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A Comparison of Competing Models for Understanding Industrial Organization's Acceptance of Cloud Services

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Abstract: Cloud computing is the next generation in computing, and the next natural step in the evolution of on-demand information technology services and products. However, only a few studies have addressed the adoption of cloud computing from an organizational perspective, which have not proven whether the research model is the best-fitting model. The purpose of this paper is to construct research competing models (RCMs) and determine the best-fitting model for understanding industrial organization's acceptance of cloud services. This research integrated the technology acceptance model and the principle of model parsimony to develop four cloud service adoption RCMs with enterprise usage intention being used as a proxy for actual behavior, and then compared the RCMs using structural equation modeling (SEM). Data derived from a questionnaire-based survey of 227 firms in Taiwan were tested against the relationships through SEM. Based on the empirical study, the results indicated that, although all four RCMs had a high goodness of fit, in both nested and non-nested structure comparisons, research competing model A (Model A) demonstrated superior performance and was the best-fitting model. This study introduced a model development strategy that can most accurately explain and predict the behavioral intention of organizations to adopt cloud services.

Keywords: cloud services; technology acceptance theory; competing model; model development strategy; structural equation modeling

1. Introduction

The official definition of cloud computing by the National Institute of Standards and Technology is as follows: "Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service-provider interaction" [1]. Because of its notable market-oriented and flexible architecture features, on-demand computing power, quick implementation, low maintenance, limited requirement for IT staff, and consequential lower costs, cloud computing has recently dominated IT press topics [2] and received increasing attention in both computer science and information systems (ISs) industries [3]. Moreover, numerous industry projects have been designed and implemented, such as Amazon Elastic Compute Cloud, IBM Blue Cloud, and Microsoft Windows Azure.

Reviews of global primary market research conducted by firms have indicated substantial growth in the cloud service market for the foreseeable future. Global Cloud IT market revenue is predicted to increase from $180 billion in 2015 to $390 billion in 2020, attaining a CAGR of 17% [4]. Market Research Media [5] estimated that the global government cloud computing market is expected to grow at 6.7%

CAGR generating $118 Billion in revenues from 2018 to 2023. With the potential to integrate business processes into existing information systems applications, reduce the cost of IT services, and build internet-based technology for transacting business with trading partners, firms are increasingly seeking cloud-based solutions to streamline business [6].

Organizations adopt new IT/IS for numerous reasons. Many theories are applied in examining new technological innovation diffusion and adoption, including the theory of planned behavior (TPB) [7], the technology acceptance model (TAM) [8], the technology–organization–environment (TOE) framework [9], diffusion of innovations (DOI) theory [10], and the unified theory of acceptance and use of technology (UTAUT) [11]. This study employed two commonly used theories, DOI theory and the TOE framework, to identify representative and critical research competing model (RCM) factors because most studies on IT adoption in organizations apply such theories [12,13]. Other frequently applied theories, such as the TPB, TAM, and UTAUT, were not considered because they pertain to the individual level [13,14].

A review of the literature revealed that many previous studies on cloud computing have addressed technical and operational issues [15], including topics such as the selection of appropriate cloud computing services according to costs and risks [16], an audit protocol for secure storage and computation in the cloud [17], an investigation of security problems as well as the specifications of key features [18], and a survey of security challenges, the encryption as well as testing techniques for data in cloud [19]. However, only a few studies have addressed the adoption of cloud computing from an organizational perspective, but have not proposed a comprehensive study and proven whether the research model is the best-fitting model. Abdollahzadegan et al. [20] evaluated the impact of organizational factors on cloud computing adoption in Small and medium enterprises (SMEs) and Hsu et al. [21] developed a cloud service adoption model that dealt with not only adoption intention, but also pricing mechanisms and deployment models. Tim [22] assessed the benefits of the cloud for small and medium enterprises. Moreover, the specific determinants used vary across studies even though all such factors can be classified under DOI theory and the TOE framework [6].

Motivated by this issue, this study introduced a model development strategy that involves constructing RCMs and identifying which RCM that can most accurately predict the behavioral intention of organizations to adopt cloud services. To achieve this, this study developed four RCMs based on DOI theory, the TOE framework, and the principle of model parsimony, and then compared the RCMs in two stages (nested and non-nested model comparisons) through structural equation modeling (SEM) for examining reasonable model fit, chi-square test, path coefficient significance, and squared multiple correlation (SMC, namely, model's explanatory power) to identify the best-fitting model.

The remainder of this study is arranged as follows. Section 2 describes the theoretical foundations, influencing factors for the RCMs, and proposes the hypotheses. Section 3 presents the methodology and research design, and Section 4 deals with the data analysis, hypotheses testing results, and the RCMs comparison. This is followed by a discussion and implications in Section 5. Section 6 provides conclusions together with limitations and remarks on future research.

2. Literature Review and Research Hypotheses

2.1. Diffusion of Innovations Theory

Rogers [23] proposed DOI theory, which is one of the most widely applied theories for predicting organization-level technology adoption in relevant IT and IS studies [24,25], and can be defined as a "process that communicates an innovation through specific channels among the members of a social system" [26]. DOI theory at the firm level [10] comprises three groups of drivers for organizational innovativeness: individual (leader) characteristics, internal organizational structure characteristics, and the external characteristics of the organization. The individual (leader) characteristic describes leader attitudes toward change, and is a specific internal organizational property. The internal characteristics of organizational structure include centralization, complexity, formalization, interconnectedness, organizational slack, and size. The external characteristics of an organization refer to system openness, which is similar to the environmental context in the TOE framework. An organization is a more complex entity than an individual. Rogers [25] suggested that innovation is a communication process using the various channels within a social system.

2.2. Technology–Organization–Environment Framework

Tornatzky and Fleischer [9] developed the TOE framework, which is consistent with DOI theory [14], to examine firm-level adoption of various IS and IT products and services [27]. The TOE framework has a distinct advantage over the DOI theory due to its consideration of environmental factors [28]. The framework identifies three contexts that influence enterprise adoption before the implementation of technological innovation: technological context, organizational context, and environmental context [29]. Technological context refers to existing technologies in use and new technologies available to a firm, such as current practices and equipment internal to the firm and the set of available technologies external to the organization. Organizational context refers to descriptive organizational measures, such as top management support (TMS), size, centralization, formalization, human resources, and managerial structure. Environmental context consists of environmental characteristics in which the organization conducts services, such as a firm's industry, its competitors, and its communications with the government. These three contextual factors influence an organization's decision-making regarding the adoption of an innovation, and eventually affect firm performance [30].

2.3. Constructs and Hypotheses Development

To identify the critical constructs of the RCMs, based on DOI theory and the TOE framework, this study conducted a comprehensive search of scholarly databases such as SDOS, SDOL, Scopus, and Google Scholar regarding innovation diffusion and adoption. Table 1 summarizes the factors evaluated in this organized approach and the IS, IT, and ICT adoption models (dependent variable) in these studies. Accordingly, this study first selected five crucial and frequently cited factors as the representative antecedents.

In addition, entrepreneurship (ES) may facilitate a firm's innovation diffusion and adoption, and ensure its long-term success [31]. This study therefore regards ES as another determinant to the relative advantage of cloud service adoption. This variable determines whether cloud service adoption would be relatively advantageous if ES is involved. Accordingly, this study incorporated the following six factors associated with the organizational adoption of cloud services to construct RCMs and then examined each RCM construct to determine its applicability to the behavioral intention of organizations to adopt cloud services.

Table 1. Literature review on model constructs from DOI theory and/or TOE framework.

Theoretical Model	Innovation Diffusion and Adoption (Dependent Variable)	Primarily Constructs (Independent Variables)										Source
		Relative Advantage	Compatibility	Complexity	Security	Tech. Readiness	Firm Size	Top Management Support	Cost	External Pressure	External Support	
TOE and DOI	E-business	✓	✓	✓	✓	✓	✓		✓	✓		[32]
TOE, DOI and institutional theory	E-procurement	✓	✓	✓				✓	✓	✓	✓	[33]
TOE and DOI	Collaborative commerce	✓	✓	✓				✓		✓		[12]
TOE	Knowledge management and enterprise systems adoption	✓	✓	✓			✓	✓		✓		[34]
TOE and DOI	RFID	✓	✓	✓			✓	✓		✓		[35]
TOE	E-commerce	✓	✓				✓	✓	✓	✓		[36]
TOE and DOI	Cloud computing adoption	✓	✓	✓		✓	✓	✓		✓		[6]
TOE	Cloud computing adoption	✓	✓	✓		✓	✓	✓		✓		[20]
TOE and DOI	Cloud computing adoption	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	[13]

2.3.1. Service Compatibility (SC)

Rogers [37] defined compatibility as consistency with a user's existing values, past experiences, and current needs, and as a critically perceived characteristic of innovation. Tan and Eze [38] observed that an innovation that is compatible with user values and job duties is more likely to be adopted. Low et al. [6] reported that technological, organizational, and environmental contexts influence cloud computing adoption, and examined the effect of compatibility in a technological context. Cloud computing is sometimes at risk of conflicting with an established corporate philosophy that contradicts the key features of cloud computing [39]. When companies consider a technology to be compatible with their existing ISs, they find adopting the new technology more feasible. Conversely, a company that recognizes technology as incompatible is likely to reject adoption when considering the extra process adjustments, considerable learning, and investment in additional equipment. Consequently, increased compatibility positively influences the adoption intention and actual adoption of cloud computing [40]. Therefore, this paper presents the following hypotheses:

Hypothesis 1. *SC exerts a positive influence on TMS for cloud computing.*

Hypothesis 2. *SC exerts a positive influence on behavioral intention toward cloud computing.*

2.3.2. Entrepreneurship (ES)

"An entrepreneur is a person who owns a company, business, or venture, and is in charge of its growth, but ES is the implementation of starting a new business or bringing back an existing business for capitalizing on newfound opportunities" [41]. "Entrepreneurial spirit is characterized by innovation and risk-taking, and is an essential part of a nation's ability to succeed in an ever changing and increasingly competitive global marketplace" [42].

Prior studies have shown corporate entrepreneurship (CE) to be a crucial factor for the prosperity of companies. Entrepreneurial capabilities are a concept utilized in technology innovation literature to understand a person's attitude toward adopting a particular technological innovation [43]. Managers must become cognizant of which factors in their sector are relevant to successful CE before they can alter their management strategies to inspire an entrepreneurial spirit that will ensure the long-term success of their company [31]. Cloud computing is the ideal platform for providing optimal technological solutions for entrepreneurs in technology and business [44]. People with a strong entrepreneurial orientation are more likely to adopt technological innovations such as cloud computing. CE can be increased by strengthening an innovation-supporting culture and offering organic structures that facilitate innovation development, including the adoption of new IT or ISs. Therefore, this paper presents the following hypotheses:

Hypothesis 3. *ES exerts a positive influence on TMS for cloud computing.*

Hypothesis 4. *ES exerts a positive influence on behavioral intention toward cloud computing.*

2.3.3. Social Influence (SI)

SI is "the degree to which an individual perceives that important others believe he or she should use the new system" and is directly associated with the behavioral intention to use a technology, which consequently affects a user's decision to adopt a technology [45]. SI is also recognized as a subjective norm in the theory of reasoned action (TRA) [46], and in its extension, the TPB [47], which is defined as "the person's perception that most people who are important to him think he should or should not perform the behavior in question" [48].

Although these concepts have distinct labels, both SI and subjective norms have been widely researched in the technology adoption literature and contain the notion that peoples' behavior is influenced by the way in which they believe others will perceive them as a result of having used the technology. Hartwick and Barki [49] concluded that a subjective norm is a crucial determinant of behavioral intention, particularly in the early stages of the innovation diffusion cycle. In the initial adoption phase, potential adopters with little or no experience with related innovation must rely on their referent groups (known as significant others) for information [50]. This means that the introduction of new technology is based upon social trends that are affected by individual environment. In the context of cloud service adoption, this study defined SI as the degree of encouragement or influence from other people that affects an organization to adopt cloud services. Therefore, this paper presents the following hypotheses:

Hypothesis 5. *SI exerts a positive influence on TMS for cloud computing.*

Hypothesis 6. *SI exerts a positive influence on behavioral intention toward cloud computing.*

2.3.4. Perceived Information Security Assurance (PISA)

Information security refers to protecting information and ISs from unauthorized access, use, disclosure, disruption, modification, perusal, inspection, recording, or destruction [51]. Cloud services contain a security function that examines customer e-mails and web traffic, external data storage (such as Amazon's S3), web services (such as Amazon's EC2, which provides resizable computation capacity in the cloud), and personal applications (such as those offered by Google) [52].

Numerous studies have documented the consequences of ICT security. ICT security and confidentiality are the principal determinants of innovation adoption [38]. Gartner [53] identified seven fundamental cloud-specific security threats that customers should carefully consider before selecting a cloud vendor: privileged user access, regulatory compliance, data location, data segregation, recovery, investigative support, and long-term viability. Subashini and Kavitha [54] indicated security concerns as the most typical reason that enterprises are disinterested in software as a service (SaaS). By contrast, studies on security risks have indicated that winning customer trust in privacy and confidentiality security issues is service providers' greatest challenge [55]. The lack of mature security protocols and identity management standards implies that organizations are reluctant to adopt cloud solutions [13]. Therefore, this paper presents the following hypotheses:

Hypothesis 7. *PISA exerts a positive influence on TMS for cloud computing.*

Hypothesis 8. *PISA exerts a positive influence on behavioral intention toward cloud computing.*

2.3.5. Perceived Cost Savings (PCS)

Tan and Eze [38] indicated that ICT cost refers to the investments companies must make to obtain ICT. A business study considered ICT cost as the most critical factor for SMEs [56]. Previous studies have shown that firms are more likely to adopt an innovation if the investment cost is lower [57]. Leavitt [58] indicated that shifting to cloud computing reduces IT cost significantly, and frees customers from the cost and hassle of installing and maintaining local applications.

By adopting cloud computing, a firm can reduce the time devoted to system maintenance and routine upgrades. Cloud computing also reduces infrastructure costs, decreases energy consumption, and lowers maintenance expenditures [59]. Another study indicated that cost was no longer a barrier for small businesses adopting new IT [60]. Although the possibility of reducing costs related to the interior supply of cloud computing services may attract companies [61], implementing high-cost IT systems and charging service fees are frequently major obstructions to their adoption [62], particularly for small businesses. Therefore, this paper presents the following hypotheses:

Hypothesis 9. *PCS exerts a positive influence on TMS for cloud computing.*

Hypothesis 10. *PCS exerts a positive influence on behavioral intention toward cloud computing.*

2.3.6. Top Management Support (TMS)

TMS is a facilitator that gathers various functional groups [63]. Ragu-Nathan et al. [64] suggested that TMS refers to the extent of supervisor recognition of the importance of the IS function and the degree to which top management facilitates and is involved in IS activities. A company lacking TMS may not be optimally implementing cloud services and cannot achieve IS investment revenues [65]. For new technology adoption, TMS is crucial for creating supportive conditions and providing abundant resources [35]. Moreover, certain empirical studies have shown TMS to be positively associated with new technology adoption [6]. A project that has enthusiastic, devoted, and supporting supervisors can easily obtain abundant resources required for IS adoption. By contrast, when top management fails to recognize the benefits of cloud computing for its business, the management is opposed to its adoption.

Rogers [37] revealed that innovation adoption is related to the innovation-decision process. Top managers often decide to adopt IS/IT according to the internal needs of the organization or environmental changes [66]. The CEO also assumes responsibility for managing and utilizing technological innovation in organizations [67]. Therefore, this study proposes that the TMS construct could serve not only as a direct influential construct but also as an indirect (intermediate) factor influencing user intention to adopt cloud services. Thus, this paper presents the following hypotheses:

Hypothesis 11. *TMS exerts a positive influence on behavioral intention toward cloud computing.*

2.4. Research Competing Models

According to a review of the literature on cloud computing adoption, most studies have empirically investigated the direct effects of innovation or contextual factors. No study has implemented a holistic evaluation method to validate the direct and indirect effects of the determinants on cloud computing adoption. In other words, other potential relationships may exist according to certain theories. Furthermore, Bollen [68] has suggested that if RCMs appropriately fit the data and also support the original theory of the structural model, the most parsimonious (the simplest) model should be selected. Therefore, this study proposed four RCMs, with two being parsimonious, for determining the best-fitting model that can predict the intention of firms to adopt cloud services (see Figure 1).

As depicted in Figure 1, Model A employs an intermediate construct (TMS) that was hypothesized to be affected by other theoretical and practical factors (PISA, SC, ES, SI, and PCS), which then influences the extent of enterprise usage intention (EUI). Thus, the relationships indicate (H1, H3, H5, H7, and H9) that PISA, SC, ES, SI, and PCS are positively correlated to TMS, which has a positive influence on EUI (H11). Based on Model A, Model B incorporates two potential direct relationship paths (from SI and PCS to EUI); the relationships between SI and EUI along with PCS and EUI were hypothesized to be direct and indirect because of the external and environmental context characteristics of DOI and the TOE, respectively. Therefore, the additional hypotheses (H6 and H10) state that SI and PCS have a positive influence on EUI.

However, according to the principle of parsimony, which states that "the explanation of any psychological construct should make as few assumptions as possible, eliminating any items or factors that make no difference in the observable predictions or explanation of a theory or hypothesis" [69], this study proposed two other possible parsimonious RCMs (Model C and Model D). Model D, which excludes the TMS construct, consists of only five direct relationship paths from the PISA, SC, ES, SI, and PCS constructs to EUI. Therefore, the proposed hypotheses (H8, H2, H4, H6, and H10) are that PISA, SC, ES, SI, and PCS have a positive influence on EUI. Model C considers TMS as a new construct and a direct relationship path from TMS to EUI in addition to the five direct relationship paths developed from Model D. Hence, the relationships suggest (H8, H2, H4, H6, H10, and H11) that PISA, SC, ES, SI, PCS, and TMS have a positive influence on EUI.

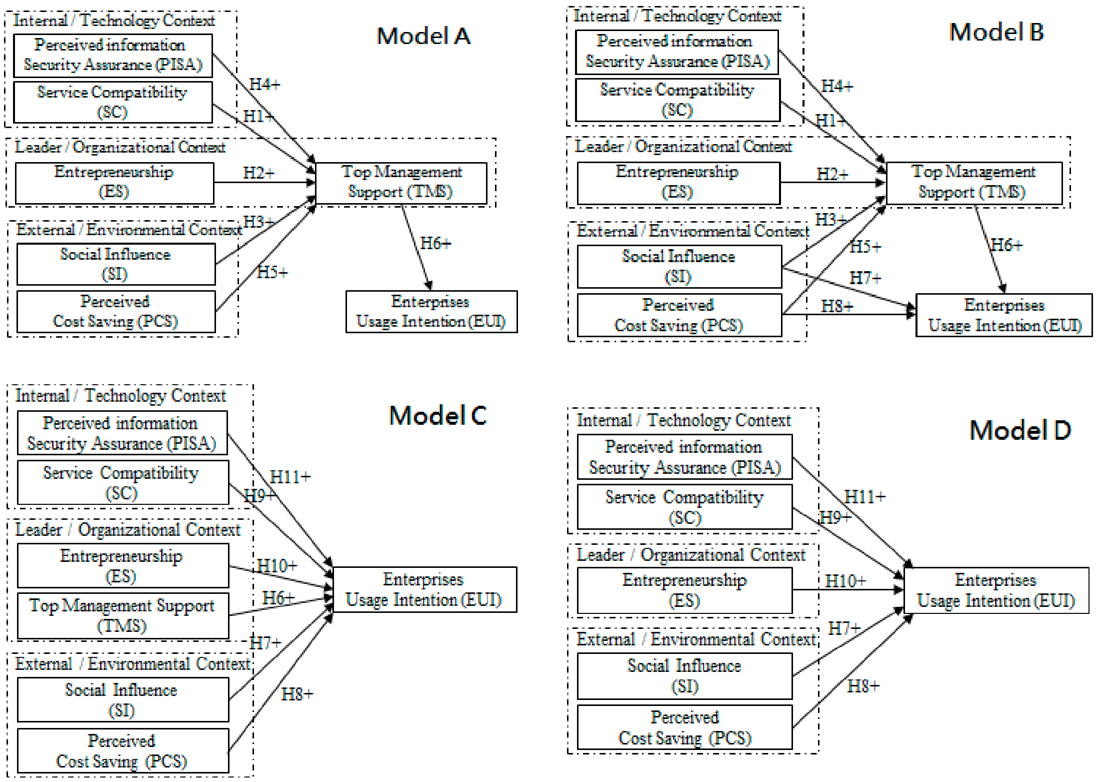

Figure 1. Four research competing models (RCMs).

3. Research Methodology

3.1. Measures

The survey involved using a questionnaire to measure the antecedents for cloud service acceptance, with multiple-item scales being employed to capture all the construct attributes. Items for measuring the model constructs were primarily adopted from previous studies that reported high statistical reliability and validity. Certain minor wording changes were applied to conform to the context of cloud services. All items were measured on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree). Table 2 lists the final scale items used to measure each construct and their reference sources.

Table 2. Constructs and measurement items.

Constructs	Measurement Items	Reference
Perceived Information Security Assurance (PISA)	The cloud services provider has an efficient replication and recovery mechanism to restore data if a disaster occurs (PISA5). The cloud services provider is willing to accept an occasional survey of contractual commitment (PISA6). The data should be viable, even when another company acquires the cloud services provider (PISA7).	[53,70]
Service Compatibility (SC)	Using cloud services fits my firm needs (SC1). Using cloud services is in line with my colleagues and my preferences (SC3).	[71,72]
Entrepreneurship (ES)	The changes in products and services have been dramatic (ES3). The owner or manager emphasizes RandD expenditure, technological leadership, and innovation (ES4). The owner or manager has a very competitive "beat-the-competitors" posture (ES6).	[73]
Top Management Support (TMS)	The owner or manager enthusiastically supports the adoption of cloud services (TMS1). The owner or manager actively encourages employees to use cloud services in their daily tasks (TMS4).	[60]
Social Influence (SI)	People or companies who influence my firm behavior think/would think that my firm should use cloud services (SI1). People or companies who are important to my firm think/would think that my firm should use cloud services (SI2). My firm has supported/would support the use of cloud services (SI4).	[11,74]
Perceived Cost Savings (PCS)	The costs of cloud services adoption are far greater than the benefits (PCS1). The costs of maintaining and supporting cloud services are not high for our business (PCS2). The amount of money and time invested in training employees to use cloud services is not high for our business (PCS3).	[60]
Enterprise Usage Intention (EUI)	If possible, my firm will use cloud services soon (EUI4). I'm certain that my firm will use cloud services soon (EUI5). My firm definitely will use cloud services soon (EUI6).	[75]

3.2. Data Collection

Data collected from a paper-and-pencil questionnaire were used to empirically test the research model. To test the instrument, a pilot study was conducted among 30 firms, who were not included in the main survey, to identify deficiencies in the questionnaire design. Based on feedback, minor changes were made to improve the clarity of the questions and survey layout. The list of random firms was chosen from the Cloud Computing Association in Taiwan. The research participants were enterprise senior engineers, managers, and supervisors in Taiwan because they are perceived to be knowledgeable and crucial people in firms, they are likely having valid perceptions of cloud service adoption, and they represent the intention of firms to use cloud services. This way, purposeful sampling was used for the data collection in which the respondents were approached through email and/or telephone to know whether they are aware of cloud computing and if yes, whether they are willing to adopt cloud computing or they are in the process of adoption.

This study issued a total of 500 questionnaires, with 304 completed and returned responses. A total of 77 were invalid, incomplete, or assigned the same rating for all items. These were discarded; thus, 227 questionnaires were retained for analysis, yielding an effective response rate of 45.4%. Demographically, 71.8% of the enterprises were in the service industry; 57.3% had more than 130 employees. Table 3 lists the descriptive statistics of the sample. All items among the constructs were tested against demographic controls (industry type, number of employees) using Student's *t*-test or analysis of variance (ANOVA). The mean scores of the items were all non-significant ($p > 0.05$); indicating the validity of analyzing the data as a single group.

Table 3. Demographic characteristics of the respondents.

Sample size	Number of distributed questionnaires	500
	Number of returned questionnaires	304
	Number of valid samples	227
	Effective response rate	45.4%
	Frequency	Percentage (%)
Industry type		
Manufacturing	64	28.2%
Service	163	71.8%
Number of employees		
More than 200	130	57.3%
100–199	30	13.2%
50–99	15	6.6%
20–49	31	13.7%
6–19	15	6.6%
Less than 5	6	2.6%

3.3. Common Method Variance (CMV) Testing

CMV refers to the amount of fictitious covariance existing among variables, arose when a single questionnaire is used to measure multiple constructs. Because this study collected data through a single source with self-reporting scales, testing for CMV was necessary. To examine the CMV problem, the most widely used technique, one-factor testing, was employed [76–79]. CFAs were used to test the null hypothesis to determine any difference between the single-factor and multifactor model by comparing the chi-square difference, and evaluate the significance to confirm whether the CMV is problematic in any dimension. The results showed that a significant difference was observed between the two models. Therefore, the results showed that the null hypothesis is rejected, suggesting that this study is free of the CMV problem (Table 4).

Table 4. CMV test results.

Model	χ^2	**DF**	Δ**DF**	$\Delta\chi^2$
Single-factor	1272.8	152	21	1079.2 ***
Multi-factors	193.6	131		

*** $p < 0.001$.

3.4. Data Analysis

SEM, an alternative multivariate technique launched by Wright [80], is a statistical technique using statistical data and qualitative causal assumptions for quantifying and testing the causal relations of a structural theory [81,82]. The SEM procedure consists of two phases. First, the measurement model, which specifies the relationships between the latent constructs and the observed measures, and analyzes the overall model fitness, data reliability, convergent validity, and discriminant validity using CFA to correctly reflect the study constructs. Second, the structural model, which specifies the relationships among the latent constructs, was analyzed using overall model fit validation, hypotheses testing, and estimates of squared multiple correlations.

For comparing the RCMs, various procedures rely on the relationship among the models. The four RCMs in this study were classified into two groups (nested and non-nested structures), and different arguments were used in these two situations for independent testing and comparison through SEM by using AMOS 20.0. A nested model is a model that uses the same constructs as another model, but specifies at least one additional parameter to be estimated [83]. Conversely, non-nested model tests are specifically designed to test competing models that involve different variables (i.e., one model cannot be derived from the other through suitable parameter restrictions) [84].

The data were analyzed using a two-stage approach. First, for the measurement model, which specifies the relationships between the latent constructs and the observed measures, the overall model fit, data reliability, convergent validity, and discriminant validity were analyzed through CFA to ensure that the model accurately reflects the study constructs. Second, the structural model, which specifies the relationships among the latent constructs, was tested to determine the overall fit (including absolute, incremental, and parsimony fit measures), path coefficient significance (hypotheses testing), and explanatory power of the four RCMs.

More specifically, to compare RCMs that are nested within one another (as in Model A and Model B), a χ^2 difference test can be employed using chi-square values and degrees of freedom from any two nested models [83,85]. However, to compare RCMs that are not nested within one another (as in Model A, Model C, and Model D), three information fit indices were also included: the expected cross-validation index (ECVI) [84], the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) [86]. By using these procedures, the RCMs in this study were evaluated to determine their overall model fit, their contributions in explaining behavioral intention to adopt cloud services, and their parsimony.

4. Results

4.1. Measurement Model

Regardless of whether the structure was nested or non-nested, the measurement model was evaluated through CFA (Table 5). For a good model fit, χ^2/d.f. should not exceed 3, the GFI should exceed 0.9, the AGFI should exceed 0.8, the NFI and CFI should exceed 0.9, and the RMSEA should not exceed 0.08 [87,88]. Because Model A is an inclusive model that includes all constructs of Model B, Model C, and Model D, only Model A was assessed. The following fit indicators were calculated: χ^2/d.f. was 1.478 (χ^2 = 193.666; d.f. = 131), the GFI was 0.920, the AGFI was 0.884, the NFI was 0.957, the CFI was 0.985, and the RMSEA was 0.046, suggesting adequate model fit.

Table 5. Analysis of measurement accuracy.

Constructs	Items	Factor Loading	*t*-Value	CR	AVE
SC	SC1	0.949	18.743	0.920	0.853
	SC3	0.897	17.053		
ES	ES3	0.903	17.153	0.907	0.764
	ES4	0.902	17.120		
	ES6	0.815	14.592		
SI	SI1	0.893	17.014	0.915	0.782
	SI2	0.847	15.634		
	SI4	0.912	17.632		
PISA	PISA5	0.901	16.845	0.889	0.727
	PISA6	0.870	15.963		
	PISA7	0.783	13.632		
PCS	PCS1	0.780	13.250	0.861	0.675
	PCS2	0.873	15.531		
	PCS3	0.809	13.953		
TMS	TMS1	0.902	17.342	0.892	0.806
	TMS4	0.893	17.057		
EUI	EUI4	0.923	18.248	0.967	0.908
	EUI5	0.979	20.301		
	EUI6	0.955	19.380		

Model fit measures: χ^2/d.f. = 1.478, GFI = 0.920, AGFI = 0.884, NFI = 0.957, CFI = 0.985, RMSEA = 0.046.

Reliability was determined using composite reliability values. A common threshold value for acceptable composite reliability is 0.6 or above [87]. As shown in Table 5, all values exceeded 0.7, indicating an acceptable level for confirmatory research. Convergent validity was evaluated for measurement scales by using two criteria suggested by Fornell and Larcker [89]: all indicator factor loadings should be significant and exceed 0.70, and the average variance extracted (AVE) for each construct should exceed the variance caused by the measurement error for that construct (i.e., it should exceed 0.50). All items exhibited factor loadings higher than 0.7 on their respective constructs, providing evidence of acceptable item convergence on the intended constructs. Moreover, the AVEs for all constructs were between 0.675 and 0.908, which exceed the recommended threshold of 0.50, showing evidence of convergent validity.

Table 6 indicates the result of discriminant validity analysis. The computed confidence interval among the latent variables does not include 1 [90]. In Table 6, all confidence intervals developed in the standardized correlation do not include the value of 1. Therefore, this study concluded that the construct validity of the measurement scales was sufficiently high. Overall, the confirmatory factor model reflected a good fit to the data. The four RCMs were then independently assessed using SEM.

Table 6. Analysis of confidence intervals.

Construct	Correlation	Standard Errors	Confidence Interval	
SC–ES	0.660	0.044	0.572	0.748
SC–TMS	0.885	0.023	0.839	0.931
SC–SI	0.871	0.023	0.825	0.917
SC–PISA	0.672	0.043	0.586	0.758
SC–PCS	0.529	0.056	0.417	0.641
SC–EUI	0.730	0.035	0.660	0.800
ES–TMS	0.788	0.033	0.722	0.854
ES–SI	0.745	0.036	0.673	0.817
ES–PISA	0.527	0.055	0.417	0.637
ES–PCS	0.485	0.059	0.367	0.603
ES–EUI	0.746	0.034	0.678	0.814
TMS–SI	0.928	0.018	0.892	0.964
TMS–PISA	0.759	0.037	0.685	0.833
TMS–PCS	0.618	0.051	0.516	0.720
TMS–EUI	0.873	0.022	0.829	0.917
SI–PISA	0.634	0.047	0.540	0.728
SI–PCS	0.506	0.058	0.390	0.622
SI–EUI	0.784	0.030	0.724	0.844
PISA–PCS	0.575	0.054	0.467	0.683
PISA–EUI	0.573	0.049	0.475	0.671
PCS–EUI	0.560	0.052	0.456	0.664

4.2. Structural Model

Table 7 and Figure 2 illustrate the structural model analysis results of the four RCMs and summarize the path coefficient significance, the degree of model fit indices, and the explanatory power of each RCM.

Table 7. Results of RCM structural model analysis.

	RCMs			
	Model B	**Model A**	**Model C**	**Model D**
Paths				
Service compatibility → Top management support	0.166 *	0.173 *		
Entrepreneurship → Top management support	0.217 ***	0.215 ***		
Social influence → Top management support	0.479 ***	0.458 ***		
Perceived information security assurance → Top management support	0.139 **	0.151 **		
Perceived cost savings → Top management support	0.103 *	0.109 *		
Top management support → Enterprise Usage Intention	0.970 ***	0.865 ***	0.514 ***	
Social influence → Enterprise Usage Intention	−0.124		0.124	0.365 **
Perceived cost savings → Enterprise Usage Intention	0.021		0.106	0.164 **
Perceived information security assurance → Enterprise Usage Intention			−0.126	0.007
Service compatibility → Enterprise Usage Intention			0.073	0.108
Entrepreneurship → Enterprise Usage Intention			0.230 ***	0.313 ***
Explanatory power (R^2; SMC)				
Top management support	0.928	0.924		
Enterprise Usage Intention	0.757	0.748	0.727	0.694
Model fit measures				
Absolute fit measures				
χ^2	209.038	201.019	255.536	219.598
d.f.	134	136	168	137
χ^2/d.f.	1.560	1.544	1.521	1.603
GFI	0.913	0.912	0.907	0.909
RMSEA	0.050	0.049	0.048	0.052
Incremental fit measures				
AGFI	0.877	0.878	0.872	0.874
NFI	0.953	0.953	0.950	0.950
CFI	0.983	0.983	0.982	0.980
Parsimony fit measures				
AIC		318.019	381.536	325.598
BIC		502.966	597.308	507.120
ECVI		1.407	1.688	1.441

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

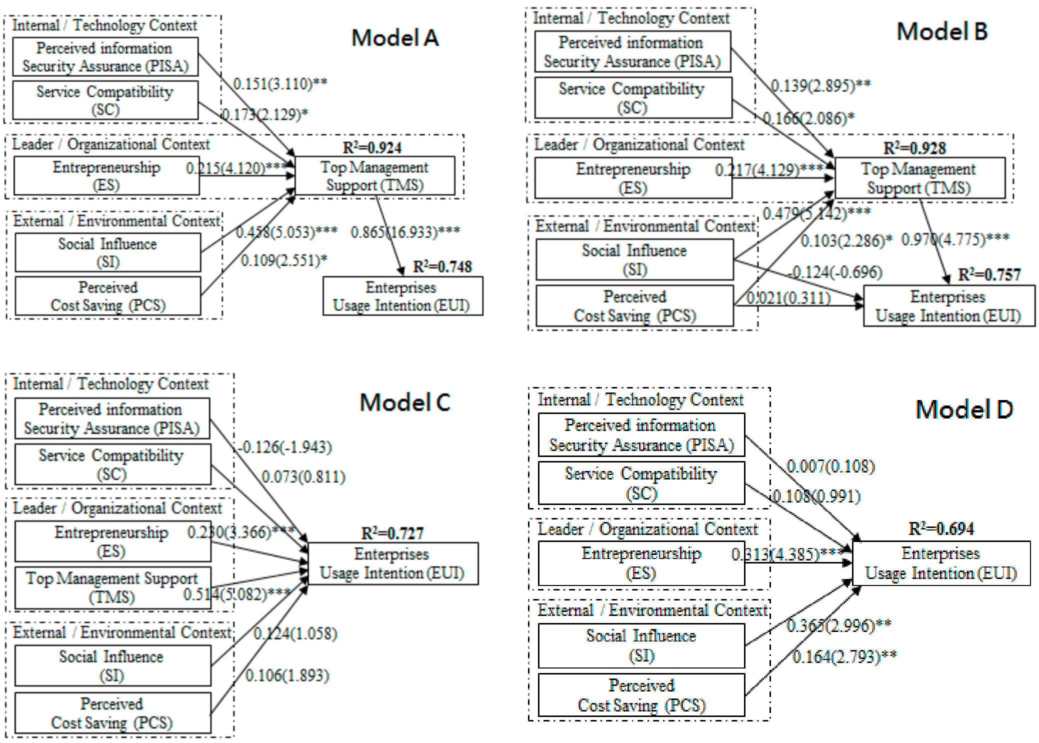

Figure 2. Structural model results of the RCMs. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Model A

The overall model fit statistics indicate that Model A provides a good fit to the data (χ^2/d.f. = 1.544; GFI = 0.912; RMSEA = 0.049; AGFI = 0.878; NFI = 0.953; CFI = 0.983). All six paths were statistically significant, and the results supported all hypotheses. Accordingly, PISA (β = 0.151, $p < 0.01$), SC (β = 0.173, $p < 0.05$), ES (β = 0.215, $p < 0.001$), SI (β = 0.458, $p < 0.001$), and PCS (β = 0.109, $p < 0.05$) were significant determinants of TMS. TMS (β = 0.865, $p < 0.001$) was a significant antecedent of EUI. A common threshold value for acceptable explanatory power is 0.6 or greater [91]. Model A explained 92.4% of the variance in TMS and 74.8% of the variance in behavioral intention to adopt cloud services, indicating that Model A has effective explanatory ability for the implicit dependent variable (EUI).

Model B

Model B also fits the data reasonably well (χ^2/d.f. = 1.560; GFI = 0.913; RMSEA = 0.050; AGFI = 0.877; NFI = 0.953; CFI = 0.983). All hypothetical paths except SI → EUI and PCS → EUI (positive but nonsignificant) were significantly positive, supporting the hypothesized causal relationships for the models. Accordingly, PISA (β = 0.139, $p < 0.01$), SC (β = 0.166, $p < 0.05$), ES (β = 0.217, $p < 0.001$), SI (β = 0.479, $p < 0.001$), and PCS (β = 0.103, $p < 0.05$) were significant determinants of TMS. TMS (β = 0.970, $p < 0.001$) was a significant antecedent of EUI. Regarding explanatory power, Model B explained 92.8% of the variance in TMS and 75.7% of the variance in behavioral intention to adopt cloud services, indicating that Model B has effective explanatory ability for the implicit dependent variable (EUI).

Model C

Fit statistics showed that all goodness-of-fit indices exceeded their common acceptance levels, suggesting that Model C exhibits a good fit to the data (χ^2/d.f. = 1.521; GFI = 0.907; RMSEA = 0.048; AGFI = 0.872; NFI = 0.950; CFI = 0.982). Regarding path coefficient significance, only two significant and positive direct impacts were observed for ES (β = 0.230, $p < 0.001$) and TMS (β = 0.514, $p < 0.001$) on EUI, supporting the hypothesized causal relationships for the models. However, the direct impact of PISA on behavioral intention was negative and nonsignificant, and the effects of SC, SI, and PCS on behavioral intention were positive, but nonsignificant. Model C explained 72.7% of the variance in behavioral intention to adopt cloud services, indicating that Model C has effective explanatory ability for the implicit dependent variable (EUI).

Model D

The results for the measurement model indicate that Model D's fit is acceptable: χ^2/d.f. = 1.603, GFI = 0.909, RMSEA = 0.052, AGFI = 0.874, NFI = 0.950, and CFI = 0.980. All hypothetical paths except PISA → EUI and SC → EUI (positive but nonsignificant) were significantly positive, supporting the hypothesized causal relationships for the models. Accordingly, ES (β = 0.313, $p < 0.001$), SI (β = 0.365, $p < 0.01$), and PCS (β = 0.164, $p < 0.01$) were significant determinants of EUI. Regarding explanatory power, Model D explained 69.4% of the variance in behavioral intention to adopt cloud services, showing that Model D also has effective explanatory ability for the implicit dependent variable (EUI).

Various fit measures in Table 7 indicate that all four RCMs have a good fit to the data. This suggests that all four RCMs successfully apply to the behavioral intention of organizations to adopt cloud services.

4.3. Comparison of the Research Competing Models

Following the satisfactory results of the model evaluations, this study conducted a two-stage comparison procedure (nested and non-nested models) to identify the superior model among the four RCMs.

4.3.1. First Stage: Nested Model Comparison between Model A and Model B

In this study, because Model A and Model B are classified as having nested structures, a chi-square difference test was employed for comparing them to determine if one of the structures performed more effectively than the other [84,86].

In Table 7, the goodness-of-fit indices indicate no significant difference between Model A and Model B. Moreover, the chi-square difference between the two models was −8.019 ($\Delta\chi^2$ = 201.019–209.038), lower than the critical value of 3.8 for two degrees of freedom, revealing that the restricted model (Model A) is not significantly different from the freely estimated model (Model B). That is, when the two nonsignificant direct hypothetical paths are excluded (SI → EUI and PCS → EUI), the structure of Model B is identical to that of Model A, even though the explanatory power of Model B (TMS R^2 = 0.928, EUI R^2 = 0.757) is slightly superior to that of Model A (TMS R^2 = 0.924, EUI R^2 = 0.748). Therefore, Model A is considered the best-fitting RCM in the first-stage tests.

4.3.2. Second Stage: Non-Nested Model Comparison among Model A, Model C, and Model D

According to the results of the first stage, this study conducted a non-nested model comparison among Model A and two parsimonious models, Model C and Model D. For this type of model comparison, the most common statistical test is χ^2/d.f. analysis [92]. As shown in Table 7, various fit measures indicate that all three RCMs have a good fit to the data, and overall, Model A has a better fit than those of both Model C and Model D.

Regarding parsimony fit measures, for Model A, the AIC was 318.019, the BIC was 502.966, and the ECVI was 1.407; for Model C, the AIC was 381.536, the BIC was 597.308, and the ECVI was 1.608. The values for Model D were AIC = 325.598, BIC = 507.120, and ECVI = 1.441. Because lower values of these criteria indicate a better fit of the model [85,87], these results indicate a preference for Model A over both Model C and Model D. Finally, the results indicate that all three RCMs provide high explanatory power for predicting the behavioral intention of organizations to adopt cloud services. Model A provides somewhat greater explanatory power (EUI R^2 = 0.748) relative to both Model C (EUI R^2 = 0.727) and Model D (EUI R^2 = 0.694). Hence, Model A is superior to both Model C and Model D.

In short, the results suggest that of the four RCMs, Model A is superior to Model B, Model C, and Model D, meaning that Model A is the best-fitting model for explaining the behavioral intention of organizations to adopt cloud services.

5. Discussion and Implications

This study developed a hybrid technology acceptance model by combining the DOI theory and the TOE framework to explore the factors affecting organizations' intention of using cloud services. To promote cloud service adoption, determining the factors and their causal relationships that affect enterprise acceptance of cloud services is crucial. For Model A, the empirical results confirmed that all six constructs (PISA, SC, ES, SI, PCS, and TMS) are significant positive factors in the decision to adopt cloud services directly or indirectly. The results also showed that TMS was a mediating variable and played a major role in clarifying the causal relationships among the constructs. Among the determinants, TMS was the most influential factor affecting EUI (0.865), followed by SI (0.396; 0.458 × 0.865) and ES (0.186; 0.215 × 0.865) through TMS. This implies that firms with enhanced TMS have stronger intention to adopt cloud services. This result is also consistent with finding [6,65] suggesting that TMS has a significant positive effect on cloud service adoption, implying that substantial TMS is one of the most crucial factors for enterprise adoption of cloud services. TMS is crucial in cloud service adoption because it strongly influences organizations' resource allocation, service integration, and process reengineering [13]. Furthermore, SI is the most crucial factor affecting

TMS, a result that is consistent with Ajzen [47] and Mathieson [39], where SI was recognized as the perceived social pressure affecting top managers' decisions to adopt a technology.

This research contributes to the extant literature by clearly describing how the best-fitting model could be achieved, improves the understanding of firms regarding the direct and indirect effects of the antecedents that influence the adoption of cloud services, and also presents several key findings and implications regarding the organizations' determinants of cloud service adoption. The findings can offer valuable insights for practitioners, including managers and decision-makers, who are responsible for assisting firms with adopting cloud services. Additionally, the findings could facilitate gauging the direct and indirect effects of the antecedents and making informed cloud-adoption decisions. Service providers should concentrate on these major antecedents to increase customer willingness to use cloud services, collaborate with customers to enhance the compatibility with their businesses, and differentiate themselves from their competitors to increase customer loyalty. For example, to raise customers' TMS, service providers should target not only IT staff but also top-level managers because these managers are often responsible for deciding which new technology to adopt. To increase customers' SI, service providers should demonstrate successful customer application of cloud services and the benefits of adopting these services, thereby leading to competitive pressure and the observability necessary for diffusion. Moreover, service providers could offer organizations the opportunity to try cloud services before committing to them to increase organizations' PISA and PCS regarding cloud services as well as evaluate the SC and complexity of their existing systems. Furthermore, service providers could offer training to facilitate the adjustment of managers and employees within an organization to new practices, processes, and governance structures related to cloud services, thus enhancing the overall ES of the company.

6. Conclusions

In the present study, a model development strategy and comparison among the four RCMs were conducted for explaining the behavioral intention of organizations to adopt cloud services. Overall, the findings of this study provide guidelines for model comparison and selection. First, regarding the nested model comparison of Model A and Model B, Model A was considered the best-fitting RCM in the first stage of the comparison according to the overall goodness-of-fit indices and chi-square difference tests. In addition, Model A accounted for 74.8% of the variance in EUI, indicating that Model A has effective explanatory ability. Second, regarding the non-nested model comparison among Model A and two parsimonious models, Model C and Model D, Model A has a better overall fit than those of Model C and Model D, not only according to the absolute and incremental fit measures but also according to the parsimony criteria (AIC, BIC, and ECVI). Additionally, the results indicate that Model A provides greater explanatory power (0.748) relative to Model C (0.727) and Model D (0.694). Hence, Model A is superior to both Model C and Model D, and is the best-fitting model for explaining the behavioral intention of organizations to adopt cloud services.

As in most empirical studies, care should be taken when generalizing the results; therefore, in this study, three limitations and future research suggestions should be recognized. First, the purpose of this study was to explore and discuss a comparison of RCMs; however, some potentially critical constructs such as firm size and relative advantage (see Table 1) were not considered in the RCMs. That is, other antecedents could yield different results, and the results may not indicate that the presented best-fitting model is an optimal research model. Future research could further refine the analytical model to enhance the understanding of the adoption of innovative technology to acquire the best-fitting model. Second, this study introduced a model development strategy and identified the best-fitting model as well as the critical determinants of cloud service adoption from the organizational perspective. Future research could further apply these factors and related results to another practical investigation, such as the optimal potential organizational customers of cloud services. Third, the cloud services in this study referred to a general Internet-based computing service, rather than to a particular type of service (e.g., SaaS, PaaS, IaaS, or open source clouds), or a specific IS, IT, or ICT service, even though

EUI may vary among cloud services. This limits the generalizability of this study to certain types of cloud services. Future researchers should focus on a specific or classification service to examine practical findings. Finally, this study may be restricted by its use of data from organizations in Taiwan, which implies that the study reflects only the cloud service perceptions in that country. The results thus may not be generalizable to businesses in other industries and nations, even though the cloud services may be argued to have no boundaries. Future studies could examine this issue in various industries and countries, as well as perform cross-country comparisons to provide a more global insight.

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