (Neicu et al., 2020). Industry 4.0 has caused automation and digitization in manufacturing and operations; thus, CC adoption has converted current business systems, offering companies with further productivity, flexibility, and agility (Sharma and Sehrawat, 2020). CC supports companies to alter traditional industrial framework to service-oriented and innovative implementations (Wang, 2022), and increase successful team creativity and performance (Zou and Jian, 2022). As CC offers great prospective advantages, companies are hastening to adopt and implement it in business activities and setups (Albelaihi and Khan, 2020; Bello et al., 2021; Lutfi, 2022).

Compared to big companies, SMEs have fewer resources (Saratchandra and Shrestha, 2022) financial ability to use technologies and are more cautious about investing in technologies (Faasolo et al., 2022; Chau et al., 2020), which does not enable them to build information and communication technology (ICT) supplies such as software and hardware by internal development and research unit. Thus, SMEs usually rely on external sources (Saratchandra and Shrestha, 2022) such as outside ICT experts to get their awaited results. CC technology opens chances for SMEs to use technological innovations through rent payment, which formerly were high-priced (Neicu et al., 2020). CC technology has been an improved management device that increases SMEs' performance and ability to stay competitive with bigger companies (Sayginer and Ercan, 2021).

Nevertheless, adopting CC technology remains in its embryonic phase amongst SMEs (Skafi et al., 2020). SMEs show a much slower CC adoption than big firms, indicating the existence of several challenges affecting SMEs in decision-makings to use CC. Thus, there is a need to examine the causes of this slow adoption (Mettouris et al., 2022). Scholars have identified some reasons for the slow CC adoption among SMEs such as (i) inadequate resources (e.g., time, experts, trained workers), (ii) data control and security concerns, and (iii) unrestrained increase of cloud costs caused by insufficient cloud knowledge (Mettouris et al., 2022).

Cloud computing adoption (CCA) is a vital academic schema for scholars and professionals, especially for SMEs having scarce assets. A recent review from Al Hadwer et al. (2021) using TOE model reveals that competitive pressure, cloud complexity, relative advantage, and top management support are the main predictors of CCA. Previous studies examine CCA among SMEs (i.e., Forootani et al., 2022; Gui et al., 2021). These studies use key predictors of CCA such as top management support, quality of service, perceived cost-benefit, relative advantage, privacy, perceived concern, cloud flexibility (Gui et al., 2021), behavioural intention, challenges, and opportunities (Athambawa et al., 2022), marketing effort, organizational readiness, perceived ease of use, perceived usefulness, technological benefits (Forootani et al., 2022). Nevertheless,

they disregard the effects of some vital variables such as cost, quality, cloud providers' support, and server position on the intent for CCA.

Furthermore, the novelty of this study lies on its research methodology. Previous studies focusing on CCA use a traditional analytical approach like structural equation modeling (SEM) to analyze data (e.g., Gui et al., 2021; Lutfi, 2022; Shetty and Panda, 2022). The latest review from Jayeola et al. (2020) denotes SEM as the most often employed quantitative data examination method to analyze CCA among SMEs in the past decade. Unfortunately, SEM only performs well in assessing the linear associations of variables, which can cause the generalization of the complex innovation acceptance procedure (Faasolo and Sumarliah, 2022). Thus, to solve these shortcomings, scholars (Mustafa et al., 2023; Alhasnawi et al., 2023) use machine learning method, e.g., artificial neural networks (ANN) as the next phase of examination involving sole concealed tier. Methodically, unlike earlier publications employing a single-phase SEM (Gui et al., 2021; Lutfi, 2022; Shetty and Panda, 2022) which cannot predict the complexities influencing multidimensional decision-makings, or using a single-phase ANN method (Shahzad et al., 2020), this study uses the integrated SEM-ANN, following the recommendation from Alhasnawi et al. (2023) and Song (2022). Due to its deep learning capacity, the use of ANN construction using at least two hidden tiers may produce more accurate non-linear relations in the framework (Kalinić et al., 2021). Scholars have revealed that the use of ANN produces outcomes with higher robustness and greater accuracy than SEM; thus, it is reasonable to state that ANN and SEM examinations complete one another (Mustafa et al., 2023; Alhasnawi et al., 2023). Hence, the paper seeks to fulfill the current literature gap by employing a deep learning two-phase method to examine linear and non-linear relationships. Using an integrated SEM-ANN to comprehend CCA among SMEs is regarded a new approach, especially in Palestine context. Besides, the paper is new and exceptional because it uses machine learning-empowered dual-phase examination in comparison to earlier publications in related field (Gui et al., 2021; Lutfi, 2022; Shetty and Panda, 2022). Thus, this study tries to fill the literature gap by examining CCA adoption using the combination of SEM and machine learning, i.e., ANN, which has been proven as an effective tool in analyzing data regarding the intention to adopt technology among SMEs (Faasolo and Sumarliah, 2022).

Besides, previous works have confirmed the significant association between technology adoptions and company performance but studies focusing on the impact of CCA on the SMEs' performance remain scarce (Kaplancalı and Akyol, 2021). Therefore, based on the arguments above, the purpose of this study is to fill these literature gaps by examining the influential determinants of CCA among SMEs and analyze whether CCA significantly affects SMEs' performance. More specifically, this study seeks to respond to these questions (QSs):

- QS1. What determinants will affect the CCA among SMEs in Palestine?
- QS2. Will CCA affect SMEs' performance?
- QS3. How significant the determinants are to estimate the CCA?

To answer the above research questions, this study uses a two-phase systematic method through combining SEM and machine learning framework that many academicians recommend for assessing technology adoption behaviors (Mustafa et al., 2023; Faasolo and Sumarliah, 2022; Hamdan et al., 2022b; Song, 2022). The potency in SEM's path examination is used to answer QS1 and QS2, whereas the machine learning approach responds to QS3. This integrated analytical method delivers an inclusive perception regarding the evaluated subject; simultaneously, the drawbacks of one approach will counteract the shortcomings of the other approach. This research helps SMEs and practitioners in identifying many imperative predictors of CCA, which causes the success in implementing CC technology.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Cloud Computing Adoption in SMEs

CC technology has been confirmed as a vital technical resolution, particularly for SMEs, by delivering numerous chances for firms to improve their performance, lessen costs, enhance flexibility and scalability, and make more effective usage of technologies (Yaseen et al., 2022). The existence of significant differences between SMEs and big companies concerning the influential determinants of the CCA has been confirmed (Gunupudi and Kishore, 2020). However, earlier publications (e.g., Alkhater et al., 2018) underline big companies than SMEs when examining the CCA. So far, this study identifies literature that assesses the CCA's determining factors and examines the CCA's impacts on SMEs' performance. The literature identification confirms that this study provides newness in the scope of knowledge related to CCA. It can be proven that from the Scopus database in the past three years (2020-2022), there are 96 journal articles with keywords "Cloud computing adoption AND SMEs"; only 12 of which provide empirical evidence using the TOE model as this study does (see Table 1). Unfortunately, these 12 publications use the only conventional analytical method or do not include a complete hypothetical structure. For example, a study by Zamzeer et al. (2020) examine the predictors of CCA among SMEs in Jordan but employ only minor sample size (13 SMEs) and exploratory study makes it problematic for the generalizability of their findings. Besides, all these 12 pieces of literature (see Table 1) use a conventional analytical method such as SEM, while this study combines SEM with a machine learning method that can explain non-linear relationships among determining factors as advised by Faasolo and Sumarliah (2022). Thus, this study develops a new conceptual framework and seeks to bridge these gaps by building an inclusive framework and employing a stronger method to justify the suggested framework. Hopefully, the research can enrich the existing empirical studies, especially in the area of enterprise information systems.

An Extended TOE Model

The technology-organization-environment (TOE) model concentrates on technological, organizational, and environmental elements that influence firms' willingness to adopt new systems and innovations (Faasolo and Sumarliah, 2022). TOE offers a more complete examination about technology adoptions as adopting modern systems in firms depends on the environmental, organizational, and technical issues (Faasolo and Sumarliah, 2022). Developed by Tornatzky and Fleischer in 1990, TOE context of a company has been influencing technology diffusion activities (Basloom et al., 2022). Some scholars (e.g., Lutfi, 2022; Ongowarsito et al., 2022; Shetty and Panda, 2022, Zamzeer et al., 2020) suggest the TOE model as a proper kickoff for scrutinizing CCA. They advise that a conceptual framework for CCA should consider determinants that influence users' intent to adopt and use CC technology, which is set in the specific technology, organization, and environmental perspectives of a company. TOE possesses more descriptive capability than other theories, e.g., TAM, DOI, UTAUT, and TPB in assessing the adoption and usage of technologies, especially an organizational perspective as it includes multifaceted factors of a company when examining the diffusion and adoption of technologies (Chau et al., 2020; Faasolo et al., 2022).

The study propositioned an extended TOE model by adding some factors such as cloud providers' support, server position, and perceived cost as predictor variables in the conceptual framework. It is because adding new factors to the current TOE framework can portray a stronger perception regarding firms' intentions to adopt technologies (Ngah et al., 2020). The study selects cloud providers' support as one of the additional factors in the framework because it has been proven to positively influence CCA in SMEs (Zamzeer et al., 2020). The next additional factor, i.e., server's geographic position is selected in this study as it matters for a company due to the storing of firms' properties in different nations: occasionally clients don't get accurate notification regarding the precise server's location which causes privacy concerns (Alkhater et al., 2018). The third additional factor, i.e., perceived cost, is chosen in this study's model because cost is found as the foremost determining factor for SMEs to

Table 1. Comparison of this study vs. previous studies on CCA in SMEs using TOE framework

No.	Literature	Framework	Method	Determining factors of CCA
1	Athambawa et al. (2022)	TOE + DOI + TAM3 + UTAUT2	Quantitative data coding and analysis with SPSS and AMOS	Behavioural intention, opportunity, and challenge positively and significantly affect CCA; behavioural intention mediates the relationship of opportunity-CCA and of challenge-CCA.
2	Ongowarsito et al. (2022)	TOE	Expert opinions	Software seller's reputation, the willingness of software seller to work with the customer/firms, and the capability to swift capital expense to operational costs are significant predictors of CCA.
3	Forootani et al. (2022)	TOE+TAM	Expert opinions	Marketing effort, quality of service, organizational readiness, perceived ease of use, perceived usefulness, technological benefits are significant predictors of CCA
4	Shetty and Panda (2022)	TOE	SEM	Trust, top management support, technology readiness, perceived ease of use, and perceived usefulness are main predictors of CCA.
5	Lutfi (2022)	TOE	SEM	Supplier computing support, competitive pressure, organizational readiness, top management support, security concern, and perceived usefulness positively and significantly affect CCA.
6	Yaseen et al. (2022)	TOE+DOI	Multiple regression	Cost reduction is the most influential predictor of CCA.
7	Alismaili et al. (2020)	TOE	SEM	Trialability, Compatibility, cost savings, Relative advantages, security concern, privacy risk, market scope and external computing support significantly affect CCA; however, top management support, firm size, firm's previous experience, and firm's innovativeness are not significant predictors.
8	Sayginer and Ercan (2021)	TOE+DOI	Confirmatory factor analysis	Complexity and top management support are the strongest predictors of CCA.
10	Gui et al. (2021)	TOE+DOI	SEM	Top management support, quality of service, perceived cost-benefit, relative advantage, privacy, perceived concern, cloud flexibility.
11	Skafi et al. (2020)	TOE+ Contextual Theory	Logistic regression analysis	Prior IT experience, top management support, security, complexity, government initiatives, infrastructure.
12	Zamzeer et al. (2020)	TOE	Exploratory study	Top management support and service providers' supports
13	This study	Extended TOE	SEM and machine learning (ANN)	Perceived benefit, perceived quality, perceived cost, upper management support, facilitating states, cloud providers' support, and server position are the predictors of CCA. Besides, this study uses CCA as the predictor of SMEs performance.

adopt CC technology (Shahadat et al., 2023). Besides, SMEs see CCA as a chance to improve their performance (Jayeola et al., 2022); thus, SMEs' performance is included as a predicted variable in this study's conceptual framework. By adding these additional factors into the extended TOE model, this study is unique and novel.

Technological Factors

The first element in TOE model is technological factors. In this study, the T factors of the TOE consist of perceived benefit and perceived quality of the CC technology. The additional factor in the extended TOE framework in this study is perceived cost.

Perceived Benefit (PBNF)

Perceived benefits mean how the prospective users perceive the adoption of technologies will give awaited pluses (Hamdan et al., 2022b), such as cost reduction, productivity enhancement, profit growth, and market expansion. Perceived benefits are imperative for adopting technologies by SMEs (Hamdan et al., 2022b; Chau et al., 2020). SMEs are more willing to adopt technology when they perceive that its advantages can compensate for its risks (Hamdan et al., 2022b). CC technology offers SMEs many benefits which were not given previously; for example, pay-per-usage choice in which SMEs do not need to pay installing costs and hardware upholding costs with the CC storing service attribute (Gui et al., 2021). Previous studies (Forootani et al., 2022; Lutfi, 2022; Shetty and Panda, 2022; Tella et al., 2020) confirm that CC technology's perceived benefit or perceived usefulness is the major determinant of CCA among SMEs. A systematic literature review conducted by Al Hadwer et al. (2021) for the last 7 years prove that relative benefit is a strong predictor of CCA. In an occupied country Palestine, financial access is very limited due to the blockade from Israel (Hamdan et al., 2022b); thus, Palestinian SMEs consider cost-saving as the highest benefit expected from CCA (AlMabhouh and Alzaza, 2015). Therefore:

H1. PBNF will significantly and positively affect CCA.

Perceived Quality (PQLT)

The quality of service in CC technology refers to the total support that cloud providers give to firms as clients (Hammouri and Abu Shanab, 2020). Scholars define the quality of service as the extent to which a service fulfills clients' hopes (Hammouri and Abu Shanab, 2020); thus, in this study, PQLT signifies the extent to which the clients perceive that CC service satisfies their expectations. The quality of service is gauges by reliability, availability, fulfillment, and efficiency of the service (Hammouri and Abu-Shanab, 2020). Reliability means a scheme that delivers online subject for clients with a great broadcast rate, least errors, and speedy recovery; meanwhile, availability means a scheme that delivers online content for clients with minimum limitations (Hammouri and Abu-Shanab, 2020). Previous studies reveal that PQLT of the CC services among SMEs strongly affects the CCA (Gui et al., 2021; Forootani et al., 2022). CC delivers services via the network and Internet at anywhere and anytime base; thus, they should be responsive, functional, speedy, and uninterrupted (Alkhater et al., 2018). Because cloud providers' support is numerous, CC clients request first-class CC services (Gui et al., 2021). CC technology is comparatively modern in emerging nations (such as Palestine); thus, the PQLT of this technology is regarded as a vital predictor of the CCA (Gui et al., 2021). Concisely, the higher the perceived quality of CC services by SMEs, the bigger chance of CCA among them. Hence:

H2. PQLT will significantly and positively affect CCA.

Perceived Cost (PCST)

Cost is imperative in technology adoption, particularly for SMEs in an emerging country (Faasolo and Sumarliah, 2022). SMEs in emerging markets tend to slow in adopting technologies due to various issues, especially the adoption costs (Chau et al., 2020), which in CC technology include the installation cost, maintenance cost (Gui et al., 2021), and staff training cost (Faasolo and Sumarliah, 2022). In Palestine, high operational costs are one of the main obstacles for SMEs to maximize industrial performance (Hamdan et al., 2022b), it makes SMEs precautious about investing in new technologies. The upper the costs of a new system that SMEs perceive, the lengthier its acceptance speed (Faasolo and Sumarliah, 2022). Therefore:

H3. PCST will significantly and negatively affect CCA.

Organizational Factors

The second element in TOE model is organizational factors. In this study, the O factor is upper management support, while facilitating states play as an additional factor of the extended TOE framework.

Upper Management Support (UPMS)

UPMS is indispensable for SMEs to adopt technologies as the decision-making process in SMEs is mainly consolidated around a few persons (Chau et al., 2020). SMEs' formation is centralized and simple: owners who are also the general managers, usually handle and operate the businesses (Hamdan et al., 2022b). Upper management (managers/owners) substantially affect technology acceptance as they are the decision-makers in both operational and strategic aspects of businesses; thus, UPMS is the most vital factor affecting CCA (Al Hadwer et al., 2021). Previous studies prove that UPMS significantly affects SME's intent for CCA (Gui et al., 2021; Lutfi, 2022; Sayginer and Ercan, 2021; Shetty and Panda, 2022; Skafi et al., 2020; Zamzeer et al. 2020). These studies indicate that efficient UPMS strongly affects CCA because upper management is the main actor in replotting industrial activities, incorporating services, and distributing various resources; thus, the CCA strongly relies on the amount of UPMS that SMEs obtain. When upper management fails to recognize the prospective advantages of CC technology, SMEs will be discouraged from CCA (Neicu et al., 2020). However, an earlier publication finds that UPMS is not a significant predictor of CCA (Alismaili et al., 2020); these mixed findings show the need for further examination. Hence, it is hypothesized:

H4. UPMS will significantly and positively affect CCA.

Facilitating States (FCLT)

How satisfactory CC technology fits with the existing industrial values and operations defines FCLT (Alkhater, 2018). From an SME perspective, FCLT encompasses compatibility with the existing industrial system, IT competencies and infrastructure, and nonstop Internet connectivity. Some experiential works disclose that FCLT plays a vital role as the determinant of CCA (Tella et al., 2020) and in adopting other technologies (Dwivedi, et al, 2017; Sumarliah et al, 2022a). Another quantitative study by Skafi et al. (2020) confirms that poor infrastructure negatively affects CCA among SMEs. Meanwhile, scholar Song (2022) finds FCLT as a significant predictor of CCA in ANN method but insignificant determinant in SEM. These mixed results make it attractive for scholars to conduct deeper research. Thus, this study hypothesizes that:

H5. FCLT will significantly and positively affect CCA.

Environmental Factors

The last element in TOE model is environmental factors. In this study, the E factor is cloud providers' support, while server position plays as an additional factor of the extended TOE framework.

Cloud Providers' Support (CLDP)

CC is mostly explained as the setup of IT units established in companies using unified control from cloud providers (Sayginer and Ercan, 2021). CLDP includes renting internet-empowered computing service to companies according their demands for bandwidth use, CPU, storage devices, and servers in the forms of applications, softwares, and operating systems (Sayginer and Ercan, 2021). It makes firms dependent on CLDP when the service provider changes; nevertheless, CC technology delivers

a chance for firms to merely concentrate on business and cost-efficiency without building a skilled IT unit (Sayginer and Ercan, 2021). CLDP encompasses cloud providers' activities such as advertising, coaching, consumer services, technical support, and troubleshooting (Zamzeer et al., 2020). Major Cloud providers' support in Palestine such as Paltel provides a series of distributed computing reserves that encompass applications, networking, storage, computing, enlargement, and deployment platforms (Paltel, 2021). Many Cloud providers' support' supports can encourage companies to adopt CC technology. Previous studies by Lutfi (2022) and Zamzeer et al. (2020) confirm that CLDP significantly affects CCA among SMEs. When adopting CC technology, managers will select cloud providers with outstanding technical and managerial skills as they can provide secure and trustworthy cloud services (Rahimi et al, 2022), and guarantee the ease of maintenance (Tella et al., 2020). Therefore:

H6. CLDP will significantly and positively affect CCA.

Server Position (SRVR)

SRVR, defined as the tangible location of cloud server, is a vital element that influence firms to use CC technology because of: (1) the absence of global regulations to protect data in cloud, and (2) data saving in different nation by several cloud providers without revealing it to their clients (Alkhater et al., 2018). CC technology can be stored in third parties' servers and cloud providers' support can possess many servers in many areas worldwide (Neicu et al., 2020). The storage of a company's reserves in other countries' servers can clash with its in-house protocols and systems, which confines the company in CCA (Alkhater et al., 2018). Thus, SRVR is an important aspect for firms to consider before adopting CC services. Although empirical findings regarding SRVR in CCA is absent, this study uses the literature review from Ahat et al. (2021) to develop measurement items. Based on the systematic review from Ahat et al. (2021), scholars examine SVRV (a.k.a. server placement) with the intentions to: (1) minimize the setting-up costs of network services, (2) minimalize the access lag among users-servers and overall energy usage of the systems, and (3) maximize the user's profit income as fulfilling the prerequisites of distinguished facilities. Thus, this study uses these three items to measure SVRV. Companies which have a narrow budget (such as SMEs) must make decisions regarding SRVR and service placement (Ahat et al., 2021). Thus, SRVR can be assumed to affect CCA.

H7. SRVR will significantly and positively affect CCA.

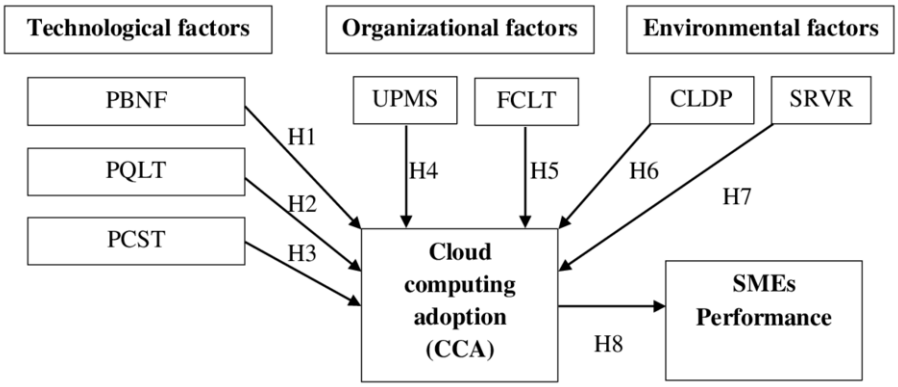
Cloud Computing Adoption and SMEs' Performance

Performance signifies the primary productivity of any planned attempt that a company initiates. For the area of CC technologies, performance denotes the CC services' abilities to supportively shape the CC-reinforced processes and operations of an enterprise. SMEs do perceive CCA as a chance to improve their performance (Jayeola et al., 2022). A previous study by Kaplancalı and Akyol (2021) also confirms that CCA significantly and positively affects SMEs' performance in a developing country. Consequently:

H8. CCA will significantly and positively affect SMEs' performance.

Based on the underpinning literature and hypotheses development above, this study's conceptual framework is developed, as seen in Figure 1. It is evident from Figure 1 that the suggested conceptual framework consists of seven independent variables which are categorized into three factors: (1) Technological factors with three variables (i.e., PBNF, PQLT, and PCST), (2) Organizational factors with two variables (i.e., UPMS and FCLT), and (3) Environmental factors with two variables (i.e.,

Figure 1. Conceptual framework



CLDP and SRVR). These independent variables are hypothesized as the predictors of CCA, while CCA is hypothesized as the predictor of SMEs performance.

RESEARCH METHOD

Measures

This study uses a questionnaire that is developed from an in-depth literature review and consultation with eight experts. The questionnaire comprises two parts. Firstly, measurement items of the 9 variables employed in the research framework. These items are adopted from previous publications as follows: four items of perceived benefit from Hamdan et al. (2021), four items of perceived quality from Alkhater et al. (2018), five items of each perceived cost, and upper management support from Faasolo and Sumarliah (2022), four items of facilitating states from Alkhater et al. (2018), three items of cloud providers' support from Liang et al. (2017), four items of server position from Ahat et al. (2021) and three items of CCA from Alkhater et al. (2018), and seven items of SMEs' performance from Usmanova et al. (2021). A Seven-point Likert scale is used where 7=definitely approve and 1=definitely disapprove. Secondly, the respondents' profiles.

Sampling and Data Collection

SMEs significantly contribute to Palestine's economy, predominantly to resist poverty and joblessness (Hamdan et al., 2022b); thus, SMEs are employed as this study's target population. The questionnaires are distributed to SME managers/owners as they are decision-makers. Data was gathered from major trade zone in West Bank and Gaza Strip, Palestine, from August until October 2021. Contributing SMEs function in the Halal service industry because it is one of the foremost sectors in Palestine (Hamdan et al., 2022b; 2022). Halal is an Arabic word which denotes 'permissible' according to Islamic law (Sumarliah et al., 2020; 2021c; 2021d). A survey questionnaire was spread to 366 participants in 366 companies, following the rule of 'one contributor from each company' advised by Faasolo & Sumarliah (2022). The returned questionnaires were 217 contributors but only 212 responses (57.9%) were complete and thus useful for further data analysis. Overall, data was gathered from 212 contributors representing 212 companies. It means that each firm's evaluation got one response from each firm (Faasolo & Sumarliah, 2022). Therefore, all statistics examination was carried out with an adequate sample size of 211 companies.

The participants' profiles are shown in Table 2. The majority of SMEs have been operating for 5 to 10 years (38.7%). Most SMEs (57.5%) have less than 100 workers. Besides, the Halal

Table 2. Sample profile

Atribute		Frequency	%
Type of Halal service business	Halal hospitality (hotel, restaurant)	116	54.7%
	Halal banking and finance	52	24.5%
	Halal logistics and shipping	44	20.8%
Company size (worker)	Below 100	122	57.5%
	100–200	68	32.1%
	Above 200	22	10.4%
Company age (years)	Below 5	42	19.8%
	5 to 10	82	38.7%
	11 to 20	65	30.7%
	Above 20	24	11.3%
Job position	CEO/owner	134	63.2%
	IT manager	78	36.8%
Work experience (years)	Below 5	36	17.0%
	5 to 10	81	38.2%
	11 to 20	77	36.3%
	Above 20	18	8.5%

service hospitality sector (hotels and restaurants) dominates (54.7%) the depiction of contributing SMEs, followed by Halal/Islamic banking and finance (24.5%) and Halal service logistics and shipping (20.8%).

Data Examination

The first step of SEM analysis is confirming constructs' validity and reliability and evaluating the framework's extrapolative relevance and the full discrepancy described. This study considers discrepancy-based Structural Equation Modelling Partial Least Squares (SEM-PLS) as the most fitting technique because its capability to test a sequence of relations concurrently, while other arithmetical techniques such as multivariate analysis of variance and multiple regression are limited to examining the relations between every variable individually (Hair et al., 2021). Further, the research' characteristics better fit SEM-PLS because instead of focusing on theory confirmation, it concentrates on theory development. The framework' intricacy with many measurement items also causes the SEM-PLS' usage. Lastly, this study uses SEM-PLS rather than covariance-based SEM because it intends to improve the discrepancy described, which is data-determined instead of model fit assessment. Though, SEM is incapable to inspect the non-linear relations amongst variables, which may lead to the real multifaceted decision-making activity to be examined merely (Song, 2022). There are non-linear relations that occur amongst the variables in this study's framework. Thus, the ANN technique is necessary to complement the SEM examination (Alhasnawi et al., 2023; Mustafa et al., 2023; Faasolo and Sumarliah, 2022; Song, 2022). As the final phase, this study performs an ANN examination to verify the SEM findings and to highlight the main determinants of CCA. Overall, firstly, SEM is carried out to find the determining factors with statistical significance, and secondly, ANN is conducted to arrange the determinants according to their comparative significance in describing their focus variables.

FINDINGS

Measurement Framework Assessment

This study's measurement framework is assessed using internal criteria such as discriminant validity, convergent validity, and reliability (Hair et al., 2021). The customary procedures to assess the variable reliability are Dijkstra-Henseler's rho (ρA) and Cronbach's Alpha. Table 3 shows that the reliability values in this research are above the recommended threshold of .7 (Henseler et al., 2009).

This study's convergent validity is assessed using the rates of average variance extracted (AVE), composite reliability, and item loadings. Table 4 reveals that the values of AVE and item loadings exceed the suggested cutoff of .50 (Fornell and Larcker, 1981). The values of composite reliability were also above the suggested cutoff point of .7 (Henseler et al., 2009). Similarly, discriminant validity is checked using the relationships amongst the instruments of probably superimposing constructs. Table 4 shows the value of AVE's square root for every construct in this study exceeds the relationship of that construct with other constructs.

Moreover, Table 5 reveals that the Heterotrait-Monotrait (HTMT) values are less than .85, which confirms the discriminant validity of this study's variables (Henseler et al., 2014).

Table 3. Validity and reliability

Variables	Item loading span		rho_A	Cronbach's Alpha	CR	AVE
	Min	Max				
PBNF	.823	.848	.858	.856	.908	.690
PQLT	.813	.901	.876	.871	.918	.713
PCST	.804	.850	.845	.839	.898	.666
UPMS	.844	.909	.835	.829	.904	.741
FCLT	.838	.876	.880	.873	.919	.715
CLDP	.765	.883	.790	.771	.874	.685
SRVR	.821	.864	.862	.861	.912	.698
CCA	.880	.917	.878	.878	.932	.800
SMEP	.752	.836	.786	.786	.869	.606

Note: AVE=Average Variance Extracted, CR=Composite Reliability

Table 4. Fornell-Larcker criterion

	PBNF	PQLT	PCST	UPMS	FCLT	CLDP	SRVR	CCA	SMEP
PBNF	*.837*								
PQLT	.692	*.851*							
PCST	.659	.627	*.823*						
UPMS	.422	.491	.385	*.867*					
FCLT	.688	.734	.721	.528	*.852*				
CLDP	.546	.587	.588	.413	.607	*.834*			
SRVR	.588	.704	.527	.486	.637	.547	*.842*		
CCA	.703	.764	.543	.593	.763	.595	.764	*.902*	
SMEP	.558	.603	.531	.465	.661	.546	.596	.633	*.785*

Table 5. Heterotrait-Monotrait

	PBNF	PQLT	PCST	UPMS	FCLT	CLDP	SRVR	CCA	SMEP
PBNF									
PQLT	.812								
PCST	.785	.741							
UPMS	.493	.573	.453						
FCLT	.806	.855	.854	.615					
CLDP	.671	.718	.741	.508	.747				
SRVR	.693	.823	.626	.576	.741	.672			
CCA	.820	.855	.637	.697	.859	.727	.848		
SMEP	.690	.739	.661	.574	.805	.708	.734	.774	

Moreover, this study verifies seven model fit indicators for its confirmatory factor analysis (Hair et al., 2021): root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker-Lewis Index (TLI), incremental fit index (IFI), adjusted goodness of fit index (AGFI), goodness of fit index (GFI), and Chi-square to (X2) to the degree of freedom (Df). The data shows an excellent fit of the measurement framework. RMSEA fulfills the recommended threshold of <.80, AGFI (.913) meets the cutoff edge of ≥.80, and X2/df (.039) meets the limit of 1.3. Also, CFI, TLI, IFI, and GFI are .999, .996, .999, and .940, correspondingly, and meets the threshold of ≥.90.

Structural Framework Assessment

The structural framework's goodness is analyzed using R^2 that gauges the determination coefficient and path coefficient (Hair et al., 2021). This study's findings reveal that the value of the adjusted R^2 for CCA is .784, indicating the variables can explain 78.4% of the discrepancy in CCA. Likewise, the value of the adjusted R^2 for SMEP is .403, implying CCA can explain 40.3% of the discrepancy in SMEs' performance. Thus, the suggested framework is statistically validated.

The research examines the links among independent and dependent variables employing t-statistics and path coefficient (β). Table 6 summarizes the findings for the entire hypotheses analysis. The findings indicate that hypotheses H1 (PBNF→CCA, β=.172, t = 3.903), H2 (PQLT→CCA, β = .121, t = 2.846), H3 (PCST→CCA, β =-.172, t=3.811), H4 (UPMS→CCA, β =.158, t=3.940), H5 (FCLT→CCA, β =.287, t=5.186), H6 (CLDP→CCA, β =.090, t=2.313), and H7 (SRVR→CCA, β =.269, t=5.158) have statistical significances. The findings indicate that the theorized associations among perceived benefit, perceived quality, perceived cost, upper management support, facilitating states, cloud providers' support, server location, and cloud computing adoption in SMEs are statistically verified. The path for hypothesis H8 (CCA→SMEP β =.636, t=15.113) is also empirically validated, confirming the positive and significant link between the adoption of cloud computing technology and SMEs' performance.

After SEM findings are obtained, this study conducts importance-performance map analysis (IPMA) to predict the significance of the independent variables and their performance in explaining dependent variable, i.e., CCA (Chuang and Chen, 2022). The examination identifies variables with a comparatively great significance or path coefficient (β) for the dependent construct but a comparatively poor performance (Hair et al. in Chuang and Chen, 2022). The performance values are calculated by rescaling the rates of predictor variables from 1 to 100. FCLT, SRVR, and PCST are variables with higher importance in affecting CCA as their β are greater than to other predictors in this study's framework. However, the performance of these variables is inferior than another predictor, i.e., PQLT. The performance of PCST is also poorer than CLDP, and PBNF. Thus, IPMA helps this study to

Table 6. Hypotheses examination results

Hypothesis	Effect	β	P-value	t-value
H1	PBNF→CCA	.172	.000	3.903*
H2	PQLT→CCA	.121	.005	2.846*
H3	PCST→CCA	-.172	.000	3.811*
H4	UPMS→CCA	.158	.000	3.940*
H5	FCLT→CCA	.287	.000	5.186*
H6	CLDP→CCA	.090	.023	2.313**
H7	SRVR→CCA	.269	.000	5.158*
H8	CCA→SMEP	.636	.000	15.113*

Note: *Significance level: p<.01, **Significance level: p<.05, Adjusted R^2 of CCA=.784, Adjusted R^2 of SMEP=.403

deduce that PQLT, SRVR, and FCLT require particular focus from SMEs' owners/leaders to increase CCA in Palestine. Thus, leaders must distribute more capitals to guarantee the perceived quality of CC technology, improve server position, and enhance facilitating states.

Machine Learning Assessment

This study uses a machine learning method, i.e., Artificial Neural Network (ANN) to complement SEM in data analysis. ANN delivers greater accuracy than SEM (Faasolo and Sumarliah, 2022; Song, 2022). The usage of ANN method helps scholars to estimate the significance of the variables (Shahzad et al., 2020), and to verify and complete the SEM outcomes (Alhasnawi et al., 2023; Mustafa et al., 2023;). ANN is an immensely similar dispersed computer that comprises uncomplicated processing components, which possess a usual predisposition to store new information and make it obtainable for usage (Shahzad et al., 2020). ANN is capable of tackling nonlinear relationships and learning by constructing output-input diagramming (Faasolo and Sumarliah, 2022). The main advantage of using ANN is to gauge the complex non-linear and linear correlations among determining factors and the adoption intention and to rank the determinants according to comparative significance (Hamdan et al., 2022b; Faasolo and Sumarliah, 2022). Further, ANN provides stronger and superior forecasting precision than the typical regression methods such as SEM (Hamdan et al., 2022b; Faasolo and Sumarliah, 2022). Thus, it is reasonable to claim that ANN and SEM methods can complete one another (Mustafa et al., 2023; Alhasnawi et al., 2023). ANN encompasses three roles: network architecture, transfer functions, and learning rule; also, it has multi-layer perception subgroup which is largely employed by scholars, including three tiers such as hidden neuron, output and input (Mustafa et al., 2023; Alhasnawi et al., 2023).

Justifications of ANN

The study conducts an ANN examination employing SPSS 23.0 software. A multilayer perceptron training technique is used to develop the framework. The study uses a concealed layer as an incessant task that can be denoted sufficiently by a single concealed layer. The overfitting issue is overpowered using the ten-folding cross-justification method to overpower (Chen et al., 2021). Of all data gathered, seventy percent is employed to train the machine learning framework, and the remaining thirty percent is for examining the calculation accuracy for the trained framework. The mean cross-justified Root Mean Square Error (RMSE) rates of the testing and training are .062 and .162 correspondingly, as presented in Table VII. Those small RMSE rates signify that the framework is practically reliable in describing the statistical associations among predictor variables and outcome.

Table 7. Root mean square error (RMSE) for machine learning framework

Network	Testing	Training
1	.056	.147
2	.038	.070
3	.053	.189
4	.032	.193
5	.087	.156
6	.107	.169
7	.060	.209
Mean	.062	.162
Standard error	.035	.047

Prioritization of Predictors

A sensitivity examination in the machine learning framework is conducted to rank the independent variables by identifying their comparative significance. The factors' comparative significance measures how the estimated machine learning framework transforms in the outcome assessments regarding the transformations of predictor variables' values (Hamdan et al., 2022b). Table 8 exhibits the standardized significance values of predictors; the strongest determinant of CCA is perceived benefit, the next are facilitating states, server position, upper management support, perceived quality, perceived cost, and cloud providers' support.

DISCUSSION

The study examines factors that affect CCA among SMEs and assess whether CCA significantly affects SMEs' performance in Palestine context. This study hypothesizes that TOE factors, which include: (1) Technological factors (perceived benefit, perceived quality, perceived cost), (2) Organizational factors (upper management support, facilitating states), and (3) Environmental factors (cloud providers' support, server position), will significantly affect CCA. The findings of SEM and ANN analysis have been revealed in the previous section, and the discussion of the findings are as follows:

Table 8. Predictors' importance values

Predictors	Comparative importance	Standardized importance	Ranking
PBNF	.2015	10.00%	1
PQLT	.0898.	44.30%	5
PCST	.0758	37.61%	6
UPMS	1167	57.46%	4
FCLT	.1546	76.32%	2
CLDP	.0708	35.22%	7
SRVR	.1377	67.84%	3

Technological Factors

The findings reveal that perceived benefit plays a significant role for CCA among Palestinian SMEs. This study's result supports previous works (Forootani et al., 2022; Lutfi, 2022; Shetty and Panda, 2022; Tella et al., 2020; AlMabhouh and Alzaza, 2015). These studies confirm that SMEs identify the perceived benefits (such as cost savings) as the driving power of CCA. Also, the findings are in line with Hamdan et al. (2021) who reveal perceived benefits as the most influential determinants of adopting new technologies. However, this result opposes the finding of Alkhater et al. (2018) that firms remain unconcerned about the perceived benefit of adopting CC technology. One possible reason is perhaps because the previous study was conducted in 2018, while this study is accomplished in 2022 when SMEs have been more knowledgeable about the benefits of CC technology than four years ago. Generally, SMEs in developing nations (such as Palestine) faced problems that constrain the use of modern technologies required to increase their companies' operations; however, after the COVID-19 pandemic started to spread the world in early 2020, SMEs have become more aware that adopting digital technologies such as CC can help them survive the pandemic-driven disruptions and highly competitive business environment of 'new normal' era (Akpan et al., 2022).

Furthermore, the paper verifies that perceived quality positively and significantly affects CCA. CC technology is a network-constructed innovation that third parties offer; thus, SMEs demand excellent high-quality services. This finding supports earlier works by Alkhater et al. (2018), Gui et al. (2021), and Forootani et al. (2022). Unlike big firms, SMEs have poorer understanding to tackle failures in CC facilities; also, they have fewer technological sources and IT competencies (Shetty and Panda, 2022); thus, the quality of services encourages them to adopt CC technology.

However, perceived cost is a constraint of CCA among SMEs in Palestine, supporting previous studies focusing on technology adoption by SMEs in an emerging country such as Faasolo et al. (2022). Nevertheless, this paper's finding does not support Faasolo and Sumarliah (2022) and Chau et al. (2020) who report that perceived cost insignificantly affects technology adoption among SMEs in Tonga. It is because in an occupied country like Palestine with a lack of financial access due to blockade by Israeli zionist, expensive operational costs and inefficiency are the major inhibitors of SMEs' industrial achievements (Hamdan et al., 2022b). Thus, the great perceived costs of CC technology capital spending initiate the low CCA amongst Palestinian SMEs. Although the rapid-transforming technologies can lessen the costs of technology adoption (Hamdan et al., 2022b), but CC technology in Palestine possibly remains in the infant stage that the perceived cost is still high.

Organizational Factors

The research finding proves that upper management supports (UPMS) such as distributing assets and involving upper management (managers/owners) in the activity are imperative for quickening the CCA among SMEs. The result supports the findings of Gui et al. (2021), Lutfi (2022), Sayginer and Ercan (2021), Shetty and Panda (2022), Skafi et al. (2020), and Zamzeer et al. (2020) which verify that there are significant effects of UPMS on CCA. Another group of scholars such as Hamdan et al. (2021) reveals that UPMS shapes the perceived benefits of a new technology, which further significantly affects the adoption of such technology. High competition in the current industrial atmosphere has made SMEs call for UPMS in a thinkable manner (Hamdan et al., 2022b). When the UPMS is absent, SMEs are not likely to espouse CCA (Neicu et al., 2020). It is likely that SMEs get essential support from managers/owners more effortlessly due to the simpler management formation than big companies. In SMEs, the decision-making process is mainly consolidated around a few persons (Chau et al., 2020). However, this finding is not in line with Alismaili et al. (2020) who find UPMS as an insignificant predictor of CCA. The possible reason is that this study was conducted in a developing and occupied country of Palestine, while the previous mentioned study was hold in a developed nation such as Australia. In developing countries, the adoption of technology still concentrates on internal-ability factors (including UPMS within the firms), while in developed nations, technology adoption depends more on technological factors (Raj et al., 2020).

Furthermore, the research reveals that facilitating states strongly and positively affect the CCA. ANN findings identify that facilitating states is a vital determinant for CCA in Palestinian SMEs. The result reinforces previous publications which focus on information systems (Tella et al., 2020; Dwivedi, et al., 2017). The paper suggests that the existence of facilitating states, e.g., technical human resources, enterprise application systems, high-speed Internet, better network technologies, technological infrastructure, and compatibility with current systems and processes encourage SMEs regarding CCA.

Environmental Factors

Cloud providers' support directly and positively affects CCA, especially among SMEs. This finding is in line with earlier studies (Lutfi, 2022; Zamzeer et al.,2020). The finding indicates that cloud providers' support reinforces SMEs when they face issues such as the lack of skilled human resources, finance, and technology for building and upholding their substructure. Cloud providers' support provides SMEs with ease of maintenance (Tella et al., 2020) and ultimately motivates SMEs to perform CCA (Zamzeer et al., 2020). CCA among SMEs is strongly affected by how cloud providers cultivate trust through offering excellent amenities and keeping cooperation with partner companies as today, SMEs await technological allies instead of technological sellers. Particularly, servers' location is the strongest predictor for CCA in Palestinian SMEs. The result implies that SMEs pay heavy attention to their supplies' precise location. Fundamentally, such concerns can happen as cloud providers put SME's supplies in various data repositories placed in various nations; occasionally, they do not even notify their consumers of the precise servers' position accurately, which can be conflicting with the compliance and privacy problems in a company (Alkhater et al., 2018). Thus, the research advises that cloud providers need to be cautious when placing the servers to tackle those problems.

CCA and SMEs' Performance

Corresponding to earlier publications (Kaplancalı and Akyol, 2021), the research reveals that CCA significantly affects SMEs' performance for cloud-based operations. The result is not surprising as companies switch to the cloud to reduce costs and increase operation. The findings indicate that the fruitful CCA can assist SMEs in gaining many advantages, e.g., improved flexibility, minimized operational expenditure, and increased revenue (Neicu et al., 2020). The appropriate usage of CC technology will provide SMEs with the accessibility of hi-tech ICT supplies, thus empowering companies to use vital assets efficiently and focusing on essential commercial processes. SMEs will also enhance their ICT capability thru improving the ICT skill of the vendors and tackling best practices.

SEM Outcomes vs. Machine Learning Findings

Table 9 shows the contrasts between findings attained from SEM and machine learning examinations to determine the significance of predictor variables. In SEM, the significance of predictor variables is decided by the aggregate unnormalized impacts of every predictor on the predicted variable. SEM findings reveal that the most influential predictor (no.1) of CCA is facilitating states. On the contrary, machine learning technique (i.e., ANN) findings show that perceived benefit is the most significant predictor. Nevertheless, cloud providers' support is prioritized similarly as the least important predictor (no.7) in machine learning and SEM outcomes. The different findings of two distinct techniques signify the advantage of employing machine learning like ANN compared to SEM. While a traditional numerical approach like SEM can only examine the linear association, ANN is capable of assessing non-linear association and possesses better analytical capacity than SEM (Mustafa et al., 2023; Alhasnawi et al., 2023; Faasolo and Sumarliah, 2022; Song, 2022). These results give new viewpoints for the experts regarding the comparative significance of the predictor variables in describing CCA.

Table 9. The findings of SEM vs machine learning

Predictor variables	SEM		Machine learning	
	Effect coefficient (β)	Prioritization	Comparative importance	Prioritization
PBNF	.1980	4	.2015	1
PQLT	.1300	6	.0898	5
PCST	-.2092	3	.0758	6
UPMS	.1523	5	1167	4
FCLT	.3260	1	.1546	2
CLDP	.1056	7	0708	7
SRVR	.2844	2	.1377	3

The findings provide solutions to SME challenges and research questions (QS1, QS2, and QS3) that were raised as follows:

(1) Regarding QS1 (i.e., "What determinants will affect the CCA among SMEs in Palestine?"), the findings reveal that all predictor variables are the influential determinants that affect CCA among SMEs in Palestine. It means that all hypotheses are supported, and CCA among SMEs in Palestine are significantly affected by technological factors (perceived benefit, perceived quality, perceived cost), organizational factors (upper management support, facilitating states), and environmental factors (cloud providers' support, server position). Thus, the extended TOE model developed in this study is an excellent tool to answer the QS1.
(2) Regarding QS2 (i.e., "Will CCA affect SMEs' performance?"), the findings exhibit that yes, CCA definitely affects the performance of SMEs in Palestine, as the hypothesis is supported with significance level (p) of $<.01$.
(3) Lastly, about QS3 (i.e., "How significant the determinants are to estimate the CCA?"), the findings show two different results of SEM analysis and machine learning (ANN) analysis, as seen in Table 8. Based on SEM, facilitating states rank number 1 in its significance of all predictors, followed by server position in number 2 and perceived cost in number 3. Meanwhile, ANN findings show that perceived benefit is the number 1 most significant predictor, followed by facilitating states and server position. Thus, academicians, managers and decision-makers must focus on these significant factors to increase the adoption of CC technology among SMEs in developing countries such as Palestine.

CONCLUSION AND IMPLICATIONS

Conclusion

The study aims to fill the existing literature gaps by examining the influential determinants of CCA among SMEs and analyze whether CCA significantly affects SMEs' performance, especially in Palestine context. This study hypothesizes that TOE factors, which include Technological elements (perceived benefit, perceived quality, perceived cost), (2) Organizational factors (upper management support, facilitating states), and (3) Environmental factors (cloud providers' support, server position), will significantly affect CCA among SMEs, and CCA will significantly affect SME's performance. To test the hypotheses, this study uses a two-phase systematic method through combining SEM and machine learning (i.e., ANN) technique that many academicians recommend for assessing technology adoption behaviors (Hamdan et al., 2022b; Faasolo and Sumarliah, 2022).

The findings of SEM-ANN method provide answers to the research questions (QS1, QS2, and QS3) that were raised. The findings for QS1 reveal that CCA among SMEs in Palestine are significantly affected by TOE factors: technological factors (perceived benefit, perceived quality, perceived cost), organizational factors (upper management support, facilitating states), and environmental factors (cloud providers' support, server position). The answer to QS2 is yes, CCA definitely affects the performance of SMEs in Palestine. Lastly, the findings show that based on SEM, the most significant predictor of CCA is facilitating states; while based on ANN, the most vital factor affecting CCA is perceived benefit.

Theoretical Implications

This study's results explore novel and applicable cloud-associated variables, e.g. perceived cost, cloud providers' support, and server position, which are not broadly measured in earlier publications. The research has also strengthened the positive and significant link between CCA and the performance of SMEs that cloud-enabled processes affect.

The presence of some related variables to the initial TOE model enhances the research framework's descriptive ability. The research framework describes 78.4% of the discrepancy of CCA and 40.3% of the SMEs' performance, which implied that the framework has a robust extrapolative capability. Hair et al. (2021) suggested that the R2 rates of .25, .50, and .75 for dependent constructs denote weak, medium, and strong determination coefficients, respectively. The research attempts the extended TOE model regarding CC technology and generalizability; hence, the research framework can be employed to analyze the adoption of other technologies.

Lastly, the study has used a mixture method by incorporating SEM and machine learning (i.e. ANN) to verify the research framework and to rank the predictors of CCA through detecting the comparative significance of every substantial variable. The research also compares SEM-PLS rank and ANN rank of the CCA's determinants and identifies several disparities. Those disparities happen because of the different features of the techniques; ANN gauges nonlinear links amongst predictor variables and predicted variables while SEM assesses linear associations. Earlier publications prove that compared to SEM, the machine learning method provides higher estimation precision (Faasolo and Sumarliah, 2022; Hamdan et al., 2022). However, the research does not neglect the rationality and prerequisite of conventional techniques of statistics, which offer a strong groundwork in previous information systems adoption literature. The study advises reexplaining earlier studies regarding information systems adoption through uniting non-linear and linear techniques, which delivers immense power to the current studies on adopting technologies.

Practical Implications

SMEs are rising marketplace for the cloud providers because it is regarded as the vital spark of the economies, particularly for emerging nations. SMEs dominate the economies of emerging nations, especially in Palestine (Hamdan et al., 2022b; 2022). Thus, the research provides substantial implications for technology practitioners and cloud providers and assists them in identifying the vital predictors of CCA. This study's findings imply that the perceived benefit, server's position/location, perceived quality, perceived cost, and cloud providers' support are indispensable for the CCA among SMEs. Prominently, the study's ANN finding proposes that perceived benefit is the most significant matter for the CCA among Palestinian SMEs, which supports that of earlier works (Forootani et al., 2022; Lutfi, 2022; Shetty and Panda, 2022; Tella et al., 2020).

CC technology is reckoned as disruptive and emergent. Companies have limited knowledge regarding the advantages of using this type of technology, particularly because SMEs in developing nations (such as Palestine) faced problems that constrain the use of modern technologies required to increase their companies' operations (Akpan et al., 2022). Thus, the cloud provider must commence numerous gauges to enhance the consciousness regarding the benefits of CCA via numerous publicity training and conferences. They must emphasize practical conveniences and the ease of use of CC

technology (Forootani et al., 2022, Shetty and Panda, 2022) to facilitate SMEs with inadequate technical understanding in utilizing the technology effortlessly. Besides, cloud providers must deliver adequate education or steering structure to direct companies regarding the easy procedure of using the technology, which will enhance the trust in using the new system (Liang et al., 2017; Shetty and Panda, 2022).

Besides, the study's SEM finding shows that facilitating states, e.g., compatibility with the current system, ICT knowledge, and technology infrastructure, is the most significant determinant of CCA in Palestine, supporting that of earlier works (Alkhater et al., 2018; Tella et al., 2020; Song, 2022). Thus, SME owners/managers must pay the heaviest attention to building those facilitating states to get the highest advantage of CCA. Besides, SME owners/managers should be able to evaluate the new system and integrate this innovation into the current ICT system efficiently and effectively (Faasolo and Sumarliah, 2022; Hamdan et al., 2022b; 2022). Due to long-term blockade and occupation by Zionist Israel, SMEs in Palestine struggle with numerous IT infrastructures (Hamdan et al., 2022b; Mousa et al., 2022) such as cloud providers, which is delaying the CCA. Thus, it is necessary to improve cloud providers' support to enlarge CCA in Palestine. Also, cloud providers' support should be in the form of providing satisfactory privacy and security events (Alismaili et al., 2020, Lutfi, 2022, Skafi et al., 2020) to protect companies from unwanted incidents of security infringements and cyber-fraud. Informing servers' positions to the firms is a form of cloud providers' support (Alkhater et al., 2018). Considering the data servers' position within emerging countries such as Palestine is a cloud providers' support that can assist firms to adhere to their rules and lessen perceived cost concerning CCA (Ahat et al., 2021). Generally, this study's results can enhance cloud providers' current awareness regarding the limited CCA among Palestinian SMEs; hence, they should maximize attempts to increase CCA.

The paper verifies that perceived quality positively and significantly affects CCA. Firms choose to employ simpler technologies, which require fewer attempts, shorter time, and less technological comprehension. Hence, cloud providers can use this study's findings that indicate verifying the excellent quality of service is vital to intensify CCA. The research strengthens that upper management support is indispensable for adopting CC technology in the company context. Overall, this study's findings can help SME leaders in evaluating cloud computing's attributes, environments, and organization, as choosing whether they will adopt the innovation. Besides, managers/owners may use the research model to examine the adoption of different ICT/information systems.

Limitations and Further Studies

Like other studies, the research has some shortcomings which give the space for upcoming studies. Firstly, the data was gathered from one nation, which indicates that the study shows only the country of Palestine. Therefore, upcoming studies can verify the framework employing a sample obtained from different emerging nations. Secondly, this study framework was built by using some vital variables from four aspects; upcoming literature can expand the framework by involving other related variables of these main aspects. Thirdly, the research framework was analyzed with single-period cross-sectional data; upcoming works may verify the research framework with longitudinal data. Next, the research tries to examine CCA among SMEs from owners'/managers' viewpoints; upcoming studies can emphasize workers and cloud supplier contexts to possess a wider comprehension of the CCA. Lastly, the study examines the intent to adopt CC technology only among SMEs in underdeveloped country. Unlike SMEs and developing countries, larger companies and developed nations may use more up-to-date CC technologies; hence, this manuscript and solutions may not be applicable for all companies and countries. Thus, upcoming studies can compare the results in large companies and developed countries.

CONFLICT OF INTERESTS

None.

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