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Assessing Determinants of Continuance Intention towards Personal Cloud Services: Extending UTAUT2 with Technology Readiness

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Abstract: In addition to the rapid development of global information and communications technology (ICT) and the Internet, recent rapid growth in cloud computing technology represents another important trend. Individual continuance intention towards information technology is a critical area in which information systems research can be performed. This study aims to develop an integrated model designed to explain and predict an individual's continuance intention towards personal cloud services based on the concepts of technology readiness (TR) and the unified theory of acceptance and use of technology 2 (UTAUT2), moderated by gender, age, and experience of personal cloud services. The key results of the partial least square test largely support the proposed model's validity and the significant impact of effort expectancy, social influence, hedonic motivation, price value, habit, and technology readiness on continuance intention towards personal cloud services. In addition to providing symmetric theoretical support with the proposed model and transforming the individual characteristics of TR into UTAUT2, this study could be used to enhance and analyze users' adoption of personal cloud services and also increase the symmetry of the model's explanation and prediction. The findings from this research contribute to providing practical implications and academic resources as well as improving our understanding of personal cloud service applications.

Keywords: extended unified theory of acceptance and use of technology (UTAUT2); technology readiness; personal cloud services

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1. Introduction

Cloud services have received increasing attention and popularity as a way to deploy and manage innovative ways of using information technology (IT) resources [1]. Cloud services are an innovative paradigm that allows users to access third-party, Internet-hosted software applications, data storage, and computing services based on individual computing needs rather than applications hosted on local computers. This enables individuals or organizations to access a broad range of resources on the Internet at any time and from any location. Cloud computing is characterized by a synergetic intersection of ICT and personal or business computing, and it drives improvements in design, delivery, procurement, and management of computing solutions [1]. Currently, numerous business organizations have outsourced their internal information technology (IT) system by adopting cloud services [2–6].

Although cloud services have grown rapidly, becoming a notable trend [7], many enterprises and individuals still hesitate while maintaining a high interest in the option.

Furthermore, scholars have analyzed and discussed various challenging issues related to the implementation of cloud services, but few studies have explored the use of cloud services in terms of the priority order and measurement quality mechanisms based on cloud services or analyzed individual or organizational behavior models [4,8].

The degree to which users accept or adopt IT has always been a key interest of information systems research [9]. Migration theory considers migration as a rational, objective-oriented behavior based on controlled and premeditated processes [1,10]. This rational model is consistent with contemporary models adopted by ICT, such as the technology acceptance model (TAM) [11] and the technology acceptance and use of unified theory (UTAUT) [12]. The two theories from these studies that have been extensively applied to forecast IT adoption are the TAM and UTAUT [13–20]. UTAUT has obtained better research results than other frameworks for evaluating behavioral intention and analyzing behavior about information system usage in the medical environment [21]. Venkatesh et al. [9] included other aspects, such as incorporating hedonic motivation, price value, and habit in UTAUT, to form a research framework referred to as the extending unified theory of acceptance and use of technology (UTAUT2). Compared with the original UTAUT, the extended aspects proposed by UTAUT2 may have critical, complementary effects and significantly improve the explanatory powers of behavioral intention (56% to 74%) and technology usage (40% to 52%).

To date, there are many empirical research results regarding the extension of UTAUT [13–16,21], but little research combined and fulfilled the research gaps of personality-based and perceptive determinants to evaluate the continuance intention of personal cloud services. Therefore, the first research contribution of this study is to develop a conceptual model for predicting and evaluating the continuance intention of personal cloud services and related issues. Second, another key point is whether personal traits of users may also affect the personal cloud services and further influence an individual's willingness to use such technological products. Therefore, including the technology readiness (TR) proposed by Parasuraman [22] as an antecedent could both help to understand the relationship between personal traits and IT usage willingness as well as supporting UTAUT2 via the incorporation of personal traits. For end users, their digital life and personal cloud service are closely linked. Thus, each cloud service should be integrated with various types of mobile devices and applied broadly and conveniently in personal areas. including careers, families, and communities. This study developed an integrated model designed to predict and explain an individual's continuous use of personal cloud services based on the concepts of TR and UTAUT2. The obtained results can be a useful reference for cloud service providers in developing new markets and improving the design of service models. This study could also enhance our understanding of the antecedents on the continuance intention towards personal cloud services, thereby providing practical implications and an academic resource to gain further insight into personal cloud service applications.

2. Theoretical Background

2.1. Cloud Services and Relevant Studies

With the integration of digital devices and the Internet, cloud services have become an important topic in the IT (information technology) field as a new computing model [23,24] and as a trend of business IT system outsourcing [3]. Cloud services were first proposed by Google in 2006 [25,26], and after 2014, they were introduced in the Top Ten Strategic Technology Trends [27,28]. This research led to further interpretations and examples from various dimensions, and these discussions have largely contributed to the development and innovation of cloud services. Relevant studies on cloud computing increased greatly after 2008 [29,30], showing clearly that cloud services play a critical role in transforming the business systems.

However, there are many other factors to be considered to shift a traditional information system to cloud services [25,31], and the application of cloud service may have its own risks. Furthermore, the scope of cloud service applications has also been expanding in several industrial sectors. Buyya et al. [29] deemed that, following water, electricity, gas,

and the telephone, cloud services will become the fifth basic utility. Kaur and Chana [32] designed a cloud-based intelligent health and care service, which could efficiently monitor patients with chronic diseases in real time. Perrons and Hems [33] argued that information sharing and cost savings for medical records kept by separate medical organizations could be achieved through cloud services, and several medical care companies in the U.S. have transferred some of their sensitive medical records and claims to the public cloud of Amazon Web Services. From the above technological development and existing research, most current studies regarding cloud services considered the establishment, implementation evaluation, security risks, and application scope of cloud services, but there is a lack of empirical evaluation of the continued usage intention towards personal cloud services.

2.2. Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

Individual acceptance of new IT adoption and the requirement for technology application are critical topics for information management research [9,12,34]. Venkatesh et al. [12] found that external variables may affect the development of studies on IT use behavior. Since there are various antecedents proposed for different fields and unique results, a single theory may be insufficient to discuss individual usage intention and behavior towards technology. To this end, eight different theories, including theory of reasoned action (TRA), TAM/TAM2, the motivational model (MM), theory of planned behavior (TPB), combined TAM and TPB (C-TAM-TPB), the model of PC utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT), and 32 sub-constructs were also integrated to propose a new framework. This approach contains the four core determinants, namely, "performance expectancy (PE)", "effort expectancy (EE)", "social influences (SI)", and "facilitating conditions (FC)", and the four intervening variables, namely, gender, age, experience, and voluntariness of use. Consequently, this new framework is in line with UTAUT2 [35–39]. To overcome drawbacks of UTAUT, Venkatesh et al. [9] further integrated hedonic motivation, price value, and habit. This study found a significant improvement in both the applicability of UTAUT2 and the technology acceptance of consumers from the new measure.

UTAUT was initially developed mainly to explain users' acceptance and use of technology. It was also key in research to determine whether it can be extended to other dimensions such as consumer technology. Since UTAUT2 was extended from UTAUT, it has primarily been applied to explain the behavior of users' adoption of technology in organizational dimensions. Compared with general theories presented in recent years, the current study focuses on some specific dimensional sectors and, thus, requires the identification of relevant forecasting indices and mechanisms.

2.3. Synthesis of Technology Readiness (TR) and UTAUT2

Technology readiness (TR) refers to the tendency to achieve goals by accepting and using new technology in life or work [22] or the degree to which an individual is mentally prepared to accept new technology [34]. TR is primarily applied to better understand the reaction of individuals to the use of technology in general and computer or web-based technology in particular [40]. It can also be applied to the general consumer population [21]. Parasuraman worked with Rockbridge Associates in conducting focus group interviews with Rockbridge's clients to assess with more expansive measuring indices the attitude of individuals towards accepting and using new technology. The obtained results were categorized as positive or negative perceptions of the service users towards the employment of the technology. Positive perceptions include flexibility, convenience, efficiency, and pleasure, while negative perceptions include security concerns, risk of being out-of-date, insufficient user-friendliness, and lack of control.

For individuals, personal cloud services are simply an information technology system, and they appear to be applied widely in users' daily life and work. The decision to use technology is an important aspect for predicting and/or explaining the adoption or acceptance of information technology or systems [41]. Moreover, the value of UTAUT2 lies

in extending the existing theories and constructing new ones for forecasting technology use behavior more efficiently [9]. Therefore, this study uses UTAUT2's strengths (i.e., the ability to effectively forecast technology use and higher explanatory power) as a basis and then integrates TR features (i.e., understanding the personality traits of users) to explore the continuance intention towards personal cloud services acceptance. According to TR and UTAUT2 proposed by Parasuraman [22] and Venkatesh et al. [9], respectively, performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation, price value, and habit may be the influencers on continuance intentions towards personal cloud services.

3. Research Model and Hypothesis Development

Venkatesh et al. [12] defined performance expectancy (PE) as an individual belief that use of IT can help one achieve better performance at work. The similar study results regarding mobile banking also demonstrated that PE and EE have significant impacts on behavioral intention, while behavioral intention and FC significantly affected use behavior [35]. Wang and Shih [42] pointed out that, in the environment of information kiosks, behavioral intention and use behavior were both decisively influenced by PE, EE, SI, and FC. Based on the relevance of personal clouding services in relation to the above applications (e.g., mobile banking and information kiosk), we believe that the relation between PE and continuance intention towards personal clouding services needs to be proved. Accordingly, this study proposes Hypothesis 1:

Hypothesis 1 (H1). *Performance expectancy of users has a positive influence on continuance intention towards personal cloud services.*

Personal cloud services should be supported by a user-friendly human interface and learning guidance that can be easily accepted and used by users: overall, the degree to which an individual thinks a cloud service is easy to use. Devolder et al. [43] believe that performance expectancy and effort expectancy are both stronger factors for predicting technology acceptance. Alalwan et al. [36] also found a highly significant correlation between EE and behavioral intention towards mobile banking. Zhou, Lu, and Wang [44] studied wireless service providers in Finland and found that PE and EE were the primary determinants of behavioral intention. According to the relevant applications regarding personal cloud services (e.g., internet banking and wireless applications), this study proposes Hypothesis 2:

Hypothesis 2 (H2). *Effort expectancy of users has a positive influence on continuance intention towards personal cloud services.*

A recent study supports the notion that SI has significant effects on NFC mobile payments [45]. Wang and Shih [42] indicated that in the environment of information kiosks, behavioral intention and use behavior were both significantly and positively influenced by PE, EE, SI, and FC. Tsai et al. [46] also discovered that FC was significantly and positively related to learning behavior. Aggelidis and Chatzoglou [47] noted that behavioral intention is significantly affected by SI, FC, and attitude towards hospital information systems. Zhou et al. [44] indicated that PE, task-technology fit (TTF), SI, and FC all had significant impacts on adoption by users. Im et al. [15] indicated that PE, EE, and SI significantly affected behavioral intention, while behavioral intention and FC generated significant results on use behavior. Further, Lian [31] argued that SI was a primary predictive factor for behavioral intention in the UTAUT2 framework towards e-invoice service. Therefore, this study proposes Hypothesis 3:

Hypothesis 3 (H3). *Social influence of users has a positive effect on continuance intention towards personal cloud services.*

FC mainly refers to training, guidance, infrastructure, and service platform support, all of which improve IT use. For example, returning goods purchased online can be achieved more successfully when no charges are collected [12]. In the environment of information kiosks, behavioral intention and use behavior were both significantly and positively influenced by FC [42]. Aggelidis and Chatzoglou [47] found that the behavioral intention of hospital staff was significantly affected by SI, FC and attitude, but FC was the main factor influencing behavioral intention positively and directly. Im et al. [15] indicated that PE, EE, and SI significantly affected behavioral intention, while behavioral intention and FC had a significant effect on use behavior. According to the above similar context including the hospital information system and the application of a self-assistance kiosk, we propose that a relation exists between FC and continuance intention towards personal cloud services. Thus, this study proposes Hypothesis 4:

Hypothesis 4 (H4). *Facilitating conditions of users have a positive influence on continuance intention towards personal cloud services.*

Hedonic motivation refers to the pleasure or happiness obtained from using a system [9,48]. Prior studies showed that hedonic motivation plays a vital role in technology acceptance and use as well as having a positive relation with the intention of consumers to use IT [9]. Combining the aspects and variables of hedonic motivation would strengthen the UTAUT model in the forecasting of practical viewpoints [9], and, moreover, users with hedonic motivation would look forward to the pleasure obtained by using a certain technology. In their study of pre-service teachers' acceptance of learning management software, Raman and Don [49] considered hedonic motivation to be the most significant predictive aspect of behavioral intention. Accordingly, this study proposes Hypothesis 5:

Hypothesis 5 (H5). *Hedonic motivation of users has a positive influence on continuance intention towards personal cloud services.*

Venkatesh et al. [9] found a positive relation between price value and consumers' intention to use technology. There is even a positive relation between technology readiness and the switching costs customers pay to switch from a current product or provider to a new product or provider [50]. Compared to organization employees, end-users generally have to bear additional monetary costs for use, but cost and price value may have a noteworthy influence on consumers' use of technology. When the advantage of using technology is greater than the associated monetary costs and price value, the price value will generate a positive influence on intention since it is a bargain [9]. Tomás and Elena [51] found that hedonic motivation positively influences online purchase intention on an airline's e-commerce website. Consequently, this study proposes Hypothesis 6:

Hypothesis 6 (H6). *The perception of price value has a positive influence on continuance intention towards personal cloud services.*

Habit is considered an attribute reflecting the perceptual construct of results from past experiences. It also refers to the spontaneous behavior presented after learning. Combining the aspects and variables of habit would strengthen the UTAUT model in the forecasting of practical viewpoints [9,52]. Habit requires learning and will adopt an automatic response within a limited range towards specific situations or stimuli [53]. Raman and Don [49] held that habit could be divided into two types: the first type is considered to be prior behavior, while the second type is the belief of individuals that behavior is spontaneous. Habit influences usage intention directly and indirectly and has an even more significant impact on the behavioral intention of using learning management software. Limayem et al. [54] emphasized the importance of habit to explain use behavior. Tomás and Elena [51] found that habit was a predictive factor for using technology in many studies and considered that it would positively influence online purchase intention on e-commerce websites.

Alalwan et al. [35] revealed that habit was a principal factor for usage intention of mobile banking. Thus, this study proposes Hypothesis 7:

Hypothesis 7 (H7). *Users' habit has a positive influence on continuance intention towards personal cloud services.*

A positive attitude towards technology may lead to a firm belief that technology can enhance the control, flexibility, and efficiency of people's daily lives [21,22,41,55–57]. In general, optimistic users tend to apply newer technologies since they enjoy the experience of technology and the excitement of being in control. Prior studies have shown that TR influences willingness to use a technological product or service, in which the drivers (i.e., optimism and innovativeness) positively affected willingness to use, while the inhibitors (i.e., discomfort and insecurity) negatively affected willingness to use [57,58].

Users with innovativeness are more willing to learn and use new technologies [59] than those without it. They have a better understanding and thus become familiar with the operation of a technological product or service without requesting additional assistance from others. Conversely, users without the driver of innovativeness may be less willing to voluntarily learn and use a new technology, even when an existing technological product or service cannot satisfy their requirements. At this point, a user realizes that they cannot control the technology, generating a sense of unbearable burden [21,41,57,60].

On the other hand, users who have fewer security concerns believe that technology can be used to protect information safety. In summary, TR is comprised of the aspects of optimism, innovativeness, discomfort, and insecurity, and it has been applied extensively in areas such as self-service technologies, the construction industry, wireless technology, online services, educational choice, and healthcare services. Lin et al. [61] integrated technology readiness and the acceptance model (TRAM) and, after testing and verification, found a significant correlation between TR and behavioral intention in the e-service environment. Similar results have also been found by other scholars [58,62,63]. According to above the relevant e-service and m-service adoption research, this study proposes a positive relation between TR and continuance intention towards personal cloud services and proposes Hypothesis 8:

Hypothesis 8 (H8). *Users' technology readiness has a positive influence on continuance intention towards personal cloud services.*

The proposed model and its figure are provided in the following section (as shown in Figure 1).

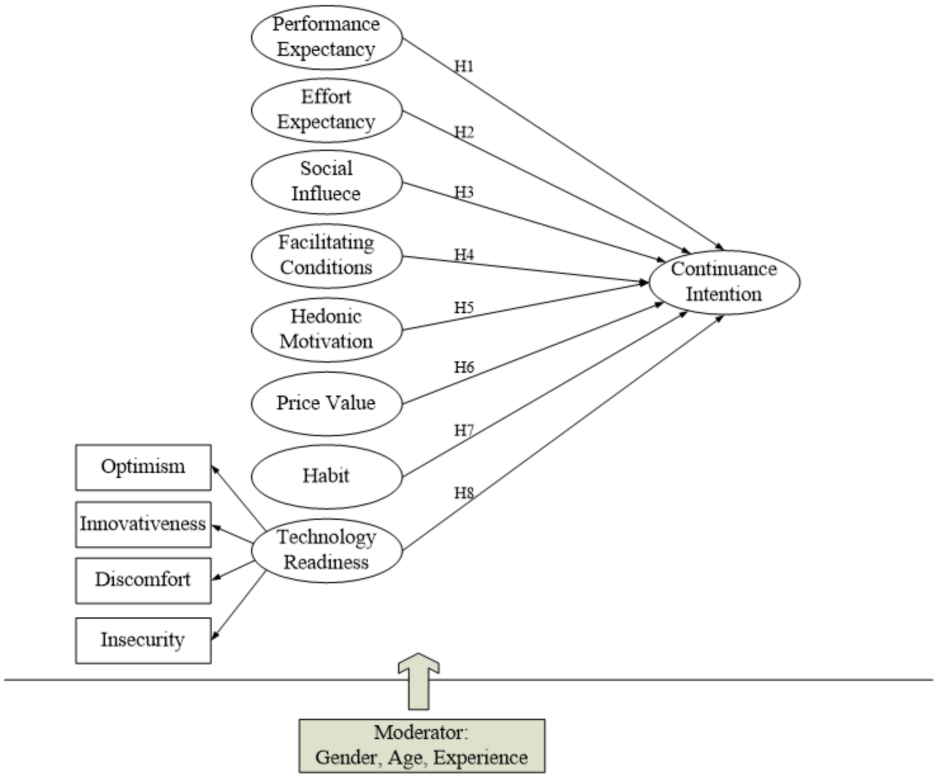


Figure 1. Research model.

4. Research Methodology

The measurement items of this research are mainly adopted from UTAUT2 and TR. To ensure the content reliability and validity of measurement items, the content of scales and dimensions modified by Yen [40], Limayem et al. [54], Lin and Hsieh [64], Parasuraman [22], Venkatesh et al. [9], and Wang and Shih [42] were considered. In addition, three professors from related fields joined the expert panel to review the questions and content, and necessary corrections and improvements were made according to their opinions.

This study used an online community to invite individuals who had experience regarding personal cloud services to complete the measurement items in the designated online questionnaire collection. Online questionnaires have the advantages of no restriction on a single geological location, flexible cost, and instant responses from users [65]. In order to improve the external validity of this research, we collected users who experience with personal cloud services rather than those without usage experience with personal cloud services. To encourage participation, a lucky draw was offered with 20 prizes ranging, including 10 power banks and 10 money-off meal vouchers. Finally, two hundred and sixty valid samples that met the general requirements were collected through the Internet. There were 127 male subjects (48.8%) and 133 female subjects (51.2%). By age, there were 79 subjects (30.4%) between 31 and 40 years old and 74 subjects (28.4%) between 41 and 50 years old. More than half of the subjects surfed the Internet daily, with an average time of 1–3 h (75 people (28.8%)) and 3–5 h (67 people (25.8%)). Most subjects (219 people (84.2%)) had used the Internet for more than 8 years. The subjects used various kinds of cloud services, including cloud document management (i.e., Google Docs or Microsoft Office Live), cloud Email (i.e., Google Gmail), SNS (i.e., Facebook), video or audio sharing services (i.e., YouTube), instant messaging software (i.e., Line or WhatsApp), governmental public cloud services (i.e., Taipei Cloud), and cloud online game or blog services. However, in the case of cloud hard drives (e.g., Dropbox), governmental public cloud services (i.e., Taipei Cloud), rental clouds server or computing services (i.e., Amazon EC2 or Hinet HIcloud), rental cloud platforms (i.e., Google GAE or APP platforms for Android and iOS), and

rental cloud information security and protection systems (i.e., Hinet HIcloud), there were significant differences in the ratio between male and female users.

5. Data Analysis and Results

Partial least squares structural equation modeling (PLS-SEM), using SmartPLS Version 2.0 by Ringle et al. [66], was employed to assess validation and test the hypotheses suggested by scholars [67,68]. PLS-SEM regression is a recent technique that combines advantages from multiple regression and principal component analysis. The PLS-SEM approach has improved communication in a variety fields in recent years with non-normal data, small sample sizes, and the use of formative indicators being the most prominent reasons for its application [69–71]. According to the criterion of Fornell and Larcker [68], the reliability (i.e., Cronbach's alpha and composite reliability) and average variance extracted (AVE) of each construct were all higher than 0.7 and 0.5, respectively, indicating the achievement of convergent validity (as shown in Table 1).

Table 1. Reliability analysis and convergent validity.

Construct	Items	Range of Factor Loadings	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy (PE)	4 items	0.784~0.898	0.863	0.907	0.710
Effort Expectancy (EE)	4 items	0.852~0.920	0.921	0.944	0.808
Social Influence (SI)	3 items	0.846~0.898	0.831	0.899	0.748
Facilitating Conditions (FC)	4 items	0.701~0.831	0.783	0.860	0.607
Hedonic Motivation (HM)	3 items	0.853~0.908	0.851	0.910	0.771
Price Value (PV)	3 items	0.820~0.902	0.846	0.906	0.764
Habit (HT)	4 items	0.848~0.931	0.912	0.938	0.792
Continuance Intention (CI)	3 items	0.836~0.912	0.860	0.915	0.782

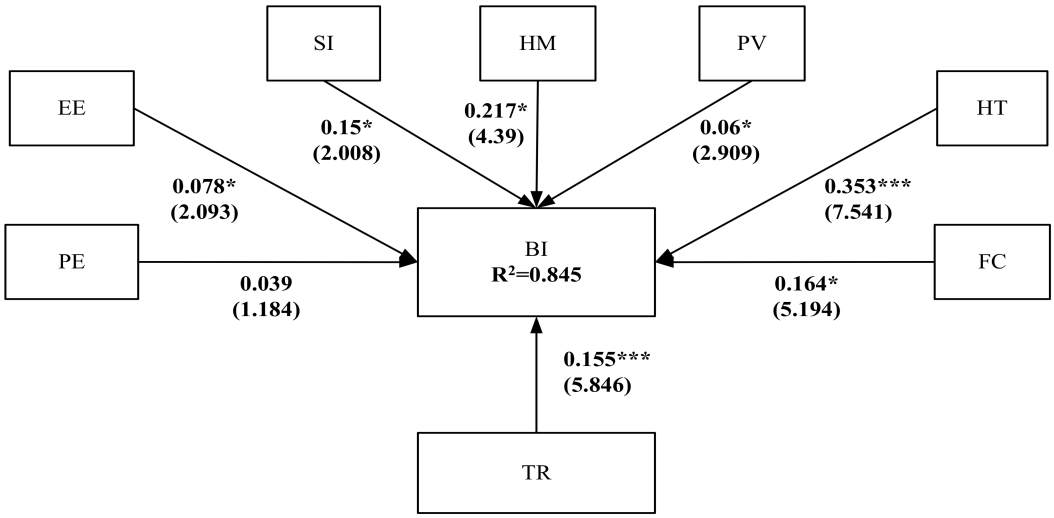
For goodness of fit (GoF), the calculation formula proposed by Moores [72] (GoF = $\sqrt{((\text{AVE})\overline{*}(\text{R\^{}2})\overline{)}}$) was used to check the results. The value after checking calculation was 0.795, higher than the general standard value of 0.36, and indicating that the GoF of the framework of the research was good.

Path coefficients represent the strength and direction of the correlation between latent variables, while the value of R-square means the percentage of exogenous variables can be used to explain endogenous variables, and it represents the prediction ability of a research framework. Higher values indicate stronger prediction ability. Path coefficients and the value of R-square show the level of fitness between the structure model and empirical data. The values of each path coefficient, t-statistic, and the results of hypotheses testing among the latent variables are shown in Table 2 and Figure 2.

Table 2. Path coefficients and results of hypothesis testing.

Hypothesis	Path	Standardized Path Coefficient	*t*-Value
H1	PE → CI	0.039	1.184
H2	EE → CI	0.078 *	2.093
H3	SI → CI	0.150 *	2.008
H4	FC → CI	0.164 ***	5.194
H5	HM → CI	0.217 ***	4.39
H6	PV → CI	0.060 *	2.909
H7	HT → CI	0.353 ***	7.541
H8	TR → CI	0.155 ***	5.846

Note: * p-value < 0.05; *** p-value < 0.001.



Note: ***p-value< 0.05; ***p-value< 0.001***

Figure 2. Results of hypothesis testing.

As suggested by Chin [73], the proposed hypotheses of this research were evaluated using the bootstrap resampling estimation of PLS. Significance of the path coefficients was assessed adopting bootstrapping (generating *t*-values and significance levels). According to Chin [73], bootstrapping is a non-parametric bootstrapping technique for estimating the precision of PLS estimates, and it was used on our empirical data to examine the statistical significance of the path coefficient. As suggested by Hair et al. [74], the *t*-statistics were computed by using 5000 bootstrap samples. It is notable in Table 2 that except for H1, the other seven hypotheses were all supported, indicating that in the framework of UTAUT2 and TR, EE, SI, FC, HM, PV, HT, and TR of cloud services all had positive impacts on CI. Their *t*-test results were 2.093, 2.008, 5.194, 4.39, 2.909, 7.51, and 5.846, respectively. Hypothesis 1 (i.e., "PE" towards "CI") had only 0.039 for the value of the path coefficient, but the probability of significance ($p > 0.05$) means that the original hypothesis of a positive impact could not be supported by the result.

For the analysis result of this study, the R-square value was 0.845, indicating that the eight determinants proposed by this framework can be used to explain 84.5% of the results of CI, indicating that it has high explanatory power.

The moderation effects of gender, age, and user experience on personal cloud services are also considered. For this, the study conducted by Lowry and Gaskin [75] was referred to in order to perform multi-group analysis with the *t*-test calculation formula for the moderation effect, and related analyses were conducted based on this (Tables 3–7).

Table 3. Comparison of groups of paths towards gender.

Path	Gender	Samples	Regression Weight	S.E.	*t*-Value
EE → CI	Male	127	0.120	0.046	1.225
	Female	133	0.054	0.030	
FC → CI	Male	127	0.113	0.031	0.622
	Female	133	0.142	0.034	
HM → CI	Male	127	0.157	0.038	3.541 ***
	Female	133	0.328	0.039	
HT → CI	Male	127	0.430	0.036	3.197 **
	Female	133	0.256	0.041	
PE → CI	Male	127	0.081	0.027	0.909
	Female	133	0.038	0.038	
PV → CI	Male	127	0.022	0.014	0.308
	Female	133	0.031	0.025	
SI → CI	Male	127	0.178	0.020	0.039
	Female	133	0.180	0.025	
TR → CI	Male	127	0.178	0.031	1.272
	Female	133	0.132	0.021	

Note: ** *p*-value < 0.01; *** *p*-value < 0.001.

Table 4. Comparison of groups of paths towards age.

Path	Age	Samples	Regression Weight	S.E.	*t*-Value
EE → CI	26–30	38	0.409	0.032	0.804
	31–35	42	0.441	0.025	
FC → CI	26–30	38	0.171	0.030	0.017
	31–35	42	0.170	0.028	
HM → CI	26–30	38	0.158	0.036	1.172
	31–35	42	0.111	0.021	
HT → CI	26–30	38	0.347	0.042	3.639 ***
	31–35	42	0.166	0.029	
PE → CI	26–30	38	0.125	0.025	0.215
	31–35	42	0.132	0.020	
PV → CI	26–30	38	0.133	0.198	0.473
	31–35	42	0.045	0.015	
SI → CI	26–30	38	0.164	0.013	5.355 ***
	31–35	42	0.254	0.011	
TR → CI	26–30	38	0.253	0.018	3.753 ***
	31–35	42	0.162	0.017	

Note: *** *p*-value < 0.001.

Table 5. Comparison of groups of paths towards age.

Path	Age	Samples	Regression Weight	S.E.	*t*-Value
EE → CI	36–40	37	0.052	0.022	0.602
	41–45	44	0.034	0.020	
FC → CI	36–40	37	0.345	0.025	6.788 ***
	41–45	44	0.152	0.016	
HM → CI	36–40	37	0.045	0.038	0.903
	41–45	44	0.085	0.026	
HT → CI	36–40	37	0.352	0.029	7.832 ***
	41–45	44	0.652	0.026	
PE → CI	36–40	37	0.152	0.024	4.499 ***
	41–45	44	0.288	0.020	
PV → CI	36–40	37	0.198	0.011	2.000 *
	41–45	44	0.232	0.013	

Table 5. *Cont.*

Path	Age	Samples	Regression Weight	S.E.	*t*-Value
SI → CI	36–40	37	0.237	0.013	2.309 *
	41–45	44	0.283	0.015	
TR → CI	36–40	37	0.227	0.021	2.880 *
	41–45	44	0.151	0.017	

Note: * *p*-value < 0.05; *** *p*-value < 0.001.

Table 6. Comparison of groups of paths towards experience.

Path	Experience	Samples	Regression Weight	S.E.	*t*-Value
EE → CI	Under 1 year	54	0.108	0.020	0.476
	1–3 years	128	0.136	0.037	
FC → CI	Under 1 year	54	0.049	0.022	5.012 ***
	1–3 years	128	0.313	0.033	
HM → CI	Under 1 year	54	0.130	0.025	0.586
	1–3 years	128	0.085	0.049	
HT → CI	Under 1 year	54	0.534	0.021	1.558
	1–3 years	128	0.391	0.059	
PE → CI	Under 1 year	54	0.215	0.020	3.239 **
	1–3 years	128	0.042	0.034	
PV → CI	Under 1 year	54	0.014	0.012	3.323 **
	1–3 years	128	0.151	0.026	
SI → CI	Under 1 year	54	0.223	0.014	5.427 ***
	1–3 years	128	0.003	0.026	
TR → CI	Under 1 year	54	0.090	0.014	3.561
	1–3 years	128	0.215	0.022	

Note: ** *p*-value < 0.01; *** *p*-value < 0.001.

Table 7. Comparison of groups of paths towards experience.

Path	Experience	Samples	Regression Weight	S.E.	*t*-Value
EE → CI	4–6 years	36	0.135	0.031	0.716
	Over 7 years	42	0.097	0.042	
FC → CI	4–6 years	36	0.388	0.032	3.165 **
	Over 7 years	42	0.260	0.026	
HM → CI	4–6 years	36	0.608	0.021	13.895 ***
	Over 7 years	42	0.017	0.036	
HT → CI	4–6 years	36	0.252	0.022	5.234 ***
	Over 7 years	42	0.549	0.050	
PE → CI	4–6 years	36	0.034	0.025	0.762
	Over 7 years	42	0.003	0.031	
PV → CI	4–6 years	36	0.072	0.014	2.109 *
	Over 7 years	42	0.015	0.022	
SI → CI	4–6 years	36	0.100	0.022	0.236
	Over 7 years	42	0.093	0.022	
TR → CI	4–6 years	36	0.098	0.019	0.709
	Over 7 years	42	0.120	0.023	

Note: * *p*-value < 0.05; ** *p*-value <0.01; *** *p*-value < 0.001.

6. Research Analyses and Discussion

The results suggest that the EE, SI, FC, HM, PV, habit, and TR for cloud service all positively influence CI, while the results for other constructs do not support the proposed hypotheses.

The path coefficient for PE on CI is 0.039, revealing that even though the function of IT products may have been a critical factor influencing consumption behavior, the continuance intention of consumers toward using cloud services is now less affected by the current expectancy. This may affect individual cloud services by placing more emphasis on the daily life services and less on the workplace. In addition, it suggests that individualized

cloud services should be divided into general services and customized services. The general services offer convenient email, along with community and message services to the customer, while the customized services may offer distance home care or a house surveillance system for customers with unique needs. These services can be offered by multiple terminal devices, such as a mobile phone, Pad, PC, TV, and/or smart phone. Doing so not only reinforces usage intention, but also realizes the individualized service by analyzing the habits and tendencies of different users.

The EE may be similar to accessibility [47,60], and the path coefficient, 0.078, for EE on CI significantly supports the hypothesis. This reveals that cloud services and accessibility are primary concerns of the public, and if the system fails to offer a secure environment and a reasonable operational interface while integrating customer accounts, it will still not be accepted by the customers. Simplification of the operational interface is expected, even though most contemporary customers can easily adapt to different interfaces. Straightforward settings and a simplified interface are concerns for potential end users, and the enterprise development of service providers should ensure that these issues are properly addressed.

The path coefficient for SI on CI is 0.15, indicating that it has a significantly positive influence. This reveals that the CI of a customer using a cloud service may be influenced by the social atmosphere. When the customer understands the merits of the cloud service, they may influence the intention of others, thereby improving the efficiency of cloud service promotions. On the other hand, the path coefficient of facilitating conditions on CI is 0.164, so the result is statistically significant. This result reveals the importance of preparing the environment for customers to accept the cloud service. Environment preparation may include items such as having a business-oriented environment, applying advertising techniques, acquisition of suitable equipment, and developing appropriate application interfaces. However, price has a slight impact on the path of CI since it has a *t*-value of 2.909, and it is still observed to support the proposed hypothesis. In this research, most of the listed basic functions of the personal cloud services are free of charge, although the findings show that the public still supports a consumption model of pay-as-you-go for cloud services. In other words, payment depends fully on user requirements. Currently, all profitable information services tend to utilize the marketing strategy of no charge to gain attention from a wide range of netizens. However, if the personal requirement exceeds the tradeoff to offer free basic services, additional fees may be incurred.

It is also notable that, with respect to CI, habit has a path coefficient of 0.353 and a *t*-value of 7.541, showing a positive influence; therefore, it is the most important factor influencing CI. This indicates that habit plays a critical decision role with respect to whether the consumers can continue accepting and/or using personal cloud services. In addition to certain powerful capabilities, closeness to human nature, compliance with customers' needs for the service itself, and exploration of big data could be factors that influence clients' use habits. With additional improvements, it may be helpful for users to continue familiarizing themselves with related services.

Not only is this study based on UTAUT2 theory, but it also integrates four other aspects, namely, optimism, innovativeness, maladjustment, and security concerns into a single aspect—"technological readiness", used to assess the influence of usage intention towards personal cloud services. This study found a path coefficient of 0.155 and a *t*-value of 5.846 for technological readiness with respect to behavior intention. Thus, the influence is clearly positive, indicating that most people intend to use cloud service technology, even though they may have different personal characteristics and attitudes towards using the technology. Furthermore, inherent physical operations and geographical area limitations are no longer an issue. It is predicted that an individual's life will be linked with cloud technologies and services even more closely in the future. Thus, cloud service providers are strongly recommended to pay more attention to the technological readiness of users to implement cloud services. For users with certain personal characteristics, some use features may have a strong need for a user friendly-design.

This study found that EE is not moderated by gender with respect to CI, and it is also not interfered with by age or use experience. This indicates that current cloud services are popular among both males and females. In addition, the cloud services examined in this study are dedicated to the public for personal use rather than for use in an enterprise/organization environment. Thus, this study found that independent of age, education level, income, or even occupation, 93.5% of the subjects have 5 years or more Internet use experience and 96.2% spend an average of more than 1 h every day on using the Internet.

This study also found that SI for CI is not influenced by the moderation of gender. SI is important for both males and female because the personal cloud services studied in this research are dedicated to the public for common use rather than for enterprise/organization environments. Under the frequent use of social tools (such as Facebook and YouTube) and instant messaging systems, males and females are easily influenced by friends or others. However, the influence of SI on CI was moderated by both age and use experience. The influence for the age level of 31 to 35 is larger than that of 26 to 30, and the age level of 41 to 45 is most susceptible to the effect of the social influence factor. Thus, elderly people make their decisions based on the maturity of the cloud service technology, reasonable price, and the compliance of personal cloud services. To this end, in practice, cloud service providers are recommended to promote cloud services on the Web 2.0 environment, as mentioned above, to utilize the social share approach in order to facilitate rapid marketing.

CI is not influenced by gender, and males and females have the same causes of CI since only age and use experience matter. Users with an age of 36–40 years old are more susceptible to the causes of continuance intention than people with an age of 41–45 years old. Users with experience of less than 1 year or more than 7 years are less susceptible than those with experience of 1–3 or 4–6 years. However, these young users are influenced by supporting services provided by the cloud service companies, and difficulty understanding issues such as base installation failure and/or poor customer services will drive them away. Therefore, it is highly suggested that companies should make sure that accompanying services and the supporting installations are sufficient.

Gender and use experience, rather than age, may influence the hedonic motivation of continuance intention. The entertainment factor is important to people of any age, but females are more susceptible to it than males. For example, a company could provide personal cloud services integrated with a real-name registration system with a humanistic human–machine interface as well as a functional and interesting design. With the gender information provided by the real-name system, the service system can change the background color of the interface to pink or warm color automatically on special occasions (i.e., birthday, Valentine's Day, Mother's Day, and wedding anniversaries) to satisfy the visual demands of female users. Moreover, people with less than 1 year of use experience and people with use experience of 1–3 years show no difference regarding the influence of the entertainment factor. People with use experience of 4–6 years are more susceptible to the entertainment factor than people with use experience of over 7 years.

PV is not affected by the gender factor on CI. This may be because personal cloud services have been promoted in recent years and quickly increased their market share and number of users, so a marketing strategy of a free user and experiential service could be adopted at the initial/early stage. Once more than the basic set of provides service is requested, a reasonable fee could be charged. In addition, price over continuance intention is affected by the age and user's experience. The 41–45 age group is more easily affected by the price than the 36–40 age group. Lastly, users with experience of 1–3 years and 4–6 years are more affected than those with less than 1 year and more than 7 years.

Habits of users can be affected by gender, age, and user experience in terms of continuance intentions. Males are more affected by habits than females. Users with an age of 26–30 years old are more affected by habits than those with an age of 31–35 years old, while users with an age of 41–45 years old are more affected by habits than those with an age of 36–40 years old. Users with more than 7 years of experience are more affected

by habits than those with 4–6 years of experience, while there is no significant difference between users with less than 1 year and 1–3 years of experience. This indicates that once male users are used to certain personal cloud services, they are less likely to change.

Gender difference has no significantly moderating effect between TR and CI, indicating that it is of equality for males and females in personal cloud services usage. It was also found that the effect of the degree of TR on CI is related to age and user experience. Users 26–30 years old and 36–40 years old are more easily affected by the degree of technological readiness than their 31–35-year-old and 41–45-year-old counterparts. This indicates that younger users more easily accept and use new technologies, including cloud services. This may be due to familiarization of technological usage by the multi-screen, i.e., mobile phone, tablets, laptops, and personal computers. Therefore, it is highly recommended that when offering cloud services, younger age groups should be given additional attention and provided with advanced functions, such as audio and visual effects.

7. Conclusions

The theoretical contribution of this study is the addition of the TR dimension to explore personal traits in the UTAUT2 model applied to a consumer environment, permitting a more complete exploration of acceptance behavior in terms of intention to use. The individual intention towards use in the acceptance behavior for cloud services can be theoretically better supported by this research framework. In addition, there was a total seven dimensions, namely, the dimensions of EE, SI, FC, HM, PV, HT, and TR, that had positive impacts on the continuance intention towards using cloud services. The EE dimension demonstrated that users are more likely to use services that have more human aspects, ease of operation, and user-friendly interfaces. In the dimension of SI, the acceptance and usage of cloud service technology for individual users are influenced by the people who are important to them, such as the elderly, family members, and friends. In the dimension of FC, the results show that if a cloud service provider offers a better technical service and a more complete system framework, then users will be more willing to accept and use that service. In the dimension of HM, if there are interesting or pleasant experiences attached to the use of the personal cloud services, users will be more willing to remain with that service. In the dimension of PV, consumers are willing to support the idea of pay-as-you-go for services, and this tendency has no significant result in terms of the gender difference. In the dimension of HT, users habitually use services, which has a positive impact on the intention towards use of acceptance behavior. In the dimension of TR, despite positive factors (i.e., optimism or innovation) that encourage users to use new technologies or the negative factors (i.e., maladjustment or security concerns) that make them unwilling to adopt new technologies, the positive and negative factors in the dimension of TR together determine the tendency of an individual to use cloud services. Finally, the research findings show that the acceptance degree of users for personal cloud services is rather high. However, in addition to diverse functions in service applications, younger customers also seek interesting features. Since the framework explains 84.5% of variance in "continuance intention," the results can also be used as a basis for future research on cloud service behaviors.

Some research limitations of this study may be considered in the future work. First, this research subjects were from Taiwan, restricting the generalizability, so future research could collect data from other areas to better understand any differences in the acceptance behavior for cloud services due to geographical, cultural, or ethnical factors. Second, for better and broader applicability, other dimensions may also be included for a multi-layer discussion, and other themes could be used to verify the generalization of the proposed model. Finally, when the conditions of the cloud service providers are available, future work can consider if a cloud service can deal with both the demands of personalization and customization. This could give a better understanding to create higher rates of usage and loyalty towards cloud services.

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