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The influence of dependability in cloud computing adoption

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Abstract
Cloud computing (CC) has many benefits, so its use has spread rapidly, particularly in the business sector. An important consideration in the acceptance of CC is whether the CC system is dependable, and it can differ among industry and service type. However, little research has considered the effect of *dependability* (composed of *availability*, *reliability*, *security*, *maintainability*) on CC acceptance. Especially, group comparisons between high IT-intensive (Hi-ITi) and low IT-intensive (Lo-ITi) industries have not been reported, nor have comparisons between software-as-a-service (SaaS) and platform-as-a-service (PaaS)/infrastructure-as-a-service (IaaS). This study aims to explore how the *dependability* of CC affects users' intent to accept it, with focus on how this intent is affected by intensity of IT use (by industry) and by the type of CC service used. To validate the proposed model, this study applied structural equation modeling and conducted multi-group analysis. A total of 230 business managers in South Korea represent the sample for our study. For the full dataset, the three *dependability* attributes (*availability*, *reliability*, *security*) do not affect the usefulness of CC, but do affect the ease of use of CC. The usefulness of CC is a determinant for positive intention to accept CC, whereas the ease of use of CC is not. *Maintainability* is the strongest determinant of CC adoption for the full dataset, and for all individual groups, except those that use SaaS. For Hi-ITi and Lo-ITi industries, results show that managers show no differences in their perceptions of the effect of *dependability* attributes (*availability*, *reliability*, *security*) on the usefulness and the ease of CC. The absence of such a difference in managers' perception also applies to the relationship between two core variables of TAM (i.e., *perceived usefulness*, *perceived ease of use*) and behavioral intention to accept CC. For SaaS and PaaS/IaaS, managers have different perceptions of *security* on the usefulness of CC, and the effect of the usefulness of CC on the intention to accept CC. The findings can provide academic researchers and industry practitioners with a differentiated and in-depth perspective on the understanding and the spread of CC.

Keywords Cloud computing · Dependability · IT intensity · Service type · Technology acceptance

Extended author information available on the last page of the article

1 Introduction

Many modern organizations depend on information technology (IT) and information systems (IS); the survival of such organizations requires IT/IS that is dependable. In IT/IS literature, *dependability* means avoiding service failure [1]; i.e., that a system's ability to deliver multi-faceted service can justifiably be trusted (i.e., it is available, reliable, secure and maintainable) [2, 3]. One of the critical concerns regarding *dependability* and its attributes is the difference between whether IS/IT is dependable itself and whether users perceive that IS/IT is dependable [3, 4]. Especially, this is a primary consideration in mission-critical and large-scale distributed systems [1] like cloud computing (CC) because CC is a service-oriented technology [5].

CC is an innovation technology that has changed the paradigm of IT/IS [6, 7]. CC enables delivery of computing resources (e.g., storage, server, applications) as services [8], similar to utility services like electricity; CC provides computing resources to users (e.g., individuals, organizations) over the Internet in the form of intangible assets rather than physical assets [9]. In CC environments, products (hardware, software) are usually owned by cloud service providers (CSPs), and are transformed to services by using virtualization technology, then mainly delivered over the internet to users in the forms of software-as-a-service (SaaS), platform-as-a-service (PaaS) or infrastructure-as-a-service (IaaS) [10]. For example, a company's IS/IT department can use PaaS to build a large database on a cloud server instead of on site. This strategy means that database maintenance, security, and even safety management are transferred to CSPs. This shift raises a variety of concerns associated with *dependability* and its attributes of CC; users perceive CC to be less trustworthy than on-premise systems because the users do not have full control of computing resources and may remain locked in to a specific CSP [11–13]. These operational and technical features of CC have fueled a need for research on users' perceptions regarding CC's *dependability* and its attributes [14–17].

Understanding users' perceptions regarding accepting a technology is critical to the development of any technology because this understanding can further facilitate the implementation of that technology [18, 19]. One important approach to obtain this understanding is to identify factors users' behavioral and psychological viewpoints that affect the adoption of new IS/IT [20, 21]. One example is *dependability* and its attributes, which are the focus of this our study. Another approach is group comparison in that considers demographic (e.g., gender, culture, industry) and technological characteristics (e.g., product/service type) [22]. To the best of our knowledge, prior studies on CC adoption have not considered these points; our analysis of literature published from 2015 to 2021 showed a scarcity of research on the effect of *dependability* and its attributes on accepting CC, and no study that performed a group comparison on the similarities and differences in CC adoption according to IT intensity by industry and the type of service that CC offers.

This study has three objectives: (1) to propose a research model to identify the influence of *dependability* and its attributes on CC adoption, (2) to empirically demonstrate the proposed model with data gathered from South Korea, and then (3) to compare groups that depend on high-IT-intensity industry (Hi-ITi) and low-IT-intensity industry (Lo-ITi), and SaaS and PaaS/IaaS. To reach these goals of our study, we developed and tested ten hypotheses regarding the relationships between *dependability* and accepting CC; hypothesis testing using a theoretical model is widely used to explore the effect of a specific factor on accepting a technology and conduct comparison between specific groups [23, 24].

The rest of this study is structured as follows. Section 2 presents basic concepts needed to the understanding of the rest of the article. Section 3 presents related works. Section 4 proposes our research model and hypothesis. Section 5 describes our research methodology. Section 6 presents the analysis results, while Sect. 7 discusses them. Section 8 presents out contributions and implications, then Sect. 9 presents research limitation and suggests future research. Finally, Sect. 10 provides concluding remarks.

2 Basic concepts

2.1 Technology acceptance theory

Technology acceptance refers to 'the extent to which a technology is preferred for use by individuals or organizations' [20, 21]. Understanding why a technology is accepted or rejected by users is as important as hardware and software engineering themselves, because this understanding can lead to successful implementation and development of the technology [19, 22]; this consequence is especially true for service-oriented technology like CC [25]. Many researchers have developed models that use behavioral theory to understand users' acceptance or rejection of technology. These studies have largely considered two contexts [20, 26]: organizational and individual. Organizational context studies mostly used technology organization environment (TOE) theory and diffusion of innovation theory (DOI). Individual-context research has used theory of reasoned action (TRA), theory of planned behavior (TPB), technology acceptance model (TAM), extended TAM (i.e., TAM2, TAM3), unified theory of acceptance and use of technology (UTAUT), and extended UTAUT (i.e., UTAUT2). TAM has been widely used in both organizational and individual contexts due to its robustness and ease of implementation [27, 26].

2.2 TAM

TAM was originally proposed to explain employees' acceptance of IT/IS in work contexts [28]. The original model was redefined to consider other factors, such as removing the 'attitude' variable and introducing the 'behavioral intention' variable [29]. The final version of TAM (Fig. 1) identifies *perceived usefulness* and *perceived ease of use* as the strongest determinants that have direct effects on behavioral intention to use a technology; *perceived ease of use* has an effect on *perceived usefulness* [28–30]. Behavioral intention is the strongest determinant of actual use in IT/IS

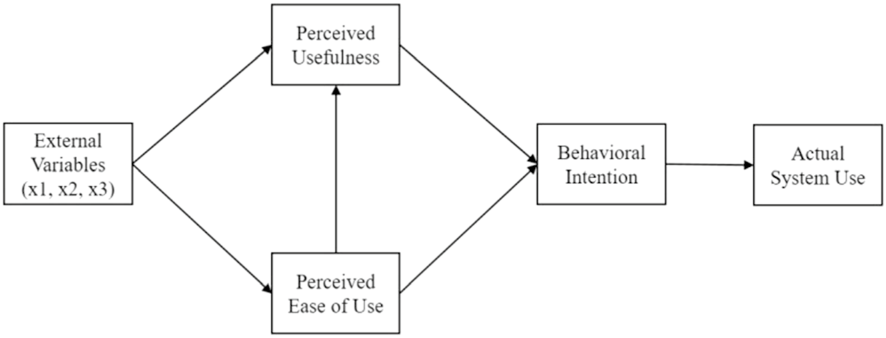

Fig. 1 The redefined technology acceptance model (Venkatesh & Davis, 1996)

contexts [18]. TAM explains about 40–50% of the variance in behavioral intention and actual use [27]; further increase its predictive power requires that TAM should incorporate other theories or consider external variables.

2.3 Discriminant validity and heterotrait-monotrait ratio

Ensuring discriminant validity is one of the general requirements for model evaluation [30] such as TAM. Despite its importance, researchers have heavily relied on the Fornell and Larcker criterion that may be not suitable under certain circumstances [23]. Heterotrait-monotrait ratio (HTMT) as a new criterion was developed [30] and imposes more stringent evaluation than the Fornell and Larcker criterion [31]. HTMT criterion is an estimate of the variable correlation at the measurement item level and should be significantly <0.9 [24, 31, 32]. If HTMT has value >0.90, there is a problem with discriminant validity.

3 Related works

3.1 Cloud computing

CC is a distributed system that supplies computing resources such as storage to users on a pay-as-you-go method over the internet [33, 34]. CC has several key features [10]: broad network access, on-demand service and rapid elasticity, resource polling, and measured service. The key enabler for these functions is virtualization [35, 36], which allows hardware, software and applications to be encapsulated into virtual machines [37] then deliver them to users. Taking storage as an example, the advantages of these features are as follows.

- *Broad network access* A user does not need to carry their own physical devices, nor worry about whether something (e.g., hardware/software crash, theft) can happen to them; instead of using local devices, a user only needs to upload data to the cloud over the internet, and then can use them on multiple devices (e.g., smartphone, laptop) at any time and place.

- *On-demand self-service and rapid elasticity* If necessary, a user can automatically provide, add, or expand storage resources. These capabilities reduce the user's worry about storage capacity constraints and inflexibility to emergencies such as data loss.
- *Resource pooling* A user does not need to install, configure, and maintain his or her own online resources (e.g., storage space). For example, security measures against malicious acts like viruses are pooled to serve multiple users, and automatic backup eliminates the need for manual data backups and the fear of backup failures.
- *Measured service* Users are provided with computing resources (e.g., storage space, security patches) on a pay-per-use basis, similar to traditional utility services like power and water.

CC typically offers three types of service model [10]: IaaS, PaaS, and SaaS. They are deployed to users through four delivery channels [10]: public (available to the public), private (operated solely for an organization), community (shared by several organizations), and hybrid clouds (a composition of two or more clouds). For a company that consumes all three types of cloud services in a public cloud, IaaS can provide computing disk storage in virtual environments, so an employee can access a virtual server and the data storage provided on physical infrastructure; the company's IT/IS department can use PaaS to develop and deploy its applications on the CC platform; and the company's other employees can use SaaS to access applications.

CC types are not really technologies but service models [38]. CC types can be interpreted in terms of 'who uses them' and 'why they use them'. SaaS is intended for business users (e.g., mainly employees in non-IT/IS departments), whereas PaaS is mainly for developers and deployers (e.g., mainly employees in IT/IS departments). IaaS is mainly used by IT/IS managers. SaaS focuses on providing applications to complete users' tasks. PaaS develops such solutions and deploys them for users. IaaS focuses on creating and maintaining platform and virtual resources (e.g., CPU, storage). Therefore, SaaS is regarded as an individual-level service, whereas IaaS and PaaS are regarded as organization-level services [39]. This difference means that each service type can be perceived differently according to user context [32].

3.2 Cloud computing dependability and its attribute

Dependability is seen as a critical consideration in all kinds of systems [2]. *Dependability* means avoidance of service failures that are more severe than users can allow [40]. Especially, *dependability* assurance is a more important concern for a complex real-time system like CC than for a non-real-time system [41]. For example, CC can encounter a variety of runtime problems triggered by hardware and software failures including faults and errors [42]. In the CC environment, as the complexity of a cloud platform increases, various faults can cause frequent downtime accidents of virtual machines, and these events seriously degrade the *dependability* of CC [37]. Moreover, CC virtualization is generally prone to technical problems such as attacks, memory dumps, and various faults [35, 37]. These can affect user's perceptions of CC acceptance; the current state of CC is not considered dependable enough for enterprise users [14, 16, 17, 27, 43].

Dependability is not a single quantity, but is composed of several attributes; suggestions include *availability*, *reliability*, *safety*, *maintainability*, *performability* and *testability* [2], *reliability*, *availability*, *safety* and *security* [44], and *reliability*, *availability*, *safety*, *integrity*, *confidentiality* and *maintainability* [3]**.** Among these, *availability*, *integrity* and *confidentiality* are elements of information security [43]. However, '*availability*' stresses the absence of service failures in the context of *dependability* [3], so we grouped *integrity* and *confidentiality* into *security*, and left '*availability*' as a single attribute. *Safety* is an extended concept of *reliability*; it is the same concept as *reliability* in that it refers to avoidance of catastrophic failures [3]. Thus, at least two overlapping properties in these classifications include *availability*, *reliability*, *security*, and *maintainability*. Enhancing these individual attributes ensures CC's *dependability* [45], and they can be used to measure users' perceptions of CC adoption [46].

3.3 Technology acceptance perspective

Our literature review of organizational-level CC adoption from 2015 to 2021 quantified the results of prior studies (Table 1). Studies for our analysis were cross-classified according to study focus and theoretical models used. Most of the studies focused on a single group to examine drivers and hindrances of CC acceptance. As far as we know, only two studies compared specific groups. One investigated the differences and similarities in IT decision makers' SaaS acceptance for core and non-core business operations [47]: *perceived cost advantage* affected SaaS adoption for non-core business operations but not for core business operations, whereas a *gap in IT capabilities* influenced SaaS adoption for core business operations but not for non-core business operations; interestingly, *perceived service quality* had a positive effect, and *management attitude* had a negative effect on SaaS acceptance for both types of business operations. The other considered adopters and non-adopter firms [48]: for both types, *perceived ubiquity* and *perceived benefits* were determinant for positive CC adoption, whereas *perceived risks* was a determinant for negative CC adoption; *perceived costs* influenced CC adoption for adopter firms but not for non-adopter firms.

However, research has little considered how CC adoption differs among industry and service type; i.e., researchers have overlooked the influence of the variation in IT intensity among industries (e.g., high vs. low) and among service types (e.g., SaaS vs. PaaS vs. IaaS). Prior CC studies have emphasized the necessity to consider those points, but have not led to empirical validation: two have suggested that different industries besides high-tech industry may adopt CC at different rate [50, 63]; and three have suggested that different cloud types may induce different adoption behaviors [64–66].

Table 1 Prior studies (32) on organizational-level CC adoption

Study focus	Baseline theories	Authors	Key external variables (or integrated other theories)
Single group (30)	TOE (11)	Safari et al. (2015, SaaS, IT professionals) [49]	DOI (e.g., trialability, observability), security and privacy
		Alharbi et al. (2016, SaaS, employee) [50]	IS strategy triangle (e.g., strategic value), HOT-fit (e.g., CIO innovativeness, internal expertise)
		Al-Jabri and Alabdulhadi (2016, CC, IT staff) [33]	–
		Tomás et al. (2018, SaaS, SMEs) [13]	PVT (e.g., representation, reach, monitoring), INT (e.g., coercive pressures, normative pressures, mimetic pressures)
		Adiyasa et al. (2018, SaaS, employees) [51]	–
		Oliveira et al. (2019, SaaS, CIO/IS managers) [32]	INT (e.g., coercive pressures, normative pressures, mimetic pressures)
		Khayer et al. (2019, CC, SMEs CEO) [52]	Computer self-efficacy, social influence, perceived risks, cloud providers influence, server location
		Ali et al. (2020, CC, government IT staff) [53]	DOI (e.g., innovation), desires framework (e.g., anticipated benefits), security concerns
		Shahzad (2020, CC MOOC, Univ. employees) [54]	Cost reduction
		El-Haddadeh (2020, CC, SMEs) [55]	–
		Bhardwaj et al. (2021, CC, Univ. Faculty and staff) [56]	TAM (e.g., recognized usability, recognized usefulness), DOI (e.g., senior leadership support), security concern
	TAM (9)	Gangwar et al. (2015, CC, employees) [25]	TOE
		Sharma et al. (2016, CC, IT professionals) [57]	Computer self-efficacy, trust, job opportunity
		Gangwar and Date (2016, CC, employees) [27]	Threat, risk, vulnerability, availability, compliance
		Chen (2017, CC, managers) [36]	Perceived risk, perceived trust
		Tripathi (2017, CC, employees) [20]	Perceived ubiquity, perceived risks, perceived costs
		Palos-Sanchez et al. (2017,SaaS,employees) [26]	Management support, communication, training, technological complexity, organization size

Table 1 (continued)

Study focus	Baseline theories	Authors	Key external variables (or integrated other theories)
		Cengiz and Bakırtaş (2020, CC, employees) [38]	Perceived enjoyment, objective usability
		Tella et al. (2020, CC, librarians) [8]	Perceived security, perceived reliability, ease of maintenance, facilitating conditions, user friendliness, perceived flexibility, increased productivity
		Jahangiri et al. (2021, CC, univ. librarians) [9]	Individual factors, social factors, organizational factors, technology factors, economic factors, environment factors
	UTAUT (3)	Alotaibi (2016 SaaS, workers) [58]	–
		Amin et al. (2017, CC, healthcare professionals) [59]	–
		Matar et al. (2020, CC, Univ. faculty and staff) [22]	–
	DOI (2)	Sabi et al. (2017, CC, IT experts) [31]	TAM (e.g., perceived usefulness, perceived ease of use)
		Sallehudin et al. (2020, CC, public sectors) [60]	TOE, IS Success Model
	Dual-factor theory (1)	Hsieh and Lin (2018, SaaS, physicians) [34]	IS success model, SQB theory
	TPB (1)	Asadi et al. (2020,, CC, Univ. faculty) [61]	–
	INT (1)	Adjei et al. (2021, CC, employees) [6]	–
	N/A (2)	Ali et al. (2021, CC, government IT managers) [7]	Complexity
		Fretschner et al. (2021, SaaS, SMEs) [62]	Strategic orientations (e.g., innovation orientation, ambidextrous orientation, operations orientation), SaaS-related Beliefs (e.g., security beliefs, strategic flexibility, cost advantages beliefs)
More than two groups (2)	N/A (1)	Cho and Chan (2015, SaaS, IT decision makers) [47]	Cost–benefit and risk evaluations factors (e.g., perceived cost advantage, gap in IT capabilities, perceived service quality, product differentiation)
	TAM (1)	Tripathi (2019, CC, CIO and senior managers) [48]	Perceived ubiquity, perceived benefits, perceived risks, perceived costs

Authors (year published, cloud service type, participants): *CC* indicates cloud computing in a broad meaning, *SaaS* software as a service, *PaaS* platform as a service, *TOE* technology organization environment, *TAM* technology acceptance model, *UTAUT* unified theory of acceptance and use of technology, *DOI* diffusion of innovation, *TPB* theory of planned behavior, *INT* institutional theory

In contrast, other research realms have showed that IT intensity and service type can affect technology acceptance: each industry may have a different behavior towards adopting a technology [67, 68]; behaviors toward technology adoption may depend on service type [28, 69]. Regarding IT intensity by industry type, executives' perceptions of adopting anti-malware differ among industries [70]. Also, an industry that sells information-intensive services may be more likely to adopt new technology than are industries that do not sell such services [71]. Regarding service types, patterns of adoption of banking channels (e.g., internet banking, phone banking) depend on service type [72]. Especially, utilitarian service type can significantly affect users' adoption of mobile data services [73].

Regarding the theories used, TOE and its derivatives were the most frequently employed (11 papers), followed by TAM and its derivatives (10), UTAUT and its derivatives (3), and DOI and its derivatives (2). Interestingly, even research on organizational CC adoption used individual-level theories (e.g., TAM, UTAUT) to study the perceptions of technology adoption at specific user levels (e.g., IT/IS managers) in organizations because of the ease of combining with other theories or extending the model using external variables. Use of these theoretical models helped to identify drivers and inhibitors of CC acceptance that fit the contexts of their studies.

To the best of our knowledge, prior studies have not considered the influence of *dependability* on CC acceptance in an organizational context from both the technology acceptance perspective and the holistic perspective on the concept of *dependability*. Instead, nine studies 'chose' one or two more of *dependability* attributes or similar concepts, and then incorporated them with the core constructs of their original models for their research goals: *availability* [27], *perceived ubiquity* [20, 48], *reliability* [8], *security* [8, 49, 53, 56], *perceived risk* [20, 27, 36, 48, 52], *ease of maintenance* [8]. Moreover, most of them focused on the direct relationships between the dependent variable of baseline model (i.e., behavioral intention in TAM) and external variables, not on the relationships between the core constructs of the baseline models (i.e., *perceived usefulness*, *perceived ease of use* in TAM) and external variables.

CC in a broad sense was the most frequently targeted technology (22 papers), followed by SaaS (10). 21 (65.6%) of the studies targeted general employees, followed by IS/IT professionals (6) [7, 31, 33, 49, 53, 57], decision makers (4) [32, 47, 48, 52], and managers (1) [36]. Interestingly, six studies targeted studies university faculty/staff [9, 22, 54, 61] and academic libraries [8, 9], four studies small and medium enterprises [13, 48, 52, 55, 62], and three studies public sectors [7, 53, 60].

This literature review found no empirical study that: (1) explored the effect of *dependability* and its individual attributes on CC adoption with a holistic point of view, or (2) examined the similarities and differences in CC acceptance in terms of industry and service type. This study fills these research gaps: (1) This study introduced *dependability* as a multi-faceted notion to CC acceptance study. This is the first empirical research that integrates *dependability* attributes (*availability*, *reliability*, *security*, *maintainability*) with technology acceptance theory. (2) This study identified the influence of *dependability* attributes on accepting CC at the

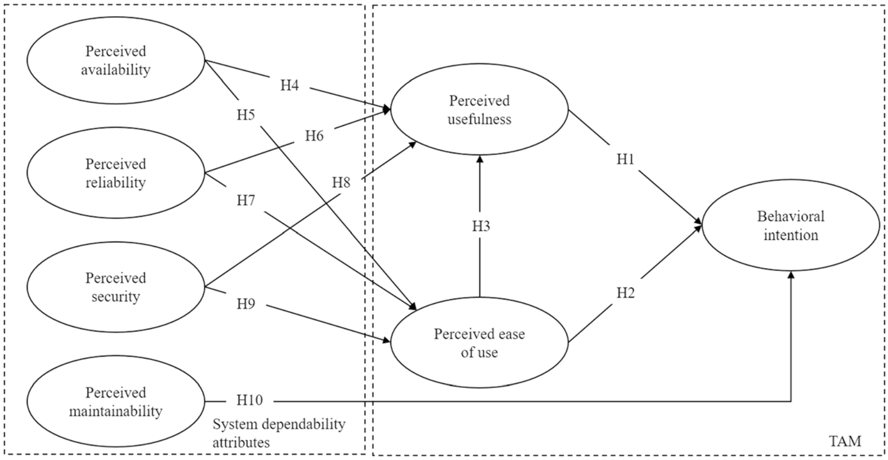

Fig. 2 Research model and hypotheses

organizational context, and showed the similarities and differences in CC acceptance between specific groups (Hi-ITi vs. Lo-ITi, SaaS vs. PaaS/IaaS).

4 Research model and hypotheses

4.1 Research model

This study proposes a reflective model that integrates four *dependability* attributes with TAM (Fig. 2): TAM is used as a baseline model because of its robustness and simplicity. This study adopted CC as a target technology because CC is a good representation of system *dependability* and its attributes. This model consists of four exogenous constructs (*availability*, *reliability*, *security*, *maintainability*), one final endogenous construct (behavioral intention), and two explanatory constructs (*perceived usefulness*, *perceived ease of use*) that simultaneously serve as exogenous and endogenous variables. Actual use was excluded because we accept that behavioral intention is the strongest determinant of actual use in IT/IS contexts [18, 29].

4.2 Hypothesis development

This study proposes ten hypotheses that connect measures of CC's *dependability* to behavioral intention to use, either directly, or indirectly via *perceived usefulness* and *perceived ease of use*.

Perceived usefulness (PUF) refers to the degree to which users believe that using a technology would enhance his or her job performance [28, 29]. It is similar to *performance expectancy* in UTAUT/UTAUT2 and *relative advantage* in TOE/DOI

[18]. In the context of CC, *perceived usefulness* concerns improvements in task productivity obtained from using CC as a result of its technical features such as broad network access. Previous CC adoption studies have showed that *perceived usefulness* has a positive effect on behavioral intention to use of CC [20, 22, 25–27, 36, 38, 49, 51, 52, 54, 56–59]. Consequently, if managers perceive CC to be useful, behavioral intention to use the system would likely increase. Thus, we propose:

H1 *Perceived usefulness* of CC increases manager's behavioral intention to use CC.

Perceived ease of use (PEU) measures the extent to which users believe that a new technology can be used without effort [28, 29]. This concept captures others such as *effort expectancy* in UTAUT/UTAUT2 and *complexity/ease of use* in TOE/DOI [18]. In the context of CC, this measure quantifies the simplicity of using a CC that operated over on the internet. The easiness of CC has a direct effect on the usefulness of CC because an easy technology reduces the effort required to accomplish tasks**.** Prior studies have shown that perceived ease of use is a critical determinant of behavioral intention to use CC [25–27, 36, 38, 49, 57–59] and is a causal antecedent of perceived usefulness [20, 25–27, 36]. Consequently, if managers believe that they need to exert little effort to use CC, then behavioral intention to use CC and *perceived usefulness* would likely increase. Thus, we propose:

H2 *Perceived ease of use* of CC increases manager's behavioral intention to use CC.

H3 Perceived ease of use of CC increases manager's *perceived usefulness* of CC.

Availability refers to the readiness for correct service in dependable systems' view [2, 3]; it is perceived by a user as the degree to which he or she believes that a new technology provides relevant service anytime and anywhere [27, 74]**.** *Perceived availability* is similar to the concept of *perceived ubiquity* in the IT/IS area [74]. Some previous studies of CC adoption have indicated that *perceived availability* (or similar concepts) positively affect the usefulness [27, 74] and the ease of CC [27]. Consequently, in the CC context, the *availability* of CC anytime and anywhere through the internet and various devices is likely to make managers feel that CC is useful and easy to use. Thus, we propose:

H4 *Perceived availability* of CC increases manager's *perceived usefulness* of CC.

H5 *Perceived availability* of CC increases manager's *perceived ease of use* of CC.

Reliability refers to the continuity of correct service in dependable systems' view [2, 3]; it is perceived by a user as the degree to which he or she believes that a new technology responds consistently and functions accurately (e.g., guaranteed service 24/7) [75, 76]. *Perceived reliability* is about reliable service delivery of CC and fault tolerance against catastrophic failures [76]**.** To the best of our knowledge, few studies have examined both the effects of *reliability* on usefulness and ease of use of

CC in an organizational context; only one study showed that *reliability* is positively related to the ease of CC when SMEs adopt CC [76]. Instead, another study that focused on individual-level CC adoption showed that *perceived reliability* works as an antecedent of the usefulness and the ease of CC in students' CC adoption of community colleges [77]. Consequently, in the CC context, increase in managers' perceptions that CC works well under any situations will lead to an increase in the likelihood that they perceive CC to be useful and easy to use. Thus, we propose:

H6 *Perceived reliability* of CC increases manager's *perceived usefulness* of CC.

H7 *Perceived reliability* of CC increases manager's *perceived ease of use* of CC.

Security refers to the prevention of unauthorized access [2, 3], and is perceived by a user as the degree to which he or she believes that the CC provides protection against disclosure, modification, destruction, fraud, and abuse [78, 79]**.** *Perceived security* concerns are seen as a key obstacle to new IT/IS adoption including CC [13, 74]**.** Similar to the case of *reliability*, few studies have explored the influence of *security* on the usefulness and the ease of CC, except for one study [76], which validated the positive relationship between *reliability* and the *ease of use*. In other IT/IS areas, *perceived security* has a positive effect on *perceived usefulness* [80] and *perceived ease of use* [80, 81]. Consequently, in the CC context, as managers' perceptions of CC as secure increase, their perceptions of the usefulness and the ease of CC will also increase. Thus, we propose:

H8 *Perceived security* of CC increases manager's *perceived usefulness* of CC.

H9 *Perceived security* of CC increases manager's *perceived ease of use* of CC.

Maintainability refers to the ability to undergo modifications and repairs [2, 3]; it is perceived by a user as the degree to which he or she believes that technology providers perform appropriate maintenance in hardware and software aspects [82]. CC helps users to eliminate the burden of maintaining hardware and software in on-premise systems because CSPs take the place of maintenance; if managers perceive that CC is accompanied by good maintenance, they will be likely to adopt CC. Contrarily, if the user's perception is that the *maintainability* is not good, the consequence is a decrease in the likelihood that they accept the technology. Although the inherent nature of CC leads to an in- creasing interest in *maintainability*, little empirical study is available for the effect of *maintainability* on CC adoption. Instead, *ease of maintenance* was found to be a more important consideration than other factors (e.g., *reliability*) in an interview of IT professionals concerning CC adoption [65] and in an analytic hierarchy process of drivers and inhibitors of SaaS adoption [82]. Thus, we propose:

H10 *Perceived maintainability* of CC increases manager's behavioral intent to use CC.

5 Methods

5.1 Measurement development

This research used a survey method. A structured questionnaire was developed to conduct a survey to collect data. Most measurements scales in the questionnaire have been validated in previous studies, and *maintainability* scales were developed due to the lack of prior studies related to the *maintainability* attribute ("Appendix 1"). Twenty- seven items regarding all the constructs in our research model were designed for the questionnaire. It was developed in English, then translated to Korean by bilingual researchers who used the back-translation technique. Scales were reviewed by 10 CC experts, then modified to fit our study. Respondents were required to evaluate their perceptions of CC by scoring a seven-point Likert scale (from 1 = strongly disagree to 7 = strongly agree).

5.2 Sample

This study targeted business managers who work in various departments within an organization in various industries, and who are aware of CC. However, the correct size of target population was not available in South Korea, so a professional online survey firm (i.e., Entrust Survey) was used to collect appropriate participants (i.e., business managers), who were recruited according to the well-organized panel-filtering policy of the survey firm. A pilot study with twenty university students was conducted first to test the wording and clarity of the questionnaire, and time required to complete it. The questionnaire was revised in response to the students' feedback. Then, the final questionnaire was given to and managed by the survey firm. Two hundred and thirty surveys were collected online during a span of 4 months (December 2019–March 2020) from the registrants pool of the survey firm. None of the scores was an obvious outlier, so all surveys were used for our analysis. All processes of this survey were approved by the academic ethics committee.

5.3 Data analysis

Data were first analyzed using SPSS 23.0 statistical software, to examine demographic characteristics of sample respondents ("Appendix 2"). Most (87.0%) of respondents had more than 6 years of experience in job positions as first and middle-line managers (96.1%); they conducted main tasks in mainly management (46.1%), R&D/IT (33.9%) and production (10.9%). The industries in which the participants are employed were manufacturing (30.0%), IT (19.6%), service (12.6%), government/public area (11.7%), engineering (7.4%), wholesale/retails (7.45%), energy/

chemicals/utilities (4.3%), telecommunications (3.9%), and finance (3.0%). Most (73.5%) of the organizations ran domestic and local businesses. The number of employees were mainly below 300 (50.4%) or 300–1000 (37.8%). Annual sales were mostly (89.6%) KRW 1 billion–5 trillion.

One of our research goals is to explore the similarities and differences between groups (Hi-ITi vs. Lo-ITi; SaaS vs. PaaS/IaaS). To conduct a multi-group analysis, we first reclassified industry type into Hi-ITi (117; e.g., financing, IT, telecommunication) and Lo-ITi (113; e.g., manufacturing, energy/chemicals/utilities, engineering, wholesale/retails) [70, 83–85]. In South Korea, the government/public sector [86] and service sector [87] are Hi-ITi. This study combined PaaS and IaaS into one group (PaaS/IaaS) because they mainly target organizational-level services; thus, service type is divided into SaaS (88) and PaaS/IaaS (82) for analysis.

Analysis then applied structural equation modeling (SEM) to validate the proposed model, using the collected data: i.e., assessment of measurement model and the structural model. SEM is a multivariate statistical method that allows analysis of casualty among latent variables [23]. SEM can use two techniques [24]: covariance-based SEM (e.g., analysis of moment structures) and variance-based SEM (e.g., partial least squares: PLS). The former is for testing theory, confirming theory or comparing alternative theories, whereas the latter is for predicting target variables or identifying key influencing variables [23] as in our study. PLS was used to conduct the test of measurement and structural model by using SmartPLS3.0, which is latent-variable modeling-software (SmartPLS GmbH) that uses a graphical user interface. We chose PLS-SEM because [24] it evaluates both the measurement and structural model at the same time, and can work with small sample size.

PLS-SEM minimum sample size should be ten times the largest number of structural paths directed at a particular latent variable in the structural model [23]. The highest number of relationship towards a latent construct in this research is that towards *perceived usefulness*, consisting of four relationships. Thus, the required minimum sample size is 40 respondents; our sample size of 230 fulfills this requirement.

6 Results

Analysis results are present in three-steps: measurement model analysis, structural model analysis, and multi- group analysis.

6.1 Measurement model analysis

A measurement invariance test is an important step to be performed when conducting a group comparison [24, 88]. This test checks whether measurement operations differ across comparison groups: in our study, Hi-ITi versus Lo-ITi, and SaaS versus PaaS/IaaS. Overall, the results indicated good measurement invariance ("Appendix 3"). However, the initial evaluation did not report full measurement invariance. Investigation of outer loadings-differences between comparison groups demonstrated that two indicators yielded different meanings across them: PUF1 of *perceived usefulness* (Hi-ITi vs. Lo-ITi) with $p=0.027$, and PUF2 of *perceived usefulness* (SaaS vs. PaaS/IaaS) with $p=0.025$, so these indicators were deleted from the original model. Finally, none of the measurement items were variant across the groups, with $0.001 \leq$ outer loadings-diff (Hi-ITi vs. Lo-ITi) ≤ 0.104, and with $0.002 \leq$ outer loadings-diff (SaaS—PaaS/IaaS) ≤ 0.080; i.e., comparison groups do not differ significantly in their measurement invariance.

PLS-SEM algorithm was run to evaluate the reliability, the convergent validity, and the discriminant validity of the scales in the outer model. Reliability was tested using composite reliability (CR). Convergent validity was assessed using factor loading and average variance extracted (AVE). Finally, the Fornel-Lacker criterion and the HTMT criterion were used to assess discriminant validity.

All indices were within the recommended values in all assessment criteria (Table 2). All CR values exceeded the minimum threshold of 0.70 [23]; this result internal consistency among the constructs. All indicators had factors loading > 0.70, except one (PRE = 0.682), and AVEs were above the minimum threshold of 0.50, this result indicates acceptable convergent validity. The square root of AVE for all constructs in each group was much larger than its correlations with other constructs, and all groups passed the HTMT.90 criterion [23, 24] (Tables 3, 4, 5, 6, and 7); these results confirm discriminant validity. The most important information on each table are highlighted in bold

To assess multicollinearity among latent variables, the variance inflation factor (VIF) method was used ("Appendix 4"). All VIF values were within the maximum threshold of 5.0 [24], with $1.440 \leq$ VIF of full data set ≤ 2.801, $1.337 \leq$ VIF of Hi-ITi ≤ 3.069, $1.548 \leq$ VIF of Lo-ITi ≤ 2.809, $1.703 \leq$ VIF of SaaS ≤ 3.126, and $1.507 \leq$ VIF of PaaS/IaaS ≤ 2.759. Thus, this model has no multicollinearity problem.

6.2 Structural model analysis

This study included a bootstrapping and blindfolding process to get the structural estimates: coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), and path coefficients (β) (Tables 8, 9 and 10). All groups had $R^2 > 0.5$, which suggests that the exogenous constructs explained more than 50% of the variance in behavioral intent. All groups had $Q^2 > 0$, which indicates that the exogenous constructs have sufficient predictive relevance over their endogenous construct. f^2 shows the relative effect of an exogenous variable on an endogenous variable [24]; $f^2 = 0.02$, 0.15, and 0.35 indicate a weak, moderate, strong effect, respectively. *Perceived usefulness* (PUF) had the highest $f^2 = 0.586$ on behavioral intention (BI) in SaaS. The effects of *perceived availability* (PAV), *perceived reliability* (PRE) and *perceived security* (PSE) on PUF in all groups were fairly weak or weak, whereas their effects on *perceived ease of use* (PEU) were moderate or much greater than their effects on PUF. *Perceived maintainability* (PMA) had large effect size on BI, and PEU had large effect size on PUF in all groups except SaaS, but the effect size

Table 2 Reliability and convergent validity of each group

Construct and indicators	Factor loading					CR					AVE				
	Full dataset	. Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS	Full dataset	Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS	Full dataset	Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS
PAV															
PAV1	0.842	0.787	0.891	0.835	0.786	0.934	0.928	0.940	0.928	0.916	0.779	0.764	0.796	0.763	0.733
PAV2	0.893	0.880	0.909	0.869	0.892										
PAV3	0.890	0.904	0.879	0.888	0.866										
PAV4	0.905	0.919	0.890	0.902	0.877										
PRE															
PRE1	0.865	0.858	0.865	0.874	0.842	0.903	0.889	0.909	0.900	0.892	0.700	0.667	0.714	0.695	0.674
PRE2	0.867	0.836	0.884	0.874	0.824										
PRE3	0.716	0.703	0.721	0.682	0.761										
PRE4	0.888	0.859	0.899	0.888	0.853										
PSE															
PSE1	0.852	0.868	0.835	0.889	0.816	0.928	0.927	0.930	0.933	0.920	0.764	0.759	0.768	0.776	0.743
PSE2	0.879	0.867	0.891	0.884	0.858										
PSE3	0.867	0.857	0.873	0.839	0.851										
PSE4	0.898	0.893	0.905	0.910	0.920										
PMA															
PMA1	0.817	0.814	0.818	0.816	0.820	0.902	0.886	0.912	0.903	0.908	0.697	0.661	0.722	0.699	0.711
PMA2	0.839	0.805	0.863	0.831	0.851										
PMA3	0.843	0.822	0.854	0.834	0.840										
PMA4	0.841	0.812	0.863	0.863	0.860										

Table 2 (continued)

Construct and indicators	Factor loading					CR					AVE				
	Full dataset	. Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS	Full dataset	Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS	Full dataset	Hi-ITi	Lo-ITi	SaaS	PaaS/IaaS
PUF															
PUF3	0.865	0.867	0.862	0.844	0.865	0.933	0.935	0.931	0.919	0.936	0.778	0.783	0.771	0.740	0.785
PUF4	0.859	0.836	0.887	0.878	0.849										
PUF5	0.906	0.921	0.886	0.848	0.924										
PUF6	0.898	0.913	0.877	0.872	0.905										
PEU															
PEU1	0.847	0.828	0.860	0.826	0.853	0.946	0.943	0.947	0.937	0.951	0.779	0.769	0.781	0.747	0.795
PEU2	0.856	0.854	0.853	0.860	0.862										
PEU3	0.908	0.907	0.905	0.897	0.920										
PEU4	0.899	0.888	0.906	0.861	0.911										
PEU5	0.900	0.905	0.893	0.877	0.909										
BI															
BI1	0.906	0.892	0.916	0.894	0.922	0.937	0.927	0.944	0.936	0.940	0.788	0.761	0.810	0.785	0.796
BI2	0.890	0.848	0.925	0.889	0.825										
BI3	0.861	0.863	0.858	0.903	0.909										
BI4	0.893	0.887	0.899	0.858	0.908										

CR composite reliability, *AVE* average variance extracted, *Hi-ITi* high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 3 Discriminant validity of full dataset

	Fornell-larcker criterion								Heterotrait-monotrait ratio (HTMT)						
	BI	PAV	PEU	PMA	PRE	PSE	PUF		BI	PAV	PEU	PMA	PRE	PSE	PUF
BI	**0.888**							BI							
PAV	0.676	**0.883**						PAV	**0.745**						
PEU	0.613	0.632	**0.882**					PEU	0.664	**0.687**					
PMA	0.676	0.612	0.546	**0.835**				PMA	0.766	0.698	**0.612**				
PRE	0.731	0.614	0.662	0.714	**0.837**			PRE	0.835	0.706	0.743	**0.841**			
PSE	0.635	0.560	0.637	0.565	0.752	**0.874**		PSE	0.702	0.619	0.695	0.643	**0.860**		
PUF	0.636	0.567	0.734	0.460	0.558	0.547	**0.882**	PUF	0.700	0.624	0.795	0.523	0.632	**0.605**	

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 4 Discriminant validity of high-IT-intensity industry

	Fornell-larcker criterion								Heterotrait-monotrait Ratio (HTMT)						
	BI	PAV	PEU	PMA	PRE	PSE	PUF		BI	PAV	PEU	PMA	PRE	PSE	PUF
BI	**0.873**							BI							
PAV	0.636	**0.874**						PAV	**0.713**						
PEU	0.584	0.610	**0.877**					PEU	0.639	**0.669**					
PMA	0.638	0.566	0.499	**0.813**				PMA	0.737	0.655	**0.568**				
PRE	0.728	0.655	0.671	0.685	**0.817**			PRE	0.858	0.765	0.755	**0.836**			
PSE	0.608	0.570	0.687	0.513	0.770	**0.871**		PSE	0.675	0.630	0.751	0.592	**0.886**		
PUF	0.566	0.483	0.702	0.389	0.523	0.529	**0.885**	PUF	0.628	0.533	0.760	0.445	0.580	**0.581**	

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 5 Discriminant validity of low-IT-intensity industry

	Fornell-larcker criterion						
	BI	PAV	PEU	PMA	PRE	PSE	PUF
BI	**0.900**						
PAV	0.718	**0.892**					
PEU	0.636	0.669	**0.884**				
PMA	0.701	0.658	0.579	**0.850**			
PRE	0.727	0.608	0.654	0.729	**0.845**		
PSE	0.657	0.555	0.586	0.606	0.749	**0.876**	
PUF	0.712	0.675	0.773	0.535	0.612	0.567	**0.878**

	Heterotrait-monotrait ratio (HTMT)						
	BI	PAV	PEU	PMA	PRE	PSE	PUF
BI							
PAV	**0.778**						
PEU	0.679	**0.721**					
PMA	0.780	0.740	**0.642**				
PRE	0.815	0.683	0.727	**0.841**			
PSE	0.723	0.610	0.635	0.683	**0.849**		
PUF	0.778	0.736	0.837	0.603	0.694	**0.627**	

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 6 Discriminant validity of SaaS

	Fornell-larcker criterion								Heterotrait-monotrait ratio (HTMT)						
	BI	PAV	PEU	PMA	PRE	PSE	PUF		BI	PAV	PEU	PMA	PRE	PSE	PUF
BI	**0.886**							BI							
PAV	0.703	**0.874**						PAV	**0.781**						
PEU	0.668	0.696	**0.864**					PEU	0.718	**0.754**					
PMA	0.643	0.634	0.595	**0.836**				PMA	0.719	0.719	**0.654**				
PRE	0.803	0.664	0.701	0.687	**0.834**			PRE	0.912	0.765	0.788	**0.800**			
PSE	0.682	0.605	0.665	0.542	0.773	**0.881**		PSE	0.751	0.670	0.720	0.604	**0.881**		
PUF	0.819	0.641	0.727	0.599	0.733	0.711	**0.860**	PUF	0.907	0.719	0.798	0.674	0.844	**0.792**	

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 7 Discriminant validity of PaaS/IaaS

	Fornell-larcker criterion								Heterotrait-monotrait ratio (HTMT)						
	BI	PAV	PEU	PMA	PRE	PSE	PUF		BI	PAV	PEU	PMA	PRE	PSE	PUF
BI	**0.892**							BI							
PAV	0.643	**0.856**						PAV	**0.712**						
PEU	0.561	0.618	**0.891**					PEU	0.606	**0.679**					
PMA	0.698	0.671	0.577	**0.843**				PMA	0.780	0.763	**0.643**				
PRE	0.712	0.643	0.654	0.735	**0.821**			PRE	0.813	0.745	0.726	**0.864**			
PSE	0.610	0.614	0.697	0.637	0.743	**0.862**		PSE	0.677	0.687	0.761	0.722	**0.861**		
PUF	0.559	0.496	0.738	0.466	0.536	0.527	**0.886**	PUF	0.611	0.547	0.797	0.524	0.586	**0.583**	

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 8 R^2, Q^2 and f^2 for full dataset

Construct	Full dataset				
	R^2	Q^2	f^2		
			BI	PEU	PUF
BI	**0.590**	0.436			
PAV				0.138	0.024
PEU	0.539	0.391	0.012		0.340
PMA			0.358		
PRE				0.064	0.001
PSE				0.056	0.005
PUF	0.554	0.405	0.134		

PAV perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 9 R^2, Q^2 and f^2 for IT intensity

Construct	Hi-ITi					Lo-ITi				
	R^2	Q^2	f^2			R^2	Q^2	f^2		
			BI	PEU	PUF			BI	PEU	PUF
BI	**0.527**	0.377				**0.641**	0.479			
PAV				0.082	0.004				0.229	0.083
PEU	0.546	0.392	0.028		0.324	0.539	0.395	0.001		0.351
PMA			0.326					0.359		
PRE				0.035	0.001				0.082	0.004
PSE				0.128	0.002				0.015	0.007
PUF	0.483	0.351	0.082			0.638	0.461	0.229		

Hi-ITi high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

did not differ significantly between comparison groups, except |SaaS—PaaS/IaaS| (i.e., PUF → BI) (Table 11).

This study investigated the hypothesized relationships in each group including the full dataset (Figs. 3 and 4, Table 12). Overall, assessing from the path coefficients alone, the TAM-related hypothesis test results were the same in comparison groups, but the *dependability*-related hypothesis test reported different results among them. This distinction suggests that manager's perceptions of adopting CC may differ between Hi-ITi and Lo-ITi, and between SaaS and PaaS/IaaS.

Perceived usefulness significantly affected behavioral intention to adopt CC for the full data set ($\beta = 0.345$, $p < 0.001$), Hi-ITi ($\beta = 0.273$, $p < 0.01$), Lo-ITi ($\beta = 0.452$, $p < 0.001$), SaaS ($\beta = 0.630$, $p < 0.001$), and PaaS/Paas ($\beta = 0.270$, $p < 0.05$); thus, H1 is supported for all groups. *Perceived ease of use* was not significant for any group;

Table 10 R^2, Q^2 and f^2 for service type

Construct	SaaS					PaaS/IaaS				
	R^2	Q^2	f^2			R^2	Q^2	f^2		
			BI	PEU	PUF			BI	PEU	PUF
BI	**0.699**	0.513				**0.541**	0.395			
PAV				0.192	0.015				0.073	0.002
PEU	0.591	0.406	0.009		0.112	0.543	0.405	0.002		0.454
PMA			0.097					0.446		
PRE				0.068	0.061				0.036	0.008
PSE				0.048	0.061				0.150	0.002
PUF	0.638	0.440	0.586			0.528	0.381	0.075		

SaaS software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Table 11 Results of effect size (f^2) differences

Construct	Hi-ITi versus Lo-ITi		SaaS versus PaaS/IaaS	
	f^2 diff	*p*-value	f^2 diff	*p*-value
PAV→PUF	0.079	0.726	0.014	0.351
PAV→PEU	0.147	0.831	0.118	0.211
PRE→PUF	0.003	0.435	0.053	0.305
PRE→PEU	0.048	0.729	0.032	0.335
PSE→PUF	0.006	0.680	0.059	0.115
PSE→PEU	0.113	0.109	0.102	0.766
PMA→BI	0.033	0.541	0.349	0.858
PUF→BI	0.147	0.832	0.512	**0.013**
PEU→BI	0.026	0.478	0.007	0.308
PEU→PUF	0.026	0.561	0.343	0.809

Hi-ITi high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

hence, H2 is rejected. *Perceived usefulness* was predicted by *perceived ease of use* in all groups (full data set: $\beta=0.572$, $p<0.001$; Hi-ITi: $\beta=0.605$, $p<0.001$; Lo-ITi: $\beta=0.523$, $p<0.001$; SaaS: $\beta=0.313$, $p<0.01$; PaaS/IaaS: $\beta=0.681$, $p<0.001$); hence, H3 is supported.

Perceived availability (PAV), *perceived reliability* (PRE), and *perceived security* (PSE) had no significant effect on *perceived usefulness* for any group, except SaaS ($\beta=0.238$, $p<0.05$); hence, H4 and H6 were rejected for all groups. H8 was accepted for SaaS, but rejected for other groups. *Perceived maintainability*

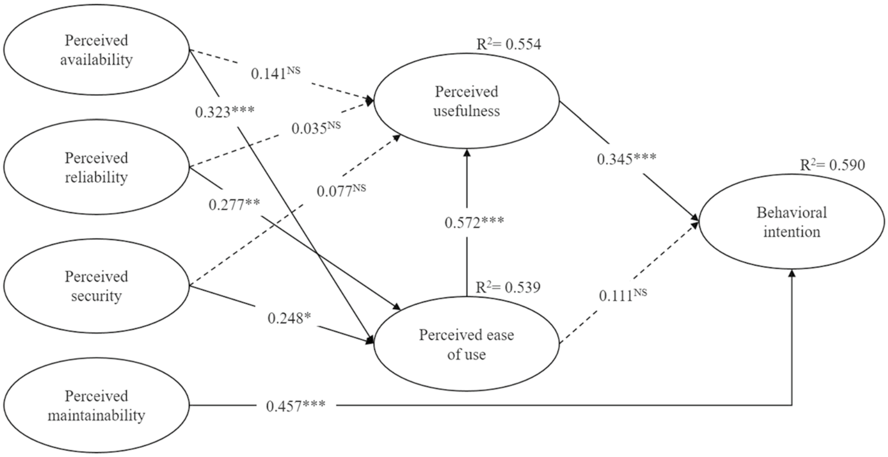

Fig. 3 Results of hypothesis test for full dataset. *Notes*. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$; NS = not supported. Solid line: significant path; dashed line: non-significant path

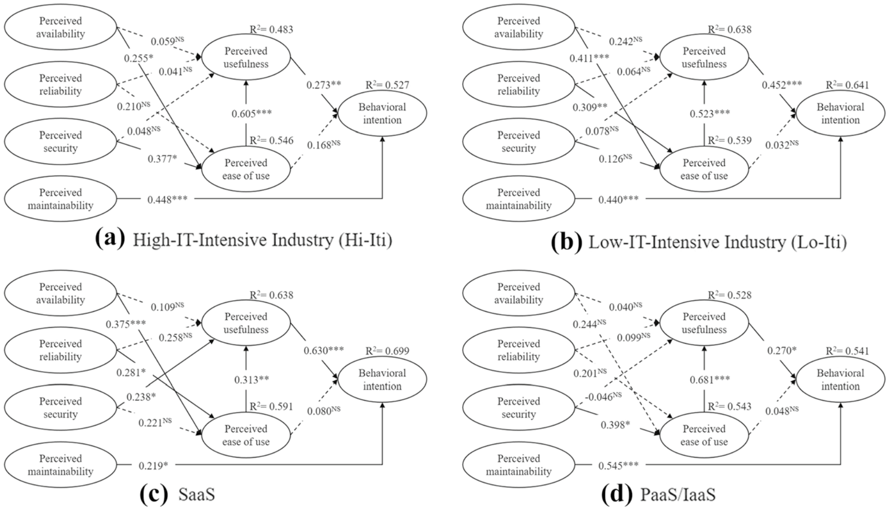

Fig. 4 Results of hypothesis text for subgroups. Notes. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$; NS = not supported. Solid line: significant path; dashed line: non-significant path

was significant for all groups (full data set: $\beta=0.457$, $p<0.001$; Hi-ITi: $\beta=0.448$, $p<0.001$; Lo-ITi: $\beta=0.440$, $p<0.001$; SaaS: $\beta=0.219$, $p<0.05$; PaaS/IaaS: $\beta=0.545$, $p<0.001$); hence, H10 was accepted in all groups.

PAV, PRE, and PSE on *perceived ease of use* were significant for the full data set (for PAV: $\beta=0.323$, $p<0.001$; for PRE: $\beta=0.277$, $p<0.01$, for PSE: $\beta=0.248$, $p<0.05$); hence, H5, H7, and H9 were accepted in the full data set. However, their

Table 12 Hypotheses test results

Path	Full dataset			Hi-ITi			Lo-ITi			SaaS			PaaS/IaaS		
	β	p-values	Results	β	p-values	Results	β	p-values	Results	β	p-values	Results	β	p-values	Results
PAV → PUF	0.141	0.159	NS	0.059	0.657	NS	0.242	0.095	NS	0.109	0.387	NS	0.040	0.793	NS
PAV → PEU	0.323	**0.000**	**S**	0.255	**0.024**	**S**	0.411	**0.000**	**S**	0.375	0.000	S	0.244	0.103	NS
PRE → PUF	0.035	0.761	NS	0.041	0.808	NS	0.064	0.655	NS	0.258	0.098	NS	0.099	0.497	NS
PRE → PEU	0.277	**0.002**	**S**	0.210	0.100	NS	0.309	**0.004**	**S**	0.281	0.025	S	0.201	0.123	NS
PSE → PUF	0.077	0.269	NS	0.048	0.700	NS	0.078	0.339	NS	0.238	0.024	S	(0.046)	0.718	NS
PSE → PEU	0.248	**0.015**	**S**	0.377	**0.013**	**S**	0.126	0.297	NS	0.221	0.070	NS	0.398	**0.021**	**S**
PMA → BI	0.457	**0.000**	**S**	0.448	**0.001**	**S**	0.440	**0.000**	**S**	0.219	0.023	S	0.545	**0.000**	**S**
PUF → BI	0.345	**0.000**	**S**	0.273	**0.008**	**S**	0.452	**0.000**	**S**	0.630	0.000	S	0.270	**0.030**	**S**
PEU → BI	0.111	0.171	NS	0.168	0.192	NS	0.032	0.751	NS	0.080	0.360	NS	0.048	0.751	NS
PEU → PUF	0.572	**0.000**	**S**	0.605	**0.000**	**S**	0.523	**0.000**	**S**	0.313	0.002	S	0.681	**0.000**	**S**

S supported, *NS* not supported, *Hi-ITi* high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Significant at: $p \leq 0.05$

Table 13 Results of path differences

Path	Hi-ITi versus Lo-ITi		SaaS versus PaaS/IaaS	
	Path coefficients-diff	*p*-value	Path coefficients-diff	*p*-value
PAV → PUF	0.183	0.821	0.069	0.355
PAV → PEU	0.156	0.847	0.132	0.235
PRE → PUF	0.023	0.546	0.158	0.224
PRE → PEU	0.096	0.716	0.080	0.327
PSE → PUF	0.030	0.580	0.284	**0.042**
PSE → PEU	0.251	0.100	0.177	0.793
PMA → BI	0.008	0.471	0.326	0.954
PUF → BI	0.179	0.887	0.360	**0.020**
PEU → BI	0.136	0.205	0.032	0.424
PEU → PUF	0.083	0.324	0.368	0.951

Hi-ITi high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

path significance on *perceived ease of use* showed different results among comparison groups.

For both Hi-ITi and Lo-ITi, *perceived ease of use* was significantly determined by *availability* (Hi-ITi: $\beta = 0.255$, $p < 0.05$; Lo-ITi: $\beta = 0.411$, $p < 0.001$), so H5 was accepted. *Perceived ease of use* was not significantly determined by *reliability* in Hi-ITi, but it was in Lo-ITi ($\beta = 0.309$, $p < 0.01$); H7 was rejected for Hi-ITi, but accepted for Lo-ITi. *Perceived ease of use* was determined by *security* in Hi-ITi ($\beta = 0.377$, $p < 0.05$), but not in Lo-ITi; so H9 was accepted for Hi-ITi, but not for Lo-ITi.

For both SaaS and PaaS/IaaS, *perceived ease of use* was significantly determined by *availability* ($\beta = 0.375$, $p < 0.001$) and *reliability* ($\beta = 0.281$, $p < 0.05$) in SaaS, but it did not in PaaS/IaaS. Hence, H5 and H7 were accepted for SaaS, but rejected for PaaS/IaaS. *Perceived ease of use* was not significantly determined by *security* in the SaaS, but was in the PaaS/IaaS ($\beta = 0.398$, $p < 0.05$); hence H9 was rejected for SaaS, but accepted for PaaS/IaaS.

6.3 Multi-group analysis

This study included a multi-group analysis to identify whether path coefficients between comparison groups (Hi- ITi vs. Lo-ITi; SaaS vs. PaaS/IaaS) differ significantly (Table 13). No paths differed significantly between Hi-ITi and Lo-ITi. Two paths differed significantly between SaaS and PaaS/IaaS: PSE → PUF ($\beta = 0.284$, $p < 0.05$), PUF → BI ($\beta = 0.360$, $p < 0.05$). The other five paths that showed different hypothesis results (i.e., Hi-ITi and Lo-ITi: PRE → PEU, PSE → PEU; SaaS and PaaS/IaaS: PAV → PEU, PRE → PEU, PSE → PEU) did not report significant differences between comparison groups.

7 Discussion

This study focuses on identifying the impact of *dependability* attributes in CC adoption in terms of intensity of IT use by industry and the type of CC. Combining the results in Table 12 (Figs. 3 and 4) with those in Tables 8, 9, 10, 11, and 13 reveals some interesting findings regarding *dependability* attributes and TAM constructs.

7.1 TAM constructs

TAM-related constructs showed the same results in all groups including the full dataset; this consistency confirms the fitness of our data for the TAM that was used as a baseline model.

Perceived usefulness directly affected behavioral intention to adopt CC in all groups including the full dataset. This influence was expected. Service type showed an interesting point: the differences in path coefficients between two groups were significant, i.e., manager' perception that CC is useful has more effect on the intention to use SaaS than to use PaaS. The reason might come from the inherent nature of SaaS, an individual-level service that is sensitive to the usefulness of a technology. This revelation shows that SaaS practitioners should pay more attention CC than PaaS/IaaS practitioners to maximizing the usefulness.

Perceived ease of use directly did not affect behavioral intention to adopt CC in all groups including the full dataset. The non-significance of the path between *perceived ease of use* and behavioral intention was not expected, and differs from the TAM's theoretical proposition [18, 29]**.** The difference might originate from the nature of CC. In the context of organization, CC is a utilitarian technology that is intensively job-related. When a technology is used in a utilitarian type, the usefulness becomes more important than the ease of use [89]. This result is in line with some prior CC studies. Thus, although ease of use has traditionally been regarded as an important factor in the adoption of technology, it is not as important in the CC environment, in which the usefulness is more directly important than ease of use to the manager's perceptions of the benefit of adopting the technology. This revelation implies that practitioners must increase the usefulness of CC as much as possible, and that they do not have to focus on satisfying the ease of use of CC.

7.2 Dependability attributes

Availability attribute had similar influences across comparison groups (Hi-ITi vs. Lo-ITi; SaaS vs. PaaS/IaaS) including the full dataset. For both Hi-ITi and Lo-ITi, *availability* did not act as a direct antecedent of *perceived usefulness*, but did act as an antecedent of *perceived ease of use*. For both SaaS and PaaS/IaaS, *availability* had the same effect on *perceived usefulness* as that of IT Intensity by industry, but a different effect on *perceived ease of use*.

For CC service type, the path coefficients of *availability* on the ease of use seemed to be stronger among SaaS than among PaaS/IaaS. A possible explanation is that *availability* had less than a moderate effect on p*erceived ease of use* in PaaS/IaaS group (PAV = 0.073). However, the multi-group analysis further showed no significant differences in path coefficients between SaaS and PaaS/IaaS, and the effect size did not differ between the two groups. These findings are valuable. This absence of difference stimulates the inference that *availability* may also serve to predict the ease of use of PaaS/IaaS depending on context factors such as technology type, user type and specific IT/IS context in each country (e.g., degree of technology maturity). Thus, this result suggests that even managers in PaaS/IaaS may evaluate the ease of use by considering whether CC is ubiquitous. Overall, these findings indicate that whether managers acquire ubiquitous connection does not affect their evaluation of the usefulness of CC, but may affect their evaluation of the ease of use by SaaS and PaaS/IaaS.

Reliability attribute also showed similar but different influences across comparison groups (Hi-ITi vs. Lo-ITi; SaaS vs. PaaS/IaaS) including the full dataset. *Reliability* did not act as a direct antecedent of *perceived usefulness* in any group. *Reliability* seemed to show different results in its relationship with *perceived ease of use* depending on IT intensity and service type: *reliability* had a positive effect on *perceived ease of use* for Lo-ITi, but no affect for Hi-ITi; it had a positive effected on *perceived ease of use* for SaaS, but not for PaaS/IaaS. The differences may be a result of the small effect size of *reliability* on *perceived ease of use* in the two groups (Hi-ITi: $f^2 = 0.035$; PaaS/IaaS: $f^2 = 0.036$).

However, the multi-group analysis further showed that the differences between path coefficients of comparison groups were not significant. These findings are interesting. This study infers that *reliability* may influence *perceived ease of use* for both Hi-ITi and PaaS/IaaS group. Thus, this indicates that managers do consider *reliability* when they assess the ease of use of CC in two groups. These interesting but controversial results require further investigation. Overall, these findings show that whether CC delivers its service reliably does not affect managers' evaluation of the usefulness of CC in all groups, but may affect their evaluation of its ease of use in all groups.

Security attribute had a complex influence as an antecedent of *perceived usefulness* and *perceived ease of use*. For Hi-ITi and Lo-ITi, *security* did not function as an antecedent of *perceived usefulness*, due to the small effect size (Hi-ITi: $f^2 = 0.002$; Lo-ITi: $f^2 = 0.007$). This lack of effect indicates that managers do not consider *security* when they assess the usefulness of CC. *Security* predicted *ease of use* in Hi-ITi, but not in Lo-ITi, but the multi-group analysis showed that the differences between path coefficients of comparison groups were not significant. This difference of conclusion is interesting, and indicates that *security* may affect *perceived ease of use* for Lo-ITi group; i.e., that managers may consider *security* when they assess the ease of use of CC in Lo-ITi group.

For SaaS and PaaS/IaaS, *security* determined *perceived usefulness* for SaaS, but not for PaaS/IaaS; the difference was significant. This finding is informative, and shows that managers in SaaS evaluate the usefulness by evaluating whether CC is secure, but that managers in PaaS/IaaS do not. *Security* affected *perceived ease of use* in PaaS/IaaS, but not in SaaS, but the path coefficients did not differ between them. This results implies that managers' perception in SaaS group that CC is easy to use may be affected by the likelihood that its services are secure. Overall, these findings show that whether CC delivers its service securely does affect managers' evaluation of the usefulness of CC in SaaS group, but may affect their evaluation of its ease of use in all groups.

Maintainability was as a strong determinant for behavioral intention to adopt CC in all comparison groups (Hi- ITi vs. Lo-ITi; SaaS vs. PaaS/IaaS) including the full dataset. This is an unexpected result. Especially, service type showed an interesting point: the effect of *maintainability* on behavioral intention to adopt CC was more than twice as high in PaaS/IaaS ($\beta = 0.545$) than in SaaS, and PaaS/IaaS had the largest effect size ($f^2 = 0.446$). The difference may originate from the differences in the natures of SaaS and PaaS/IaaS, and in the resources serviced. SaaS focuses on delivering individual-level services, whereas PaaS/IaaS focuses on organizational-level services (e.g., development platform, hardware resources); this difference in focus may affect the perceptions of *maintainability* among business managers, because they tend to have a relatively enterprise-wide view, so *maintainability* may be perceived as more influential in PaaS/IaaS than in SaaS.

Furthermore, hardware maintenance differs from software maintenance [90]. Hardware wears out physically, and is generally not delivered with undiscovered flaws. However, software generally does include undiscovered flaws, but does not wear out physically. These characteristics of hardware resources may affect the managers' perceptions of *maintainability*. Overall, among three factors (*perceived usefulness*, *perceived ease of use*, *maintainability*) that directly affect behavioral intention to adopt CC, *maintainability* has the largest effect size and strong path coefficient in all groups except SaaS.

7.3 Additional information

Considering the three *dependability* attributes (*availability*/*reliability*/*security*), one informative observation is that a non-path effect occurs between these attributes and *perceived usefulness* across all groups including the full dataset, except one path between *security* and *perceived usefulness* in SaaS. This observation contradicts the results of some studies in the literature review [25, 33, 76, 77, 87]. The reason may be a result of Korea's ubiquitous digital environment (i.e., 95.9% penetration by the internet) [91], and its high internet connection speed (27 Mbps) [92], which four times the global average. Such an environment makes people in this country perceive that even CC services can be always used securely at anytime from anywhere without interruption. They also take this excellence for granted. This high exposure to the internet and the high expectation of a superior environment may account for *availability*/*reliability*/*security* having no significant effects on *perceived usefulness*.

In contrast, SaaS showed a direct effect of *security* on usefulness. This path of influences may occur because SaaS focuses on delivering applications to users; SaaS users are sensitive to security concerns and are directly responsible for application-level security [11].

Another observation is that three *dependability* attributes (*availability/reliability/*security) affected the ease of CC for the full dataset. Their effects on the ease of CC seemed to differ across comparison groups. However, our study showed that most of these differences were not significant. In addition, among three factors (*perceived usefulness*, *perceived ease of use*, *maintainability*) that directly affect behavioral intention to adopt CC, *maintainability* has the largest effect size and strongest path coefficient in all groups except SaaS. This result suggests that practitioners recognize that *maintainability* attribute is a high-priority consideration by members of all groups in decisions to adopt CC, except for SaaS where *maintainability* is the second-most-important consideration. From a technical and managerial standpoint, obstacles that hinder good maintenance of CC should be removed.

8 Contribution and implication

8.1 Theoretical contribution

This study makes several theoretical contributions to IT/IS research. First, the theoretical framework proposed in our study successfully synthesizes four *dependability* attributes (*availability*, *reliability*, *security*, *maintainability*) through the TAM. The research model for full data set explained > = 59% of the variance in the dependent variable, followed by SaaS group (R^2 = 69.9%), Low-IT-Intensive Industry group (R^2 = 64.1%), PaaS/IaaS group (54.1%), and High-IT-Intensive Industry group (R^2 = 0.527%). Overall, our research models showed high predictive powers when compared to those of TAM (40% ≤ R^2 ≤ 50%).

Especially, by introducing *dependability* as a multi-dimensional notion, this study offers a fresh theoretical approach concerning CC acceptance in the organizational context. This is the first research that integrates *dependability* attributes with technology acceptance theory. Previous studies have overlooked the effect of *dependability* attributes on CC adoption. The observation deserves academic attention because no other research has considered the multi-dimensional approach to *dependability*. Overall, this study identifies the mechanism by which individual *dependability* attributes works in the CC context according to IT intensity and service type.

Second, this study advances the existing knowledge base related to IS/IT technology adoption. This is because our study identifies the similarities and differences in the importance of *dependability* to managers in industries that have different levels of dependence on IT and different requirements for CC service. This study further performed multi- group analysis beyond traditional hypothesis testing, by conducting path differences and effect size differences. The importance of *maintainability* is also noteworthy: it is a strong determinant of CC adoption in all groups. *Availability*, *reliability* and *security* do not differ significantly between high and low IT-intensive industries, but differs slightly between SaaS and PaaS/IaaS. Especially, *security* significantly differs by service type. Regarding the core TAM constructs, *perceived usefulness* significantly influences CC adoption in all groups, whereas *perceived ease of use* does not in all groups. One interesting point is that *perceived usefulness* significantly differs by service type.

Third, this study advances the existing literature in terms of sample diversity. Our literature review revealed a scarcity of studies that targeted business managers. Among specific user groups in an organization, managers deserve attention for research, because they have an important role in recognizing the value of a new technology, and in adopting and implementing the technology within an organization [93]. Especially, in an organization they control information transfer because they bridge between employees and top management [94]. Moreover, a huge decision to invest, such as introducing CC, is not made solely by IT/IS managers [95]. For example, application of CC is enterprise-wide, so the decision to migrate an existing system to CC is affected by various managers [96] including functional managers (e.g., service manager). Despite the importance of a manager's role in embracing new technologies, prior studies have failed to consider it. Thus, this study enhances the diversity of target population in CC technology acceptance.

8.2 Industrial implications

This study practically makes three implications for business. The first is for cloud service providers such as CSPs. This study shows that the usefulness of CC is an important determinant in all groups, whereas the ease is not. This distinction implies that cloud service providers must consider usefulness of CC more than its ease of use when delivering the cloud services.

This study has also shown that three attributes of *dependability* (*availability*, *reliability*, *security*) do not differ significantly between high and low IT-intensive industry groups, but differs between SaaS and PaaS/IaaS group. *Maintainability* is found to be an important predictor of CC adoption across all groups, but the priority varies by service type. For example, *maintainability* is a high-priority consideration by members of all groups in decisions to adopt CC, but it is the second most important consideration in the SaaS group. This difference suggests that CC service providers must either take the same market approach or take a different market approach, depending on the type of customer. Thus, CC service providers should consider each characteristic of the *dependability* attribute according to the customer type when retaining current business customers and attracting new ones.

The third is for CC service consumers such as business firms. This study shows that the CC service type to be introduced is a more important consideration than the type of industry to which one belongs. In particular, managers' perceptions of *security*, *maintainability* and u*sefulness* differed according to the service type, but not according to IT intensity. For example, the usefulness of CC is the most important consideration for the SaaS group, while *maintain-ability* is the most important consideration for Pass/IaaS group. *Security* is an important factor for SaaS users, but not for PaaS/IaaS users. This comparison indicates that when designing and introducing CC for their organizations, industrial practitioners must prioritize considerations differently depending on the type of CC service.

9 Limitations and future research

This research had some limitations. The first comes from the simplicity of our baseline model; the simplicity can limit the generalizability of the findings. This simplicity is both an advantage and a disadvantage. One of the most widely known criticisms is that TAM does not consider external and internal drivers such as price and subjective norm [34], Despite this objection, we used TAM because we focused on how *dependability* attributes work with two key factors (i.e., usefulness, ease of use) that are generally accepted as the strongest predictors of behavioral intention in the IT/IS research area. Therefore, researchers are encouraged to conduct a similar research method using other theoretical models (e.g., TOE, UTAUT), and to include additional variables.

Second, we ignored other *dependability* attributes such as *performability*, t*estability*, *integrity* and *confidentiality*. We extracted four overlapping attributes of *dependability* from several classifications by other researchers, and applied these attributes to our study. Future research should consider other types of *dependability* attributes to increase the completeness of the integration between *dependability* notion and technology acceptance theory.

Third, we did not overcome data bias. Data of respondents were gathered from a specific country that has a superior digital environment. Thus, the findings may vary among countries, depending on the IT/IS contexts; i.e., the effect of dependability on CC acceptance may be different in countries that have superior digital environments than in countries that have inferior digital environments. Furthermore, this is a cross-sectional study. The study focused on a specific-level group within an organization, but managers are exposed to internal and external information, possibly more than other specific groups of users, so managers' perceptions of CC may be more likely to change over time than those of such other groups. Moreover, *dependability* attributes change over time with respect to system performance [14]. Thus, an inter-country comparative study and longitudinal study with a similar research approach might be informative.

10 Conclusion

This study identified the influence of *dependability* attributes (*availability*, *reliability*, *security*, *maintainability*) on adoption of CC in the context of organization. To do this, we combined *dependability* attributes with TAM and test it with the data collected from business managers in South Korea. This study used PLS-SEM to validate the proposed research model, and then conducted multigroup analysis in terms of IT intensity and service type, along with testing casualties among constructs. Overall, the intention to accept CC was affected by its usefulness, not by its ease of use. Interestingly, *maintainability* was a strong predictor of the intention to accept CC. For comparison groups, we showed how similarities and differences between groups of managers depend on the intensity of IT and the type of CC that they use. Managers' perceptions of *dependability* attributes and TAM variables in adopting CC to their organizations did not differ between industries with high IT intensity and those with low IT intensity. However, for SaaS and PaaS/IaaS, managers showed differences in their perceptions of the effect of the usefulness on the intention to adopt CC, and the effect of *security* on *perceived usefulness* of TAM variables. *Maintainability* is a strong determinant of CC adoption in all groups except SaaS. The findings can provide academic researchers and industry practitioners with in-depth perspective on the understanding and the spread of CC. In particular, our results that were obtained using behavioral theory give CC developers a differentiated perspective on how to facilitate successful CC implementation.

Appendix 1: Measurement items

Construct		Measurement items	
Perceived availability	PAV1	In organization affairs, CC providing accessibility "anytime-and-anywhere" is very crucial	Arpaci [74]; Gangwar and Date [25]; Tripathi [48]
	PAV2	Employee can access to CC anytime for the necessary service	
	PAV3	Employee can access to CC anywhere for the necessary service	
	PAV4	Overall, employee can use CC "anywhere", "anytime" at the point of need	
Perceived reliability	PRE1	CC service are reliable	Sintonen and Immonen [75]; Tella et al. [8]
	PRE2	CC operates reliably without interruption (e.g., shutdown)	
	PRE3	CC would reduce burden of various hazards (e.g.; fire, flooding)	
	PRE4	Overall, CC is as reliable as on-premise systems	
Perceived security	PSE1	In CC, data is safeguarded from unauthorized changes or use	Yousafzai et al. [78]; Goode et al. [79]; Safari et al. [49]
	PSE2	In CC, data is protected from those who should not have access to it	
	PSE3	CC has proper anti-virus protection	
	PSE4	Overall, cloud computing is as secure as on-premise systems	

Construct		Measurement items	
Perceived maintainability	PMA1	CC would reduce burden of hardware maintenance	Developed by researcher
	PMA2	CC would reduce burden of software maintenance	
	PMA3	CC would reduce operational burden of IS/IT resources	
	PMA4	Overall, cloud computing is as easy to maintain as on-premise systems	
Perceived usefulness	PUF1	Using CC in organization affairs would enable employee to accomplish tasks more quickly	Davis [28]; Venkatesh and Davis[29]; Venkatesh et al. [18]
	PUF2	Using CC would improve employees' job performance	
	PUF3	Using CC in my job would increase employees' productivity	
	PUF4	Using CC would enhance employees' effectiveness on the job	
	PUF5	Using CC would make it easier to do employees' job	
	PUF6	I would find CC useful in employees' job	
Perceived ease of use	PUE1	Learning to operate CC would be easy for employee	
	PUE2	I would find it easy to get CC to do what employee want it to do	
	PUE3	Interaction with CC would be clear and understandable	
	PUE4	It would be easy for employee to become skillful at using CC	
	PUE5	I would find CC easy to use	
Behavioral intention	BI1	My organization plans to use CC in the future	
	BI2	My organization intends to use CC as much as possible	
	BI3	It is worth using CC in my organization	
	BI4	My organization will continue to use CC if we have access to the services	

CC cloud computing, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention

Appendix 2: Sample profiles

Respondents profiles (n = 230)	Frequency	Percentage (%)
Job experiences		
2–5 years	30	13.0
6–10 years	83	36.1
11 years ~	117	50.9
Job positions		
First-line manager	113	49.1
Middle-line manager	108	47.0
Senior manager	9	3.9
Main tasks		
Production	25	10.9
Marketing/Sales	21	9.1
Management (strategy/planning, organization/HR, financing/procurement)	106	46.1
R&D	22	9.6
IT	56	24.3
Organization profiles (n = 230)	**Frequency**	**Percentage (%)**
Main industry		
Manufacturing	69	30.0
Energy/chemicals/utilities	10	4.3
Engineering	17	7.4
Financing	7	3.0
IT	45	19.6
Telecommunications	9	3.9
Wholesale/retails	17	7.4
Government/public area	27	11.7
Service	29	12.6
Business scope		
Global business	61	26.5
Domestic business	158	68.7
Local business	11	4.8
Employee size		
< 300	116	50.4
300–1000	87	37.8
> 1000	27	11.7
Sales (KRW)		
< 1 billion	26	11.3
1–5 billion	42	18.3
5–10 billion	29	12.6
10–50 billion	45	19.6
50–2 trillion	41	17.8

Organization profiles ($n=230$)	Frequency	Percentage (%)
2–5 trillion	23	10.0
5–10 trillion	6	2.6
> 10 trillion	18	7.8

KRW Korean Won

Appendix 3: Measurement invariance test

Construct and indicators	Hi-ITi versus Lo-ITi		SaaS versus PaaS/IaaS	
	Outer loadings-diff	*p*-value	Outer loadings-diff	*p*-value
BI1 ← BI	0.024	0.793	0.028	0.793
BI2 ← BI	0.077	0.976	0.064	0.166
BI3 ← BI	0.005	0.452	0.007	0.583
BI4 ← BI	0.012	0.661	0.051	0.923
PAV1 ← PAV	0.104	0.972	0.049	0.245
PAV2 ← PAV	0.029	0.832	0.023	0.727
PAV3 ← PAV	0.026	0.236	0.021	0.331
PAV4 ← PAV	0.029	0.194	0.025	0.264
PEU1 ← PEU	0.031	0.760	0.027	0.687
PEU2 ← PEU	0.001	0.493	0.002	0.535
PEU3 ← PEU	0.003	0.458	0.023	0.803
PEU4 ← PEU	0.017	0.722	0.050	0.908
PEU5 ← PEU	0.011	0.350	0.032	0.775
PMA1 ← PMA	0.004	0.540	0.004	0.535
PMA2 ← PMA	0.058	0.924	0.020	0.665
PMA3 ← PMA	0.033	0.768	0.007	0.571
PMA4 ← PMA	0.051	0.773	0.003	0.513
PRE1 ← PRE	0.007	0.564	0.032	0.264
PRE2 ← PRE	0.047	0.871	0.050	0.167
PRE3 ← PRE	0.018	0.599	0.080	0.842
PRE4 ← PRE	0.040	0.809	0.035	0.272
PSE1 ← PSE	0.033	0.254	0.073	0.065
PSE2 ← PSE	0.023	0.730	0.025	0.284
PSE3 ← PSE	0.017	0.641	0.012	0.600
PSE4 ← PSE	0.012	0.635	0.010	0.638
PUF3 ← PUF	0.005	0.449	0.021	0.696
PUF4 ← PUF	0.051	0.801	0.029	0.344
PUF5 ← PUF	0.035	0.131	0.076	0.968
PUF6 ← PUF	0.036	0.152	0.033	0.817

Hi-ITi High-IT-intensity industry, *Lo-ITi* Low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention.

Appendix 4: Multicollinearity test

Construct	Full dataset			Hi-ITi			Lo-ITi			SaaS			PaaS/IaaS		
	BI	PEU	PUF	BI	PEU	PUF	BI	PEU	PUF	BI	PEU	PUF	BI	PEU	PUF
BI															
PAV		1.665	1.895		1.786	1.933		1.645	2.023		1.860	2.216		1.835	1.970
PEU	2.459		2.199	2.236		2.262	2.741		2.230	2.316		2.530	2.593		2.271
PMA	**1.440**			**1.337**			**1.548**			**1.703**			**1.507**		
PRE		2.632	**2.801**		2.966	**3.069**		2.595	**2.809**		2.926	**3.126**		2.550	2.642
PSE		2.388	2.523		2.507	2.829		2.362	2.397		2.580	2.703		2.399	**2.759**
PUF	2.190			1.980			2.555			2.332			2.209		

Hi-ITi high-IT-intensity industry, *Lo-ITi* low-IT-intensity industry, *SaaS* software as a service, *PaaS* platform as a service, *IaaS* infrastructure as a service, *PAV* perceived availability, *PRE* perceived reliability, *PSE* perceived security, *PMA* perceived maintainability, *PUF* perceived usefulness, *PEU* perceived ease of use, *BI* behavioral intention.

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Declarations

Conflict of interest The authors declare that they have no competing interests.

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