



Article Interpreting Usability Factors Predicting Sustainable Adoption of Cloud-Based E-Learning Environment during COVID-19 Pandemic

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Abstract: The COVID-19 pandemic affected educational institutions in an unrivaled way around the globe and forced them to switch from conventional classroom learning mode to e-learning mode within a short time period. Neither instructors nor students had ample time to prepare. The purpose of the current study is to accomplish two objectives: to explore the functional relationship between attitudinal readiness (ATR), subjective well-being (SWB), and cloud-based e-learning adoption intention in Taiwan and examine the constancy of recommended proposed relationships among different students' groups. The model was then empirically tested using data of 256 university students by structural equation modeling. The current study demonstrates that ATR is completely explained through four dimensions: peer reference, perceived ease of use, perceived usefulness, and perceived ubiquity. SWB is positively interpreted through four dimensions: online course quality, system quality, perceived service quality, and perceived closeness. Self-efficacy has a significant relationship with both attitudinal readiness and adoption intention of a cloud-based e-learning system. Finally, the invariance test explores substantial variance among students who intend to use the system and students who reject it. Therefore, researchers and practitioners regarding educational, technological innovation must consider this empirical evidence to develop and validate a sustainable cloud-based e-learning program in higher education.

Keywords: e-learning adoption; learning process; information communication technology; COVID-19; attitudinal readiness; subjective well-being

1. Introduction

Learning environmental motivations has always been the critical determinant influencing students' learning intention [1]. The literature has explored good learning environmental motivations for developing students' inherent learning stimuli and supporting them to attain the essential information and skills, achieving the intended objectives [1,2]. Mashau [3] stated that universities are accountable for making a positive learning environment to endorse effective learning. They also found that students would benefit from mutual support among peers, updated courses, and superior teaching policies in such an atmosphere.

The severe spreading of coronavirus (COVID-19) has posed phenomenal threats to public safety, the economy, and education. It intensely affected educational institutions worldwide and almost entirely shutdown schools, colleges, and universities [4]. Education is the backbone, therefore, for the development of individuals and the sustainability of any society. To keep up sustained and efficacious education during the COVID-19 pandemic,



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). educational institutions of several countries switched their teaching mode from classroom to online teaching [5].

Higher educational institutions (HEIs) in Taiwan, like their counterparts in other countries, are among the organizations confronting the COVID-19 effects in their operations inclusive and specifically on sustainable development teaching [6]. HEIs have had to promptly switch from a face-to-face teaching mode to online teaching mode [4]. Most of the students and instructors have no prior online learning experience nor are they acquainted with the technical jargon required for online learning [2,6–8]. Thus, HEIs pursue strategies for bringing the instructive and rational usefulness of e-learning to every student and instructor, and encouraging students to engage in learning has become a topic of increasing attention [7,8].

Electronic learning (e-learning) is the delivery of learning and training through digital resources [1]. It is an environment that provides a medium for interactive communication between the instructor and the learner [5,9,10]. It is also considered the digital transformation of the traditional education system and study materials into a digital one [5,11,12]. The e-learning systems have been visible on the horizon for many years. Despite the several benefits of the e-learning system, including enhanced student-instructor relationships, improved both students and instructors' empowerment, teaching efficiency, coordination, and quality, the literature indicated that e-learning system adoption continues to be slow due to numerous reasons [10–12]. Lichoro [13] found instructors do not consider themselves fully ready and competent enough to teach online. On the other hand, Abuhassna et al. [10] explored the learning effect positively influencing e-learning taken by students in a stable environment. Al-Rahmi et al. [11] adopted the technology acceptance model to explore students' behavioral intention in using the e-learning system and found a positive relationship between students' attitude and e-learning adoption. However, the COVID-19 pandemic has brought a fresh resurgence in learning, and HEIs in Taiwan are keen to ensure continuity of a successful e-learning system and practice as it is confirmed that e-learning could replace classroom learning for an extended period of time as well as emerge as a novel way of learning in the post-COVID-19 period. However, whereas students need to adopt e-learning because of the situational perspective extended by sudden detailed changes, the gap in their psychological cognition may lead to differences in learning effect and learning process. Thus, to understand this gap, the current study further explores the psychological, cognitive process in which students are involved in e-learning in the context of a pandemic outbreak.

The term 'sustainable cloud-based e-learning system' has several potential interpretations. From the current study perspective, it is defined as a learning configuration including data and communications in which innovation has been created and executed inside an e-learning system. It has experienced a proof-of-idea stage and has been helpful for instructing and learning based on the proof delivered. Secondly, the e-learning idea, plan, framework, or resources can be embraced and perhaps improved for adoption further than the earliest development environment. Finally, the organization depends on the preservation, adoption, and further development of the e-learning perception, strategy, and resources. The overall aim is to develop a sustainable cloud-based e-learning system that could transform teaching, learning, and higher education organizations to perform better in any contrary context.

There is a need for a better understanding of the factors affecting students' intention to adopt a sustainable cloud-based e-learning system as they are key users. Therefore, their intention determines the overall success of the system's implementation, optimizes development policies, and ensures that expected benefits show up. The purpose of the current study is to identify the factors influencing initial readiness to adopt a sustainable cloud-based e-learning system. We employ several factors based on the existing literature to develop a construct termed attitudinal readiness (ATR) in the current study. Additionally, subjective well-being (SWB) and self-efficacy are also incorporated as the factors of adoption intention. Thereby, the current study further explores and compares the correlation between adoption intention and its antecedents among student subgroups based on adoption intention.

2. Theoretical Model

2.1. Cloud-Based E-Learning System

E-learning can be defined as the online transfer of information to determine education, teaching, knowledge management, and performance management [14]. It incorporates learning with technology and instruction delivered through simply digital technologies such as the internet [15]. Cloud-based e-learning can be defined as a mode of learning aimed at improving the quality of teaching and learning through the use of information communication technology (ICT) [16], emphasizing a learning management system as a platform that connects lecturers and students [17]. In other words, a cloud-based e-learning system is a software application or web-based technology that is used to plan, deliver, or access a particular learning process through information technology (IT) and computer networks. A sustainable cloud-based e-learning system supports online course creation, maintenance, and delivery; student enrolment and management; education administration and student performance reporting using a simple web-based software application platform.

Although e-learning is not new, only recently, especially during the COVID-19 pandemic, has it received substantial interest from educators and the government. As it is a generally accepted view that higher education institutes (HEIs) play a key role in transforming societies by educating learners, decision makers, leaders, entrepreneurs, etc., and HEIs are among the organizations facing the COVID-19 impacts in their operations as a whole and on sustainable development teaching in particular. McCowan [18] also emphasized that universities were attributed a central role, namely in the post-2015 development agenda and the achievement of the sustainable development goals (SDG). This role in a post-COVID-19 world will only be more urgent. In fact, Gewin [16] went further and stated universities continue to cope effectively and sustainably with the dynamic nature of sustainability by displacing barriers, changing teaching paradigms, developing social competencies, communication skills, and community relations. Bizerril et al. [19] mentioned the significant contributions to higher education (HE) sustainability, especially in the dimensions of education, research and assessment, and reporting.

The implementation of sudden online teaching could also create a challenge as most instructors and students do not have a track record of using HEI to aid pedagogical goals. Additionally, e-learning is a challenge for the current teaching practice model, face-to-face. Thus, successful responses of HEIs of Taiwan include developing a sustainable cloudbased e-learning system that can continue to contribute during the time of the COVID-19 pandemic as well as learning teaching for after the COVID-19 inclusive crisis.

2.2. Stimulus, Organism, Response (S-O-R) Model

The concept of the S-O-R model was initially developed from stimulus–response theory. This model describes how individuals respond to external stimuli. Later, the SOR model was improved by incorporating the concept of organism between stimulus and response by Mehrabian and Russell [20]. The SOR model treats environmental cues as stimuli that affect an individual's cognitive and affective reactions, affecting an individual's internal cognitions and emotions and, in turn, affect behavior.

With the spread of the global COVID-19 pandemic, many learning patterns have begun to transform from the offline classroom to the online classroom, and the sudden changes in the learning environment have compelled students to try to adopt multimedia tools for learning [21,22]. The psychological changes may induce students to have different learning styles and engagement behaviors; thus, it is necessary further to explore the development of their entire learning process.

In the e-learning context, stimulus factors include content, network, and interaction characteristics. An organism refers to the individual's internal cognitions and emotional

states, such as value perception, social- or relational-oriented perception and affection, and response, including evaluation and learning engagement. The SOR model, the current study perspective, helps understand the impact of interpersonal interaction factors and flow experience on e-learning intention. Additionally, the stimuli perceived in the e-learning environment can be considered stimuli of the external environment and are correlated with the mental response generated in learning (subjective well-being), attitudinal readiness, and self-efficacy.

2.3. New Technology Adoption Intention

Ongoing technological transformation concurrently creates turmoil among users. Davis [23] proposed a theory called the technology acceptance model (TAM) to model users' acceptance of new information systems or technology. The TAM proposed two particular beliefs that are the key drivers for the adoption of a novel system: perceived usefulness is defined as the degree to which a person believes that using a specific system would enhance his or her job performance, and perceived ease of use is defined as the degree to which a person believes that using a particular system would be free of physical and mental efforts [24]. One of the key notions of TAM is individuals are rational in their decision-making processes and actions so that cognitive approaches can be used to predict behaviors.

As theories, perceived usefulness and perceived ease of use are considered as cognitive situations. According to Moon et al. [25], perceived usefulness (PU)and perceived ease of use (PEOU) are the motivations that characterize the system and features competencies. At the same time, attitudinal readiness signifies the reason to use the system, leading to consumers' retort to adopt the system. Students come to decisions about what is received as motivation and dealt with. Regarding the process, students do a component of sensation or emotional and component of reasoning [24,26,27]. After obtaining the stimulus, students' adoption intention can be determined positively or negatively toward the system [27–29].

2.4. E-Learning Adoption Intention

E-learning adoption or engagement is students' intention of taking part in learning behaviors for attaining better information or skills [30]. It is the readiness for the possibilities of an e-learning environment. E-learning adoption points out the significance of behavior (commitment), regard (wellbeing or satisfaction), and rational commitment in e-learning [31]. As revealed by the literature, it is one of the critical determinants for enhancing e-learning results [32,33].

While students involve themselves in e-learning on their own inventiveness, they take inventiveness in and/or focus on attaining and putting on novel skills or understanding, resolve difficulties through motivating methods, and demonstrate an encouraging attitude toward their e-learning practice [34]. Developing prototypes and processes that endorse students' e-learning adoption is critical to developing the arena of education [14]. The more students participate in e-learning, the greater their eagerness for e-learning is, and the more developed they become.

3. Model and Hypothesis Development

3.1. Attitudinal Readiness (ATR)

Adopting a new information technology (IT) system requires prospective users have a substantial degree of eagerness for a similar system. Considering the features of the cloud-based e-learning system, the current study went through the literature on factors influencing prospective students' readiness to adopt a new technological innovation. Drawing from TAM [23] and S-O-R (stimulus–organism–response), the literature shows AR can be described through perceived usefulness (PU), perceived ease of use (PEOU), peer reference (PR), and perceived ubiquity.

Davis [22] proposed that PU and PEOU are the two fundamental constructs for building users' intention to adopt any new technology. The precondition for users to consider any system or technology practice is that the new system or technology should be useful and easy to use for users to employ the system [27]. Utilizing TAM and incorporating other appropriate theories, S-O-R offered effective influence of peer reference in the adaptive intention of any new system. PR is stated as the extent to which an individual identifies how essential others consider adopting the new technology. E-learning adopted students may be recognized by their friends and other students as being more modern and up-to-date with technology, more intelligent, or more successful. Perceived ubiquity characterizes a conclusive form of spatial, time-based, and circumstantial capability to access cloud-based e-learning technology irrespective of place and time [35].

There is intense proof from previous studies reinforcing the excellent level of correlation between factors in TAM (PU and PEOU) perceived by investigators in diverse technologies across the planet. A study intended to confirm the influence of standard method variance using TAM by Sharma et al. [36] stated the intense relationship between PU and PEOU. A meta-analysis comprising 26 studies using TAM also detected influential associations testified by researchers between PU and PEOU [37].

Previous studies in different perspectives observed the levels of the ubiquity of the technology influence the levels of users' involvement in the system, such as commercial sharing systems [38], mobile internet [39], and e-learning systems [40]. The literature indicated the capability to access the system anyplace and anytime is exceptionally pertinent to using the e-learning system. The advantage of ubiquity impacts students' overall assessment of the learning system [13,37]. In cloud-based e-learning contexts, students' familiarities of a significant level of flexibility are more likely to boost their well-being using this e-learning technology [9].

Studies on point-to-point social influence in the student learning environment have revealed student individualities and activities that are inclined spatially and temporally to quintessence [41]. The instrument for this is usually chosen to be peer references [9]. Eagly and Karau [42] recommended individuals be positively or negatively assessed based on the acquiescence of their behaviors to their role and surroundings. Thus, the persuading procedure on collaborative behavior between peers cannot be overlooked. The literature in interpersonal relationships publicized that peer references play an imperative role in compelling discernment and behaviors; the more individuals perceive peers to be involved in a definite behavior, the more likely they are to engage in the same or similar activities [9,43]. If students observe that many peers engage in e-learning, they are more likely to be involved as well [43]. Regarding online group behavior, having more peer references induces the students to boost their opinion of themselves, and students further consider that their peers appreciate their behaviors.

Whereas different studies recommended different directional relationships between peer reference, PU, PEOU, and perceived ubiquity, these constructs remain the most commonly studied and endorsed factors influencing the usage intention of a new technology or system. Moreover, regardless of recommended relationships, the existing works make us infer that these determinants are not actually independent constructs influencing one another and are intensely associated instinctively. Still, they are essential dimensions of a single construct named ATR in the current study. The current study thus suggests ATR as a second-order construct with four dimensions: peer reference, PU, PEOU, and perceived ubiquity. ATR in the current study is stated as the extent to which a student considers himself/herself ready to adopt a cloud-based e-learning system. Thus, we hypothesize:

Hypothesis 1 (H1). *ATR is described through peer reference, perceived usefulness, perceived ease of use, and perceived ubiquity.*

3.2. Attitudinal Readiness and Behavioral Intention

The literature found dimensions of attitude significantly influence new technology or system adoption intention [23,44,45]. Dutta et al. [44] found positive attitudes improved users' adoption intention positively. Studies from different perspectives, such as an e-

learning system and adaptive learning, perceived attitude positively influencing adoption intention [9,12,40]. Hence, we hypothesize:

Hypothesis 2 (H2). Attitudinal readiness positively influences cloud-based e-learning adoption intention.

3.3. Subjective Well-Being (SWB)

Subjective well-being is considered that which evaluates opinions of the satisfaction considering prospective positive outcomes (well-being). Students' adoption can be viewed as a precedent of satisfaction and feeling of well-being [46]. Prior studies comprehensively investigated and established users' opinion of well-being as being crucial to their assessment and engagement to new technology or system [47,48]. Yang et al. [49] suggested that while SWB is fundamental to user engagement, the same diverges across engagement methodologies with nontraditional motility. The adoption of e-learning technology is recognized as unexplored than traditional face-to-face teaching [46]. The dimension of well-being is incredibly outcome specific and can be self-regulating of each other [48]. The current study reviews the literature precisely about students' behavioral intention toward systems empowered by information technologies such as sustainable cloud-based e-learning, online teaching, mobile learning applications, etc., to come to well-being segments that are important for a sustainable cloud-based e-learning system. Based on the evaluation of prior studies precise to students' intention to adopt educational, technological innovations, in the current study, subjective well-being refers to the four significant dimensions: online course quality, system quality, perceived service quality, and perceived closeness.

3.3.1. Online Course Quality

Online course quality, from a current study perspective, determines the quality of course content delivered through a cloud-based e-learning system. Course content quality is the decision by the students of the extent to which cloud-based e-learning technology is offered with effective content, regarding the definite requirements of the students [50]. The metrics for online course quality incorporate personalization, comprehensiveness, being easy to understand, safety, appropriateness, accessibility, significance, and format of course contents delivered through the sustainable cloud-based e-learning system. The literature showed that online course content quality significantly influences students' well-being of an e-learning system [51,52]. Thus, the quality of course content is one of the critical considerations for students to apprehend the effectiveness of a sustainable cloud-based e-learning system and to have better extents of well-being by adopting a sustainable cloud-based e-learning system.

3.3.2. System Quality

In the perspective of the current study, the system quality states the preferred features of the cloud-based e-learning system. Instruments of system quality incorporate receptivity, usefulness, user-friendliness, trustworthiness, and adaptability [53]. The literature explored system quality as an essential determinant of students' well-being of an e-learning system [54,55]. Therefore, the more students consider that the cloud-based e-learning system is consistent, accessible, and understandable, the more willing they are to adopt it, simultaneously boosting their well-being.

3.3.3. Perceived Service Quality

Perceived service quality states that the inclusive assistance is provided by the service provider, such as the ICT department or definite unit of a university or an organization [53]. Perceived service quality, according to the current study context, implies that the support is delivered by ICT technical personnel of the university. Instruments of perceived service quality incorporate receptiveness, usefulness, and accessibility of technical personnel [53]. The literature explored how perceived service quality positively influences students' wellbeing in an e-learning system [51,53].

3.3.4. Perceived Closeness

Perceived closeness is the wisdom of mutual belief and consideration developed from consistent interpersonal interaction and satisfying communication [56,57]. While being employed in the association between instructors and students, it is inferred as the outcomes of interaction with instructors regarded by students [56]. The association between students and instructors is a significant interpreter of subjective well-being [58]. The literature indicated that students have the highest inspiration while they considered a significant association with instructors [57,59]. Constructing a convincing, considerate association with instructors makes students feel secure, care for, and skillful in the university environment, influencing intuitive motivation [60]. Students' inspiration to adopt an e-learning system is attentively associated with instructors' capability to inspire association. Such a relationship also influences the teaching outcomes, incorporating the students' consideration of engaging with the new e-learning system. The literature indicated that students' well-being score is not reasonable if their instructors exhibit ambiguity and displeasure while students demonstrate their presentation in class [56,60]. Koca [61] and Hershkovitz [62] explored students who are more affectionately nearby with instructors demonstrate encouraging improvement approaches in humanity and the academic sector. That could also be prolonged to a further pervasive educational context. For instance, in a cloud-based e-learning environment, instructor-student closeness positively influences students' well-being.

Hypothesis 3 (H3). *SWB is explained through online course quality, system quality, perceived service quality, and perceived closeness.*

3.4. Subjective Well-Being and E-Learning Adoption

Students' subjective well-being generally states the quality of teaching and a constructive response and reasoning assessment of the learning system [63]. According to Huppert and So [64] and Steptoe et al. [65], subjective well-being is a fundamental determinant of a student's positive learning engagement. It endorses effective learning, analytical intellectual, optimum presentation, learning involvement, and substantial psychological health. Considering the circumstance deriving from the COVID-19 pandemic, colleges and universities in Taiwan adopted e-learning rather than traditional face-to-face teaching methods for a prolonged duration, and students can recognize the more familiar environment and are more self-interested [66]. Students' well-being significantly influences adopting innovative learning, fronting new problems, and preserving learning inspiration. The literature found students' well-being is a significant factor that affects their e-learning adoption intention [63,65]. Thus, we hypothesize:

Hypothesis 4 (H4). Subjective well-being positively influences e-learning engagement.

3.5. Self-Efficacy

Sustainable adoption is motivated by inherent factors that incorporate individuals' characteristics and the adaptation motivations of the environment [67,68]. Inherent factors are the internal constituents that propel individuals to accomplish something. Bandura [69] states self-efficacy is one of the fundamental perceptions in human functionality. It is the principal determining factor for an individual how he/she considers, senses, and inspires [69]. It is not an inherently gifted characteristic feature. Instead, it emphasizes an individual's determined ability to synchronize his/her skillfulness and aptitudes to attain the anticipated objective in a specific domain. The individual's self-efficacy views are determined across dimensional and progressive discrepancies and understandings.

The literature contends an individual's behavioral conclusion is influenced by ecofriendly determinants, in certain specific circumstances [70], specifically for those considered to be aiming at achievement. This consideration is termed self-efficacy, and it is a key reasoning factor employed to explore personal determinants in individual determinative behavior and communications with the environment [71,72]. Self-efficacy has been extensively employed in the educational arena to explain students' emotional reasoning factors and

their significant impact on career development. Tims et al. [73] stated more investigation on the association between self-efficacy and learning performance development desires need to be conducted. Tims et al. [73] also emphasize that while individuals have a great extent of self-efficacy, they make further determination to attain learning-related resources that can support them to involve more intensely in learning [70]. It can, therefore, be inferred that while students have a great degree of self-efficacy, their learning engagement advanced further.

Jeong et al. [74] and Winstanley et al. [75] predicted that individuals who considered attitude as significant and pertinent to self-efficacy not only developed encouraging attitudes toward sustainable engagement, but they also had greater degrees of attitudinal constancy. They further asserted self-efficacy influences developing the perspective that sustains the steadiness of attitude-sustainable behavior relationship. Self-efficacy plays as a twofold mechanism on attitude and adoption. Based on the assurance in competencies, it supports the individual in achieving a purpose.

Students' self-efficacy, according to the current study perspective, acts as a navigation means that orchestrates the students' resources toward the objective. It is decisive of the degrees of the undertaking and is determined of a student under environments. While students sense self-confidence, they sense value about themselves during the learning procedure, and, in this manner, better degree learning happens [76], which subsequently supports the students to counter other peripheral determinants that encounter the students' attitude. Thus, we hypothesize:

Hypothesis 5 (H5). Self-efficacy positively influences e-learning adoption intention.

Hypothesis 6 (H6). Self-efficacy positively influences attitudinal readiness.

Based on the above discussion, a research model is proposed and presented in Figure 1 to explore and predict the students' adoption intention of a cloud-based e-learning system.



Figure 1. Conceptual measurement model for the current study. Note: Second order, First order.

4. Materials and Methods

The current study used mixed methodologies for the development and validation of the proposed study model. The proposed study model development comprised the literature review and in-depth interviews with experts of the related subject both from industry and academia. The study model was then empirically verified by administering the research instrument developed for the study by survey method. The items employed in the current study were adapted from previously published articles and modified based on the suggestions recommended by experts to fulfill the purpose of the current study more clearly. The source of items is mentioned in Appendix A. Afterward, focus group discussions on developing conclusive conversation, and interpretation of the empirical investigation's answers were later pointed out.

Due to the rapid increase in COVID-19 cases, Taiwan's colleges and universities started online instead of traditional classroom teaching. As the current study investigates the learning procedure and adoption of students affected by the modifications in the learning environment under the COVID-19 pandemic, purposive sampling is adopted to collect samples. To meet the requirements of the study purposes, some conditions were applied during the selection process of study participants. Firstly, the students must have the experience of face-to-face or classroom learning and were not about to graduate. Thus, the senior students were omitted, and the sophomore and junior students were invited. Secondly, the students must have experience using multimedia devices such as laptop, iPad, etc., for online learning to ensure basic technology literacy level. Thirdly, the hours for students using multimedia devices for online learning must be no less than 15 h weekly. Students who fulfilled the above-mentioned three conditions are considered as potential participants of the current study.

Demographic Information of Participants

Principal data for the current study were collected through structured questionnaires administered to respondents. For data collection, 297 questionnaires were distributed online, and 265 responses were returned, with nine responses were unable to be used due to incomplete responses, missing data, etc. Thus, 256 responses were finally used for the final data analysis. Table 1 reports the percentages of the respondents set apart as stated by gender, age, and educational qualification.

	Option	Frequency	Percentage (%)
Gender	Male	132	51.45
	Female	124	48.55
Age	18–24	155	60.48
	25–30	101	39.52
Educational Qualification	Bachelor	158	61.62
	Associate degree	56	21.87
	Master	42	16.51

Table 1. Demographics of survey respondents.

5. Data Analysis

Three steps were adopted for the data analysis. The first verifies the factor structure of measurement items of antecedents of cloud-based e-learning adoption intention. The second explores the relative significance of each measurement in the student's intention to adopt cloud-based e-learning. The third examines invariance between student subgroups based on adoption intention.

5.1. Validity and Reliability Check

To evaluate the dimension reliability and validity of the proposed measurement model, exploratory factor analysis (EFA) subsequently confirmatory factor analysis (CFA) was performed. Based on the analysis, 35 out of 39 items were retained for further analysis. While perceived usefulness (3), perceived ease of use (3), online course quality (4), and system quality (3) were retained with reduced indicator items. Constructs peer reference (4), perceived ubiquity (3), perceived service quality (3), perceived closeness (4), self-efficacy (4), and e-learning adoption intention (4) were retained with all recommended items.

The fit indices ($\chi^2(221) = 452.16$, RMSEA = 0.05, CFI = 0.96, GFI = 0.92, NFI = 0.92) recommend the model with the nine latent variables characterizes a good fit to the data Tables 2 and 3. The instrument validates confirmation of both convergent (significant critical ratios, average variance extracted >0.50 in all instances) and discriminant (AVE

Construct	Item	Standardized Loading	SF	CR	AVF	Construct Reliability
Construct	PR1	0.74	-	CK		Construct Renability
	PR2	0.91	0.056	23.876		
Peer reference	PR3	0.89	0.071	20.070	0.91	0.87
	PR4	0.85	0.068	29.641		
	PFOU1	0.88	-	22.041		
Democryand again of was	PEOU2	0.84	0.055	24 592	0.82	0.88
reiceived ease of use	PEQU3	0.76	0.073	26 561	0.82	0.00
	PU4	0.92	-	20.001		
Domosized usefulness	PU1	0.92	0.072	12 537	0.86	0.86
rerceived userumess	PU2	0.78	0.057	15.638	0.86	0.00
	PUB3	0.77	-	10.000		
Perceived ubiquity	PUB2	0.87	0.077	26 127	0.04	0.87
i elceived ubiquity	PUB1	0.94	0.059	32 012	0.94	
Online course quality	0002	0.82	-	02.012		
	0003	0.76	0.079	23 626		
	0004	0.84	0.072	34.238	0.95	0.87
	0005	0.91	0.065	31.116		
	SO4	0.89	-			
System quality	SO1	0.81	0.042	24.468	0.86	0.81
-)	SO2	0.77	0.039	28.118	0.00	
	SEO3	0.87	0.066	22.512		
Perceived service quality	SEQ2	0.89	0.046	30.117	0.85	0.75
	SEO1	0.91	_		0.00	0.10
	PC4	0.83	-			
	PC3	0.78	0.072	28.467		
Perceived closeness	PC2	0.82	0.051	26.819	0.91	0.88
	PC1	0.90	0.067	22.378		
	SEF4	0.81	-			
	SEF3	0.86	0.049	21.117		
Self-efficacy	SEF2	0.84	0.051	30.258	0.84	0.78
	SEF1	0.92	0.068	24.147		
	INT1	0.89	0.070	21.856		
E learning adaption interfer	INT2	0.81	0.059	32.657	0.07	0.04
E-learning adoption intention	INT3	0.92	0.065	35.541	0.87	0.84
	INT4	0.87	-			

Table 2. The measurement model

other constructs) validity [77].

evaluation of each construct is higher than the squared correlations of this construct to any

	PR	PEOU	PU	PUB	OCQ	SQ	SEQ	РС	SEF	INT
PR	0.954									
PEOU	-0.01	0.906								
PU	0.446	-0.10	0.927							
PUB	0.902	-0.08	0.530	0.969						
OCQ	0.451	-0.11	0.560	0.532	0.974					
SQ	0.002	0.786	-0.12	-0.08	-0.13	0.927				
SEQ	0.477	-0.15	0.711	0.559	0.678	-0.15	0.921			
PC	0.442	0.188	0.719	0.521	0.576	-0.17	0.718	0.953		
SEF	0.453	0.421	0.527	0.641	0.288	0.629	0.615	0.411	0.916	
INT	0.352	0.372	0.521	0.621	0.387	0.618	0.517	0.626	0.519	0.932

Table 3. The correlation matrix and discriminant validity.

5.2. Measurement Model

Attitudinal readiness (ATR). AR was hypothesized as a second-order latent construct in the proposed study model. To endorse the structure statistically, first-order and second-order CFA was carried out [78,79].

Based on first-order CFA, 13 items were retained for further investigation. These four constructs measured with 13 indicator items converged into a new construct of ATR justifying 82% of variance explained by the four constructs. The fit indices ($\chi^2(42) = 117.64$, GFI = 0.932, RMSEA = 0.076, NFI = 0.96, and CFI = 0.94) recommend an acceptable level of model fit. These findings positively support hypothesis H1 that ATR is described through the four dimensions: namely, peer reference, PU, PEOU, and perceived ubiquity.

Subjective well-being (SWB). SWB was conceptualized as a second-order latent construct in the proposed research model. To endorse the structure statistically, first-order and second-order CFA were sustained.

Based on the results of CFA, fourteen items were recalled for further investigation. Four constructs measured with fourteen items converged into second-order construct SWB, rationalizing 72% of variance explained by the four constructs. The model fit indices ($\chi^2(13) = 27.18$, GFI = 0.98, RMSEA = 0.057, NFI = 0.98, and CFI = 0.98) recommend an acceptable level of model fit. These findings positively support H3 that SWB is explained through the four dimensions called online course quality, system quality, perceived service quality, and perceived closeness.

Second-order CFA. Based on the hypotheses proposed in Figure 1 and subsequent investigation represented in Tables 2 and 3, eight first-order factors, including peer reference, PU, PEOU, perceived ubiquity, online course quality, system quality, perceived service quality, and perceived closeness, loaded on the two second-order factors—ATR and SWB. Findings from the first-order CFA offer substantial correlations among factors that replicate the validity of the theorized second-order factor model. Subsequently, the hypothesized second-order model was assessed using AMOS 21.0. The AMOS output generated ($\chi^2(242) = 485.068$, $\chi^2/df = 2.027$, GFI = 0.89, RMSEA =0.060, NFI = 0.90, CFI = 0.96) replicates a reasonable model fit.

Together with the goodness-of-fit indices, the appropriateness of the second-order factor is also mandatory to be assessed, employing the degree of the loadings of the first-order factor loadings on the corresponding second-order factors [80]. Each of the first-order factors loads intensely and suggestively on the second-order factors (Table 4). The correlations between the higher-order factors ranged from 0.41 to 0.82. As the second-order explanation did not affect a substantial reduction in the model fit, it can be determined that the proposed second-order model offered a proper interpretation for the correlations among the first-order factors.

Second-Order Factor	First-Order Factor	Loadings	Variance Explained (%)
	Peer reference	0.792 **	71
	Perceived ease of use	0.881 **	61
Attitudinal readiness	Perceived usefulness	0.861 **	64
	Perceived ubiquity	0.701 **	41
	Online course quality	0.772 **	62
Calladauthan	System quality	0.867 **	58
Satisfaction	Perceived service quality	0.720 **	76
	Perceived closeness	0.894 **	82

Table 4. Second-order model.

Note: ** Significant at p < 0.001.

5.3. Path Analysis

The following step in the investigation involved analyzing the structural model and corresponding theoretical hypotheses. The measurement model is adapted based on the exclusive patterns developed in the preceding segment to explore the independent hypothesis.

After the SEM methods, data analysis exploring the association between ATR, SWB, and adoption intention for the total sample was performed. The overall fit measures ($\chi^2(240) = 808.42$, GFI = 0.94, RMSEA = 0.057, NFI = 0.91, and CFI = 0.95) specify that the hypothesized model is a rational depiction of the structures causal the experiential data. The structural model with standardized weights is exhibited in Figure 2 (Tables 5 and 6).



Figure 2. Path diagram and causal relationships. Notes: \square Second order, \square First order. $\chi^2 = 808.42$, df = 240, Normed $\chi^2/df = 3.36$, GFI = 0.94, AGFI = 0.90, CFI = 0.95, NFI = 0.91, RMSEA = 0.057. * p < 0.05; *** p < 0.001.

Table 5. Summary of test results.

	Hypothesized Path	Path Coefficient	CR Value	Result
H2	$\text{ATR} \rightarrow \text{INT}$	0.772	14.216	Supported ***
H4	$SWB \rightarrow INT$	-0.074	-1.618	Supported *
H5	$\text{SEF} \rightarrow \text{INT}$	0.424	3.218	Supported ***
H6	SEF ightarrow AR	0.562	12.342	Supported ***

Notes: * *p* < 0.05; *** *p* < 0.001.

Index	Score	Recommended Value	Reference
GFI	0.94	>0.80	Hair et al. [81]
RMSEA	0.057	<0.08	Hair et al. [81]
NFI	0.91	>0.90	Hair et al. [81]
CFI	0.95	>0.90	Hair et al. [81]
χ^2/df	3.36	<5.0	Hair et al. [81]

Table 6. Fit indexes for structural model.

Note: n = 256.

The findings of the investigation generated a reasonable representation concerning the significance of considered coefficients. All four evaluated structural paths were substantial in the projected way.

5.4. Invariance Analysis

One of the most significant steps in exploring cross-group student behavior in a relative perspective is validating that theories and qualities are considered to happen in a related manner across distinct groups. Steenkamp and Baumgartner [82] proposed a progressive method that can be employed to institute invariance across groups. The study respondents were grouped into two groups based on adoption intention (intended to use and reject). The invariance investigation was employed in the current study to determine the impact of adoption intention in the relationships in the research model.

First, measurement invariance investigation (measurement weight) was carried out for adoption intention to determine whether students intended to use and students who reject the use of groups would utilize the same paradigm in evaluating the observed items. After determining invariance at the measurement level ($\Delta \chi^2 = 26.916$, $\Delta df = 21$, p = 0.067), invariance analysis was carried out at the structural level to ascertain if adoption intention had invariance in identifying the relations between the unobserved constructs. Having noted substantial variance at the structural level ($\Delta \chi^2 = 54.42$, $\Delta df = 30$, p = 0.006), it is determined that:

Hypothesis 7 (H7). There is a significant difference between relationships in adoption intention and its antecedents among students who intend to use and reject it.

To find out which relationships bestow this inequity, constraints were brought down on relationships in the conceptual framework [82] across students' intention to use and students' intention to reject it. Table 7 indicates substantial differences between students who intend to use it and students who reject it in the relationship SEF-INT (at a 95 percent confidence level).

	Student	s Intend f	to Use	Stude	ents Reje	ct It			
Path	Estimate	CR	p	Estimate	CR	p	$\Delta\chi^2$	<i>p</i> -Value	Interpretation
$\text{SEF} \to \text{ATR}$	0.618	7.98	***	0.712	8.127	***	0.52	0.742	ns
$ATR \rightarrow INT$	0.75	1.18	***	0.817	8.462	***	0.81	0.523	ns
$SWB \rightarrow INT$	-0.072	-1.96	0.068	0.034	0.561	0.718	1.56	0.215	ns
$\text{SEF} \rightarrow \text{INT}$	0.217	5.16	***	0.04	0.315	0.821	-3.45	0.028	Significant

Table 7. Results of path coefficient invariance analysis for students' intent to use and students' rejection of it.

Note: *** *p* < 0.001.

6. Discussion and Conclusions

The findings of the current study endorse ATR is a critical factor for intention to adopt a cloud-based e-learning system. The study also explores the effect of self-efficacy and SWB on ATR and adoption intention and endorses that adoption intention moderates the significant relations in the proposed research model.

6.1. Antecedents of Behavioral Intention

Measurement model assessment findings point out peer reference, perceived usefulness, perceived ease of use, and perceived ubiquity are dimensions of ATR of students, which mediates the association between these subconstructs and adoption intention of a cloud-based e-learning system. These findings go along with the previous findings where usefulness and ease of use have been determined to have a significant assessment by respondents [35–37]. Investigators have also perceived significant peer reference evaluation in China [14] by respondents toward e-learning adoption. Perceived ubiquity has also been observed to play an important part in the adoption intention of learning or other similar technologies [38–40].

The current investigation is one of the first in exploring the ATR as an exclusive construct. ATR developed as a multifaceted construct that is determined through four subconstructs. These four constructs are significant and are hypothetically significant. Applying the substantial regulation of student decision making, we theorized that in a novel information system (IS), these four subconstructs must be present concurrently for the system's adoption to materialize. Therefore, attitudinal readiness points out each subconstruct should be present at significant levels simultaneously for acceptance to come about.

The current study findings undoubtedly point out ATR has a substantial positive influence on adoption intention. However, suppose one studies the subconstruct usefulness and ease to use. In that case, one recognizes the two dimensions that require both the HEIs and Taiwan government to provide students with a user-friendly and useful system. Students believe in engaging in learning through an e-learning system wherever. Thus, constant access is essential for usefulness. Sluggish access speed, service unattainability, or disruption due to the untrustworthy system lessen students' perception of the system's utility. Therefore, the e-learning system provider (university) needs to bestow helpful assisting conditions such as providing real-time technical support, support to communicate and share study materials reliably and safely, keeping track of students' attendance, etc.

Moreover, e-learning system designers need to present students with a well-developed interface, comprising perfect layout, influential navigation, and quick answers. Students may sense e-learning is not challenging to use. This could also considerably reduce their attitude as well as perceived usefulness toward e-learning systems. Additionally, peer references, school friends, and family members significantly impact the perception of effectiveness and indirectly in the decision making to adopt the information system. Rogers [83] explored how peer reference strongly determines students' preference in adopting learning technology. According to Richmond et al. [84], peer reference is one of the critical factors influencing the emotional status of students. This suggests that a student might consider the pressure to adopt e-learning just because his/her classmates are adopting it. The ubiquitous feature of e-learning systems for timely identification and surveillance has been illustrated as students' need to connect with e-learning systems whenever and wherever influences their attitudinal readiness. In total, the findings recommend that both constructs, ease of use and ubiquity, are more relevant and significant factors for students to make a positive attitude toward the sustainable cloud-based e-learning system. The existing literature, together with the statistical support, thus leads to consent to the second-order construct of ATR [14,18].

Subject well-being developed as a multilayered construct which is exhibited through four subconstructs. The current study explicitly specifies that SWB has a positive influence on adoption intention. However, if one studies the subconstruct online course quality, system quality, and perceived service quality, one understands that the three dimensions need both the technical personal of maintaining a cloud-based e-learning system and university authorities to provide students correct, proper, and quality services. The attractive system features, such as definite response time, instructiveness, interface, and improved design functionalities, are significant determinants in developing the subjective well-being and adoption intention of a cloud-based e-learning system. Students generally consider an elearning system to be beneficial, and they are pleased with using a system that offers better quality information and user-friendly operations—a result that resembles the findings of Chen [54] and Gherhes et al. [66].

Additionally, if students consider the e-learning system to have precise, up-to-date, consistent, understandable, and decent formatted course content, they consider e-learning to be more beneficial for their learning processes, which in other ways improve their wellbeing too. Richmond et al. [84] and Rogers [83] have set forth that perceived closeness is one of the most important determinants that impact students' well-being of using the system. In e-learning, modifications in the learning setting and a long-staying at household unavoidably create learning complexities. Therefore, while instructors have a cordial relationship with students, they are inclined to rely on their instructors, considering that they identify the learning problems and endure their indolence, which eventually significantly influences their well-being. Altogether, the findings endorse that both constructs system quality and perceived closeness are more pertinent and substantial factors that influence students' well-being and make a positive intention toward the sustainable cloud-based e-learning system. The current literature supports reciprocally with the statistical backing; therefore, results align with the second-order construct of SWB [63–65].

6.2. Other Findings

As registered in Table 4, all hypothesized relationships are supported by the collected data. Self-efficacy influences ATR, while ATR, self-efficacy, and SWB jointly impact adoption intention.

Among the factors impacting adoption intention, ATR has a comparatively more significant influence. This finding is along the line with prior investigations supporting the constructive assessment of peer reference, perceived usefulness, perceived ease of use, and perceived ubiquity by users. ATR is probably the most significant determinant in the adoption of not only a cloud-based e-learning system but any novel information technology or system. As recommended in the current study, students take an all-inclusive assessment of any novel technology regarding the practical and social value, contrary to solitary assessment on distinct elements.

SWB has a significant positive influence on adoption intention. This result is in line with the previous studies where subjective well-being was found a critical determinant resulting in student engagement in the usage of e-learning technology [14,63,65], as students consider adopting an e-learning system based on their consideration of using the system more than their understanding and perceived effectiveness.

The direct and positive effect of self-efficacy toward e-learning ATR and adoption intention validates similar findings attained in previous studies [14,73]. Self-efficacy is important for altering and utilizing aptitudes and is one of the determinants for developing academic performance. The findings of the current study are in line with the interpretation of self-learning, signifying that students with learning characteristics of self-determination have more constructive and active learning ways, that can set real-world and reasonable learning objectives based on their own learning, identifying accessible resources, selecting suitable learning approaches, and assessing their own learning attainments [73].

6.3. Differences among Groups

The invariance analysis verified that adoption differences moderated the associations among the constructs. The results show how the influence of self-efficacy on adoption intention is meaningfully different among students who intend to use it and students who reject it, signifying the key role of self-motivation in the adoption intention of the cloud-based e-learning system. Diffusion of online learning and the e-learning environment's consciousness has empowered similar observations about the facilities regardless of the adoption engagement among university students in Taiwan. Self-efficacy is the motivating factor in adoption at the initial phases of the innovative system introduction, along with the extant literature [67,68,72,73].

HEIs and the Taiwan government could consider sponsoring by recognizing and inspiring the innovators to adopt the system. Similarly, the level of greater efficacy is a personality measurement that may be embedded in the respondents' demographical, professional, or sociological features of the respondents. However, it might need further examination and offers room for future study.

7. Implications

7.1. Implications for Theory

The current study explored the impact of ATR, SWB, and self-efficacy on cloudbased e-learning adoption from a theoretical context. As stated in the literature review, though components of ATR have received significant consideration in terms of innovative technology adoption, it has seldom been explored in the e-learning perspective that requires the highest level of attitudinal readiness of students as they need to switch entirely to a new form of learning method. Thus, students needed psychological readiness to overcome the risk factors involved with it to adopt it. Additionally, the existing literature has primarily adopted information technology adoption theories, such as TAM, IDT, and UTAUT, to explore online system user behavior [24,25,85], which has seldom explored the effect of students' psychological readiness on cloud-based e-learning adoption. Encouraging student to engage in online learning during the pandemic to develop a sustainable learning program has gained the motivation of collective consideration. Therefore, it is necessary to recognize a more inclusive set of determinants influencing the adoption intention of a cloud-based e-learning system.

The current study authenticated a combined role of ATR against the contributing role of its subfactors in adoption intention. The findings point out the influence of self-efficacy on adoption intention differs among students who intend to use it and reject it. Therefore, self-efficacy acts as a facilitator of students' behavior. The results of the current study have developed our understanding of an underattended subject. The current study has augmented the application of prior hypothetical models concerning technology adoption and has developed the knowledge of the critical online learning system adoption attributes in terms of a cloud-based e-learning system adoption.

7.2. Implications for Practice

A close relationship between instructors and students, students' self-governing adaptation over class, and mutual support and referents among peers are deemed analytical factors for attitudinal readiness, subjective well-being, and adoption intention. Exterior environmental motivations influence the emotional status and help students attain more encouraging innermost sensations; thus, they can be interpreted as critical for enhancing student learning engagement. Instructors should emphasize inspiring students to participate in learning on their own inventiveness while querying them to attain purposes. We thus suggest the succeeding propositions for long-standing learning at home during the COVID-19 pandemic. First, instructors should be incited to allow students more regulation over their learning, offer a more compelling online learning environment, and include appropriate functions to boost students' feeling of engagement. HEIs should arrange a workshop to train instructors on how to guide students in e-learning.

Second, students are inclined to be influenced by the concepts of their peers. Thus, instructors should intensify prospects for interaction among students, making a favorable learning and societal atmosphere to maintain association and reinforce communication. The current study findings not only improve the study on student communication in e-learning but also provide platforms that help HEIs to take corrective measures for the future.

Third, instructors ought to develop better instructor-student relations. The current study recommends that instructors clearly mention the course content and objectives undoubtedly to students while forming an intimate association to lessen environmental barricades. Instructors must pay close consideration to the understated transforms in the instructor-student association in the online setting and perceive students' psychological and learning situations while schooling. Instructors ought to have a positive viewpoint toward student indolence and sensibly comprehend the enhancement of contrary psychological circumstances.

8. Limitations and Future Study

Despite its substantial outcomes and implications, the current study has some limitations. First, the inferences are from a single source with samples collected from a single university in Taiwan. Therefore, researchers ought to be cautious when oversimplifying the findings about other online learning perspectives. Future studies ought to conduct research in a multicultural context to examine and equate the dissimilarities in the antecedents toward adoption intention. Second, the sample in the current study possibly does not precisely exemplify all student clusters because of the limitations of interval and space. Therefore, future studies ought to take in and equate distinct indigenous and ethnic clusters to offer supplementary notions on e-learning, increasing the sample size and enhancing the study representativity. Third, out of 297 eligible participants, 265 responses were returned, representing 89% of the eligible participants who participated in the current study. Though the response rate is rationally satisfactory in the context of a university students' sustainable cloud-based e-learning system adoption, the sample size is ascetically small. Comparatively small sample size may be associated with selection bias. Thus, the future study must improve the sample size to represent the entire population of students in Taiwan.

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Appendix A	
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Table A1. Measurement items.

Construct/Item Code	Item	Source	
Peer referent			
PR1	In the e-learning mode, I sense appreciated while I finish problem my classmates do.		
PR2	In the e-learning mode, I sense approved while I finish problem my classmates do.	Bapna, and Umyarov [40];	
PR3 In the e-learning mode, I feel more individually recognized while I finish problem my classmates do.			
PR4	In the e-learning mode, I do tasks analogous to my classmates.	-	
Perceived ease to use			
PEOU1	I expect that my interactions with the e-learning system would be clear and understandable		
PEOU2	I expect it would be easy for me to become skillful at e-learning system	Dutta et al. [41]; Davis [22]	
PEOU3	Learning to operate e-learning system will be easy for me	-	
PEOU4	Learning to operate e-learning system is not easy for me	-	

Table A1. Cont.

Construct/Item Code	Item	Source
Perceived usefulness		
PU1	I expect e-learning system will be useful in my life	
PU2	Using e-learning system will enable me to accomplish learning more quickly	Dutta et al [41]: Davis [22]
PU3	Using e-learning system will not enhance my effectiveness in terms of learning	
PU4	Using e-learning system will increase my efficiency	-
Perceived Ubiquity		
PUB1	The e-learning system providing communication and network accessibility "anytime-and-anywhere" is crucial.	
PUB2	The e-learning system provides me with anytime-and-anywhere communication and connectivity.	Van Steen and Tanenbaum [35]; Merhi et al. [39]
PUB3	I will use the e-learning system very often for learning and acquiring knowledge purposes.	-
Online Course Quality		
OCQ1	E-learning tool provides important and helpful knowledge and information for my study.	
OCQ2	The knowledge or information provided from the e-learning system is available at a time suitable for its use	A devinka and Mutula [47]:
OCQ3	The information provided by the e-learning system appears understandable, clear and well formatted	Ramayaha and Leeb [48]
OCQ4	Overall information provided by the e-learning tool is reasonable	-
OCQ5	E-learning tool makes it easy for me to share ideas with my group mates	-
System quality		
SQ1	E-learning system can give the means for taking tests and turning in assignments.	
SQ2	E-learning system supports interactive communication between the instructor and students	Chen [51]; Baber [52]
SQ3	The response time of the e-learning system is consistent.	-
SQ4	The design of the e-learning system is user-friendly	-
Perceived Service quali	ty	
PSEQ1	Technical staff is available for assistance with system difficulties	
PSEQ2	Information communication technology staff replies quickly	Ramayaha and Leeb [48]; Delone and Mclean [50]
PSEQ3	Overall, support services of the e-learning system are acceptable	
Perceived closeness		
PC1	In the e-learning mode, I sense a closeness with instructor.	_
PC2	In the e-learning mode, I feel a familiarity with instructor.	
PC3	In the e-learning mode, my interaction with the instructor is dissimilar from that in face-to-face learning.	Frisby et al. [53]; Hershkovitz [59] -
PC4	In the e-learning mode, I consider I can talk to my instructors about anything.	

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Table A1. Cont.

Construct/Item Code	Item	Source
Self-efficacy		
SEF1	In the e-learning mode, I am capable to resolve the problems more easily.	
SEF2	In the e-learning mode, while I come by problems, I can find solutions of these.	- Caruana et al [64].
SEF3	I will attempt my best to attain the cloud-based e-learning objectives set by myself.	Shaw et al. [65]
SEF4	I am outstandingly ready to face and handle the demands of cloud-based e-learning.	
E-learning adoption int	tention	
INT1	When it is available in my learning exercise, I intend to use e-learning system for all my learning activities	
INT2	When it is available in my college/university, I intend to adopt e-learning system for all my learning activities	Dutta et al [41]: Davis [22]
INT3	The probabilities that I adopt e-learning system for all my learning activities when available in my college/university are very high	
INT4	Whatsoever the environments, I do not intend to adopt e-learning system when it becomes available in my college/university	-

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