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Exploring the Critical Factors, the Online Learning Continuance Usage during COVID-19 Pandemic

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Abstract: In order to enable online learning to continue developing when the COVID-19 pandemic passes, this study aimed to identify the critical factors that affected the use of e-learning by university students during the pandemic. These critical factors will help to increase the efficiency of future development and deployment of online learning systems. Through a literature review, this study employed the technology acceptance model, social support, and task–technology fit as the theoretical basis to establish the framework of the online learning environment with regards to the technology acceptance model in the context of emergency management. A questionnaire survey was administered to students in universities that had implemented online teaching during the pandemic, and 552 valid responses were collected. The survey explored the factors affecting the willingness of higher education institution students to continue using online learning, and the following conclusions were drawn. (1) The easier an online learning platform was to navigate, the better it was perceived by the students, and thus the students were more willing to use it. (2) Ease of use and usefulness were associated with the teachers' choice of platform and their ability to achieve a satisfactory fit between the course design and platform navigation, which thereby affected the students' learning outcomes and attitude towards use. (3) The positive attitude of teachers towards teaching increased the students' perceived ease of use of online learning. (4) During the pandemic, family support—a major support for teachers in online teaching—enhanced teachers' attitudes towards, and willingness to provide, online teaching. A high level of support showed that the parents urged the students to learn and complete online learning tasks as instructed by the teachers, implying that family support could affect the students' habits towards, adaptation to, and identification of online learning. The study results provide insights into the factors affecting the willingness of teachers and students to continue using e-learning platforms.

Keywords: COVID-19; technology acceptance model; e-learning; task–technology fit

1. Introduction

During the COVID-19 pandemic, most universities have become aware of the features of online teaching and learning, and thus have actively encouraged teachers across all levels of education to promote online learning. During the pandemic, the Ministry of Education, to reduce the risk of being infected by going out, released the *Guidelines on Organization and Management of Online Teaching of General Institutions of Higher Education During Epidemic*, and required that institutions of higher education should not suspend education, although offline classes were suspended, but should actively offer online classes to ensure the smooth continuation of teaching and the improvement of teaching quality during the pandemic [1]. It later released the *Notice on Coordinating COVID-19 Epidemic Prevention and Control and*

Education Reform and Development in the Education System to require that institutions of higher education should provide better guidance on learning from home when students were taking classes at home [2].To this end, the Ministry of Education announced platforms of course resources and technologies for online teaching according to the conditions of universities under COVID-19 pandemic prevention to facilitate the selection of suitable platform systems according to their pedagogical features [3]. The pandemic has forced a rapid shift in higher education toward distance and online learning. However, China is a vast country, and the economic gap and uneven development between different regions has become the main obstacle for online education, which is more significant in rural areas such as the northwest or the west of China where there is a shortage of resources and a lack of sufficient teachers, equipment, and technical support [4]. In addition, a talent shortage in western regions hinders the implementation of online teaching. Teachers are insufficiently informed, with some sticking to only one existing teaching method. The aforementioned difficulties considerably reduce student enthusiasm for learning, inevitably causing imbalances in the development of distance education, and negatively affecting higher education [5]. This has had numerous consequences, such as challenges for pedagogical workers and learners, a lack of knowledge about information and communications technology, poor network infrastructure, and weak content development inevitably affecting the general adoption of online learning [6]. In this regard, students using online learning are susceptible to external factors influencing online learning. These factors can decrease satisfaction with online learning and prevent its continued use [7].

During the pandemic, university students were required to take online classes given by respective institutions according to the policy of the Ministry of Education, thus the utilization of online education increased significantly. However, whether online education will be as desirable without such external support and whether such external support will lead to its continued use in the future is a topic worth discussing. Particularly with regard to the COVID-19 pandemic, various countries are endeavoring to shift traditional classroom teaching to online learning in an attempt to strengthen social distancing measures and maintain normal school operations. Thus, the use of various forms of online learning is strongly advocated. However, such a radical approach has exposed inadequacies in online teaching, such as the limited feedback of students about online teaching, the lack of a valid course certification processes as well as scientific and high-quality content, and insufficient student self-motivation and commitment, all leading to a sudden decline in students' intention to use online learning following the pandemic [8]. Thus, maintaining the stable development of online teaching following the pandemic requires the determination of the key factors influencing its use and suggested measures for improvement. In this respect, a review of prior studies revealed that, whether online learning successfully becomes an educational tool depends mainly on students' intention to use and accept the e-learning systems [9]. Thus, to understand students' opinions and adoption intentions regarding online learning systems, the effect of external factors should be considered, and these factors should be examined through consideration of environmental features [6]. The technology acceptance model (TAM) has provided a theoretical base for studies on the intention to adopt and use online learning systems [10]. The theory has been widely applied to challenges in the national implementation of numerous types of online learning [11–14].

A review of studies on online learning suggests that platform quality (e.g., the quality of content, system stability, and technical support), students' personal factors (e.g., student attitude and the effect of immersion), and the quality of teaching (e.g., the timing of instructor response, instructor attitude (IAT) towards online learning, and interaction and communication between instructors and students) are the main factors by which researchers make conclusions [6,15,16]. However, during the current pandemic, students are spending time at home engaging in online learning, indicating that three aspects, namely, family, students, and the teacher, may be crucial indicators of students' intention to use online learning. These three aspects have rarely been jointly discussed. Thus, this study focused on higher education institutions in China and expanded the TAM framework to

examine how family, the teacher, and the students themselves influenced the use of online learning among students affected by COVID-19 and whether students' intention to use online course platforms will continue.

2. Literature Review

2.1. Technology Acceptance Model

The TAM was proposed by Davis to explain how people's attitude and behavior predict the adoption of a technology with the presence of other external variables [10]. The model is frequently applied in usage behavior research in attempts to comprehend the reasons for the acceptance or rejection of an information system. In teaching, information technology plays a prominent role because it can encourage innovation, provide new learning spaces, and transform instructional activities [17–19], all of which are closely associated with the ease of information technology operation. Ease of operation—convenience in the user experience and whether the user can proficiently command and use digital information and communications technologies—directly affects user perceptions and motivation to learn [20]. Studies have demonstrated the positive effect a student's proficient command of information technology has on learning performance [21]. A review of the relevant literature indicated that the TAM has been widely applied in studies of online learning. The literature is synthesized in Table 1.

Table 1. Research topics on the technology acceptance model (TAM).

Authors	Research Contexts	Constructs	Fundamental Theories
Baby & Kannammal [22]	e-learning	Perceived Usefulness, Perceived Ease of Use, Perceived Trust, Perceived Security, Perceived Privacy, Information Quality	TAM
Ayele & Birhanie [23]	e-learning	Training, top management support, incentive	TAM
Ashrafi et al., [14]	Learning management system	Subjective norm, enjoyment, confirmation, satisfaction, content quality, navigation, presentation	ECT + TAM
Chang, Hajiyev, & Su [24]	e-learning	Self-efficacy, subjective norm, enjoyment, computer anxiety, technological innovation, experience	ECT + IS success model + continuance theory
Francis B. Osang et al. [25]	e-learning	systems in terms of attitude towards use, IT usage, user satisfaction and performance	TAM + TRA + IS
Scherer, Siddiq, & Tondeur [26]	e-learning	Facilitating conditions, subjective norms, technology self-efficacy	TAM
Weng, Tsai, & Weng [27]	e-learning	e-learning self-efficacy, managerial support, peer support, family support	TAM + social support theory
Wu & Chen [28]	MOOCs	Individual–technology fit, task–technology fit, openness, reputation, social influence, social recognition	TAM + TTF
Vanduhe, Nat, & Hasan [29]	Gamification for training in higher education	Social influence, task–technology fit, social recognition	TAM + TTF
Pozón-López et al. [30]	MOOCs	Vividness of content, interactivity, controlled motivation, autonomous motivation, entertainment, course quality, emotions, satisfaction	TAM
Lee [31]	e-learning	Confirmation, satisfaction, enjoyment, concentration, subjective norm, behavior control	ECT + TAM + TPB + Flow theory
Zhonggen & Xiaozhi [32]	Mobile learning	Peer influence, superior influence, enjoyment, subjective norm, image, job relevance, output quality, result demonstrability, adjustment, experience, anchor, voluntariness	TAM2
Al-Rahmi et al. [33]	MOOCs	Compatibility, trainability, complexity, observability, relative advantage	TAM + IDT
Sun & Gao [34]	Mobile learning	Intrinsic motivation, task–technology fit	TAM + TTF + intrinsic motivation
Cheng [35]	e-learning	Subjective norm, behavior control, self-esteem	TAM + TPB
Romero-Frías et al. [36]	MOOCs	Loyalty, external regulation, intrinsic motivation	TAM + self-determination theory

A review of these studies revealed that most approached and examined topics from the angles of platform, students' personal factors, peer factors, or quality of teaching [14,18,24,37–39]. As suggested by Benbasat and Barki [40], TAM-themed studies should focus on determining the antecedents of perceived usefulness (PU) and the

consequences-of-use behavior to propose a more comprehensive model. Thus, three expanded variables, namely, family support (FS), task–technology fit (TTF), and IAT, were adopted as the main external variables for the current study.

2.2. Family Support (FS)

Social support reflects how an individual is willing to become a member of a group because she/he feels respected and valued during interpersonal interaction [41]. Social factors are affected by the cultural background of a group, and an individual is prompted to behave according to group norms, which further affects the individual's beliefs. Social influence is formed when the beliefs of a group are sufficiently accumulated; it determines the extent to which an individual perceives the "right" thing to do according to the opinions of others [42]. An individual's faith, beliefs, and behavior are affected by the admonition of others [43]. An individual experience of being cared for, responded to, and helped in a social group when they are directly or indirectly influenced by others was termed by Cobb and Sidney as "social support". [44] Through this support, an individual can obtain help (through interaction with others) and thus feel a sense of belonging and cohesion, which indirectly affects their intention to use online learning [45]. Huang et al. suggested that social support has a multidimensional structure, and its components might differ according to environments [17]. Cheng and Chan suggested that social support per se implies three aspects, namely, the support of family, friends, and others, and, through these forms of support, social support is reflected as being multifaceted [46].

Both teachers and families provide social support to students engaging in online learning. Regarding teacher support, studies have indicated that the number of perceived benefits of online learning increases when teachers support students and interact with them online [47]. Harvey et al. and Maurer et al. indicated that FS greatly affects learning satisfaction, particularly in continuing professional education [48,49]. As elaborated by Weng et al. [27], for a company employee participating in online learning, the frequency of their continued use of online learning increases with FS. In the university context, family factors are typically ignored in consideration of conventional online learning mainly because the majority of university curriculums are offline with only one or a few courses online. Second, the lives of Chinese students revolve around the campus, as most live on campus. However, online learning during the pandemic differs from the online teaching method pre-pandemic; it represents a new online learning model. The living environment of students has shifted from the campus to their family home. In particular, due to the delay in work resumption for most parents during the pandemic, many parents are at home most of the time and supervise or accompany students engaging in online learning [50]. Thus, during the pandemic, FS has played a prominent role in online learning.

2.3. Instructor Attitude

By definition, IAT involves how the instructor's attitude is perceived by a student, as well as an instructor's real-time response, teaching style, and attitude in helping the student through online learning platforms [51–53]. Thus, IAT involves an instructor's real-time feedback on student questions [54,55] to reduce learning gaps and build a more comprehensive learning mechanism. An essential aspect of IAT consists of the instructor conceiving of a series of instructional activity designs and learning resources and encouraging effective learning through interaction and exchange, and with appropriate instructional tools [56]. In online learning courses, a positive IAT contributes to continuous learning, and learning outcomes are improved when the instructor's response to student needs and inquiries is rapid [57]. Thus, the exhibition of a positive attitude, a passion for teaching, and the assistance and guidance of students affect student intention to use online learning systems [16]. In studies extending the TAM, Lwoga as well as Rodríguez-Ardura and Meseguer-Artola elaborated on the antecedents affecting online learning and proposed combining IAT with the TAM to explore students' intention to adopt online learning [56,58]. Given the pandemic in the context of the present study, online learning has been adopted

for all courses and IAT is crucial. In this period, instructor engagement is a particularly crucial factor that indirectly prompts students to accept online learning.

2.4. Task–Technology Fit

From the viewpoint of TTF theory, technology implies computer systems as well as support and services meeting user needs; tools are provided to assist users in performing tasks [59]. The theory is intended to explain how technology adoption is affected by technology and task characteristics [60]. In the TTF model, technology utilization rate and perceived TTF increase with the amount of support provided by technology for a user's task [61]. Thus, correspondence between a task and an online learning system user's needs contributes to maximal learning results [11–13,62,63]. In TTF, importance is placed on the influence of task characteristics, which, in the context of TAM, is another approach to explaining technology adoption. Numerous researchers have attempted to integrate TTF and TAM to investigate technology adoption in online learning [28,29,34]. When technology closely fits a task, a good result can be expected. Thus, TTF theory compensates for the insufficient focus on the role of tasks in the TAM. In addition, studies have indicated that integrating TTF and the TAM can predict a change in technology adoption more reliably than either TTF or the TAM alone [64,65]. Moreover, such integration is similar to perceived usefulness and perceived ease of use (PEU), and TTF is considered an external motivation factor in technology adoption due to its close association with external goals [66]. Consequently, from the perspective of student learning, the implementation of online learning in China during the COVID-19 pandemic employed e-learning to meet the needs of closed schools, where teaching through offline courses was unfeasible. Thus, understanding whether the teacher's choice of online learning platforms or their adoption of various types of online courses corresponds with student needs is crucial both to understanding e-learning during the pandemic and to its future development.

3. Research Model and Hypotheses

3.1. Research Model

Prior research suggests that an extension of the TAM can provide a stronger explanation for the behavior under study [29,67–69]. Venkatesh and Davis also confirm the applicability of this model in both voluntary and mandatory contexts [69]. Benbasat and Barki suggest that future adoption research should place more emphasis on the factors that impact antecedents of the belief [40]. The research model is shown in Figure 1. In this section, the theoretical model based on previous research and literature is proposed in the current study. Subsequently, the hypotheses of the study are listed below.
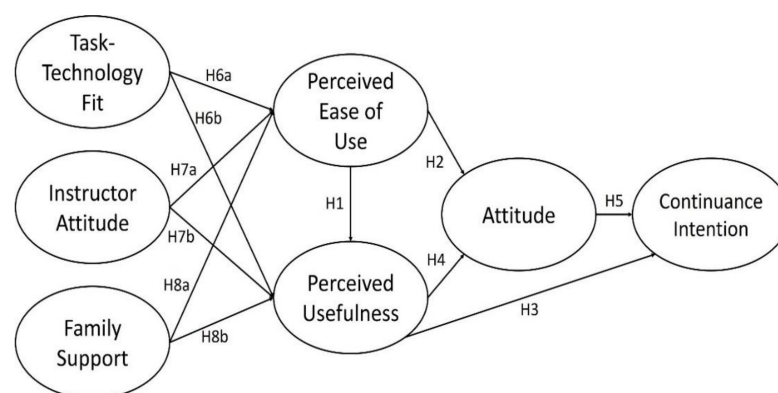

Figure 1. Research model.

3.2. Hypotheses

Davis et al. [10] proposed the TAM and held that PU and PEU affect the user in terms of attitude toward use. PU is affected by ease of use; one's attitude toward using technology and their intention to use determine whether the user will adopt the technology. The TAM has

been widely used for empirical purposes in studies in information management [28,70–72]. Most studies on online learning have proved that PEU affects PU, PU and PEU positively affect attitude, and attitude and PU affect continued use [16,29,73]. Hypotheses 1 through 5 were formulated according to the theoretical basis of the TAM:

H1. *Perceived ease of use has a positive effect on the perceived usefulnessof using online learning.*

H2. *Perceived ease of use has a positive effect on attitude towards using online learning.*

H3. *Perceived usefulness has a positive effect on continuance intention to use online learning.*

H4. *Perceived usefulness has a positive effect on attitude towards using online learning.*

H5. *Attitude has a positive effect on continuance intention to use online learning.*

People's understanding of a system is based on their knowledge and experience [69,74,75]. In attempting to complete tasks using technology, people rationally assess its advantages, gradually adopt efficient behavior, and construct opinions and perspectives on the system. Researchers have proved that TTF affects both the usefulness and the ease of use of online learning [29,34]. According to the argument of Dishaw and Strong [76], when a user finds that an information system involves numerous inextricable functions, they naturally perceive learning to use it as being much more difficult than learning to use a system with simple functions. After a while, as a user gradually perceives a system to have good TTF, its functions are considered capable of meeting the requirements of a task, which naturally improves the perceptions of the system's usefulness. Because ease of use affects usefulness and because technological functions and task requirements should fit, the user should perceive a certain degree of ease of use. The following hypotheses were formulated accordingly:

H6a. *Task–technology fit has a positive effect on the perceived ease of use of online learning.*

H6b. *Task–technology fit has a positive effect on the perceived usefulness of online learning.*

Regarding IAT towards teaching, previous studies have indicated that this attitude has a crucial influence on student usage [16,52,56]. In a pandemic, IAT can encourage students to agree to use online learning by highlighting its usefulness and ease of use. Thus, hypotheses 7a and 7b were formulated.

H7a. *Instructor attitude has a positive effect on the perceived ease of use of online learning.*

H7b. *Instructor attitude has a positive effect on the perceived usefulness of online learning.*

Weng et al. [27] reported that FS contributes to an increase in the frequency of online learning. Research on technology acceptance emphasizes how social influence affects student attitude and efforts regarding technology. Social influence describes the extent to which students perceive the opinions of significant others, namely, peers, teachers, and parents [77]. Studies have revealed that social influence does not affect student attitude towards computers and the use of other devices because society's overall positive views cancel the effect of these forms of social influence [78,79]. However, Zheng and Li [80] demonstrated that in student acceptance of computers and the use of other devices, FS was a significant predictor of usefulness and ease of use. Overall, as students stayed at home and followed online courses during the pandemic, this study reasonably assumed that supporting students in their use of computers in online learning induced a positive effect on the students' perceived usefulness and ease of use of online learning. Thus, hypotheses 8a and 8b were formulated:

H8a. *Family support has a positive effect on the perceived ease of use of online learning.*

H8b. *Family support has a positive effect on the perceived usefulness of online learning.*

3.3. Construct Operationalization

In terms of the choice of scales, the items of Gefen [81] were adopted and adjusted for perceived usefulness, the items of Mohammadi [82] were used for perceived ease of use, the items of Hsu, Chen, and Ting [39] were employed for attitude, the items of Rodríguez-Ardura and Meseguer-Artola [56] were used for instructor attitude, the items of Ashrafi et al. [14] were used for continuance intention, the items of Weng, Tsai, and Weng [27] were used for family support, and the items of Isaac et al. [12] were used for task–technology fit.

3.4. Data Collection

Through the WJX platform, an online questionnaire survey was administered in 18 universities in China that implemented full online teaching during the pandemic period. The questionnaire was distributed to 857 students between May and June 2020, during which the final exams took place. Because offline surveys could not be performed during this period, convenience sampling was adopted to select students. Members in the chat groups of university teachers created in WeChat and Tencent QQ were invited to distribute the questionnaire to their students. To improve the sample quality, the following four principles proposed in previous studies [83–85] were used to screen for valid samples. First, respondents require 8–15 min to complete the questionnaire, thus, samples that were completed within 3 min were considered invalid. Second, samples with outlier values or identical answers throughout the questionnaire were excluded. Third, samples with the same IP address were excluded by the WJX platform. Finally, reverse questions were designed to identify respondents who provided their answers randomly. According to these principles, 305 invalid responses were excluded, and a total of 552 valid responses were collected, including 156 male and 396 female samples. Of these respondents, 74 were male. Table 2 details the respondents' demographics. Among them, 182 students used online learning for 1 h every day, 112 students for 1 to 2 h every day, 156 students for 2 to 4 h every day, and 102 students for more than 4 h every day. Prior to the COVID-19 pandemic outbreak, 55% of students reported zero experience with e-learning and 45% of students had more than six months of experience.

Table 2. Factor loading, alpha, composite reliability, and average variance extracted (AVE).

Construct	Factor Loading	α	CR	AVE	VIF
Perceived usefulness	0.943 *** 0.949 ***	0.882	0.943	0.895	2.337
Perceived ease of use	0.894 *** 0.924 *** 0.941 ***	0.909	0.944	0.846	1.722
Attitude	0.913 *** 0.898 *** 0.885 ***	0.881	0.926	0.808	1.552
Continuance intention	0.956 *** 0.958 *** 0.947 ***	0.950	0.927	0.909	DV
Instructor attitude	0.875 *** 0.908 *** 0.912 ***	0.882	0.968	0.807	2.249
Family support	0.903 *** 0.908 *** 0.892 *** 0.850 ***	0.911	0.937	0.789	2.253
Task–technology fit	0.914 *** 0.938 *** 0.914 *** 0.854 ***	0.926	0.948	0.820	1.945

Notes: VIF (variance inflation factor); AVE (average variance extracted); DV (dependent variable); *** significant at $p < 0.01$; CR (composite reliability).

4. Results

This study applied SPSS and SEM-PLS for measurement and structural model analysis of the collected data. Furthermore, regarding multicollinearity, Hair et al. [86] suggested the variance inflation factor (VIF) value below 5. Results indicate that VIF ranged from 1.552 to 2.337, thus indicating that multicollinearity meets the requirements (see Table 2).

4.1. Measurement Model

In reliability and validity analyses of the measurement model, the main indicators for assessment were factor loading, composite reliability, convergent validity, and discriminant validity [87–89]. Reliability for each item was assessed and analyzed mainly through factor loading and Cronbach's α. According to suggestions in the literature, all construct outcome values and the factor loading of each item should be greater than 0.7 [90]. Cronbach's α value was greater than 0.7. Regarding composite reliability, studies have suggested that the indicator value be greater than 0.7 [91]. When measuring convergent validity, the average variance extracted (AVE) of each construct needed to exceed 0.5. Table 2 shows that all the AVEs exceeded 0.5, indicating satisfied convergent validity.

The goal of verification discriminant validity is to examine any discrepancy of measurement variables concerning the constructs. The square root of the AVE for each construct must be greater than the correlation coefficients between constructs [92]. Table 3 presents the correlation coefficient matrix of the constructs. The values along the diagonal line represent the square roots of the AVE values. The square root values of the AVE were greater than the correlation coefficients between the constructs, indicating that the results for each construct good discriminant validity.

Table 3. Analysis of discriminant validity.

	AT	CIT	PEU	PU	TTF	FS	IAT
AT	0.899						
CIT	0.723	0.954					
PEU	0.639	0.520	0.920				
PU	0.756	0.674	0.596	0.946			
TTF	0.807	0.668	0.621	0.758	0.905		
FS	0.653	0.496	0.609	0.538	0.593	0.888	
IAT	0.657	0.376	0.603	0.513	0.598	0.693	0.899

Notes: Attitude (AT); continuance intention (CIT); perceived ease of use (PEU); perceived usefulness (PU); task–technology fit (TTF); instructor attitude (IAT); family support (FS).

4.2. Structural Model

To test the research hypotheses, the bootstrap resampling method in SmartPLS was used to evaluate the PLS results, with the responses resampled 5000 times [90]. The overall R^2 value of our results was 55.9%. The R^2 for ease of use was 49.6%, the R^2 for attitude was 62.6%, and the R^2 value for usefulness was 60% (Figure 2). The results indicate that the research model proposed for the study has high explanatory power.
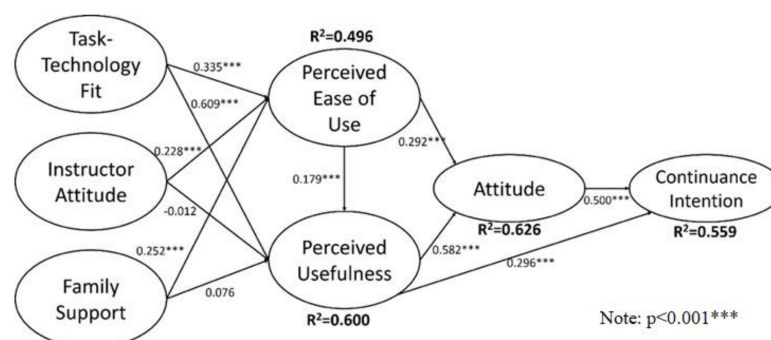

Figure 2. PLS results of the research model (Note: $p < 0.001$***).

The result supports H1 to H6a, H7a, and H8a. Perceived ease of use has a positive significant influence on perceived usefulness ($p < 0.01$), thus supporting H1. Perceived usefulness has a positive significant influence on attitude ($p < 0.01$), thus supporting H4. Perceived usefulness has a positive significant influence on continuance intention ($p < 0.01$), thus supporting H3. Perceived ease of use on attitude (H2) was significant at $p < 0.01$. Attitude has a significant influence on continuance intention, thus supporting H5.

The results showed that task–technology fit has a significant influence on perceived ease of use (H6a) and perceived usefulness (H6b), which provides support for H6a and H6b, respectively. The study found that instructor attitude significantly influences perceived ease of use (H7a) and perceived usefulness (H7b). Finally, we also found that family support has a significant influence on perceived ease of use (H8a), and perceived usefulness (H8b) was not significantly supported.

5. Discussion and Conclusions

5.1. Discussion

According to the research results, PEU, PU, and attitude regarding the use of online learning during the pandemic achieved statistical significance, and all of them have been proven to be prominent predictors [14,25,37]. Differing from those in prior studies on online learning, the online learning resources of higher education institutions in China during the pandemic were largely learning platforms provided by the Ministry of Education (MOE) of the People's Republic of China [3]. Additionally, because the platforms were provided by the state, when the platform interface was simple to use and the content contained materials useful for learning, online courses were perceived by university students as being more helpful. Second, ease of platform operation can induce a positive attitude towards using a platform. Regarding the implementation of online learning during the pandemic, universities may conceive diverse approaches to focusing on student needs, improving the quality of course content in learning systems, and strengthening the operation interface. Universities can enhance student attitudes and their continuance intention by simplifying system processes and improving the practicality of course content. Furthermore, the result suggesting that TTF had a significant influence on PEU and PU concurs with previous reports [28,29]. Under the impact of COVID-19 and at a time when the fit between task and technology greatly affected the use of online learning, whether the current approaches to conducting courses correspond to the goals of students particularly affects their use of online learning platforms. Thus, teachers and educational institutions should consider deploying course content according to course requirements and types, thereby enabling easy operation and encouraging students to perceive the learning as useful.

In addition, this study discovered that IAT had a significant effect on PEU but not on PU, whereas the literature reported otherwise [58,93–95]. Doubtlessly, feedback regarding a teacher's instruction via online platforms and their timely response to, and interaction with, students are elements indispensable to the success of online learning systems [17,51,52]. For online courses during the COVID-19 pandemic, the effects of teacher–student interaction, course guidance, and teacher responses to questions were crucial in improving learning outcomes. However, in online learning platform use, ease of platform operation determined whether students completed assignments.

Finally, this study reported that the effect of FS on PEU was statistically significant, but FS had no direct effect on PU. This finding contains two implications regarding FS in this context. FS was not the main influence on the perceived usefulness of online learning among the students. According to the survey results, the main impact factor was arguably the necessity of online teaching during the pandemic leading to its extensive implementation on campuses in China; online courses are necessary for students to complete so-called learning performance appraisals by performing online tasks while following teacher instructions and meeting university requirements. Therefore, although the effect of FS on PU was non-significant, FS functioned as auxiliary supervision and thus indirectly affected PU,

indicating that, in the context of student use of online learning platforms, FS is affected by PEU.

5.2. Practical Implications

This study addressed the continuance intention of university students for online learning in China during the COVID-19 pandemic. With the online learning environments built in the context of emergency management, the post-COVID-19 era is propitious for expanding online learning. Because COVID-19-induced online learning differs to some extent from conventional online learning, this study used SF, TTF, and IAT as expanded variables to investigate the TAM structure of online learning environments during emergency management, as well as their influence on the continuance intention of students.

From a theoretical perspective, the combination of TTF and TAM has been thoroughly explained; TTF has direct effects on both PEU and PU in online learning environments [29]. The present findings indicate that teachers' choice of online learning platform and their subsequent deployment of course content during the pandemic directly affected the perceived usefulness and ease of use for students using the platform. In particular, the course curriculum and design were perceived by the students as easier to grasp when the fit between the design and the platform was closer, which in turn improved learning effectiveness, provided assistance in learning, and increased students' positive attitude toward online learning. This indicated that teachers must select suitable online teaching platforms according to the characteristics of the subjects they are teaching. For example, mathematics and statistics courses involve the teaching of calculation processes; hence, the requirements of platforms used to teach these subjects are more complex than those of the platforms used to teach subjects that solely involve textual description. Crucial discussion topics emerge regarding how teachers and students can use two-dimensional screens to examine abstract logic and equations, and how extra learning burdens caused by difficulty with using an online platform can be alleviated to encourage students to engage in active learning. In addition, regarding the correlation of IAT with PU and PEU, a significant correlation between IAT and PEU but not PU was present. This result differed from that of a previous report where PU and PEU were both significantly correlated with IAT [56]. An inference from the result is that students are relatively motivated to acquire knowledge when the teacher provides appropriate learning materials, conducts relevant learning activities, and provides timely and effective instruction and support through a process of continuous exchange and interaction. Thus, the teacher's positive approach to online teaching and learning is motivating and induces a perceived ease of use of online learning systems among students.

Finally, the MOE implemented policies for students to learn at home during the pandemic. This allowed parents to observe the learning status of their children as well as the teaching styles of the teachers. When parents witness a favorable interaction between their children and teachers during online learning, they are more willing to trust and accept this teaching mode and encourage the children to learn. According to Harvey et al. [48], FS prompts parents to spur students on to learn. Because online teaching prevents comprehensive supervision by teachers, FS can be a major supporting factor for teacher instruction, and the auxiliary support it provides enhances, to an extent, the teacher's intention to engage in online teaching and to invest in online teaching work. Stronger FS during the pandemic represented greater parental supervision and parental help with resolving problems in courses. Thus, students were able to complete online tasks designed by their teacher. Moreover, teachers are likely to put more effort into their teaching and pay closer attention to learning outcomes when they know that students' parents are watching and supporting them. Accordingly, students can receive more learning resources. This improves students' habits and increases the need to use online learning, in addition to improving the suitability of online learning. Without FS, students are susceptible to distractions from online learning, such as mobile phone games, television dramas, and social software, which disrupt their intention to use and eventually prevents them from completing assigned tasks. Accordingly, students stop using platforms they perceive as irrelevant and difficult to use.

5.3. Limitations and Future Research

This study had limitations. First, the sampling in various regions was constrained due to the adoption of snowball and convenience sampling. Thus, it is suggested that subsequent studies focus on collecting samples from various regions so that the results can be more be generalizable. Second, the study conducted a survey, but the data were collected during a pandemic. Investigations into promoting the continuance intention of online learning in the context of emergency management is probably beyond the scope of future work. Therefore, qualitative research methods may be adopted in the future to facilitate the determination of continuance intention of online learning in the post-COVID-19 pandemic era to come [96–98].

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