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Continuance Intention of University Students and Online Learning during the COVID-19 Pandemic: A Modified Expectation Confirmation Model Perspective

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Abstract: The prevalence of COVID-19 has changed traditional teaching modes. For many teachers, online learning effectively compensated for the absence of traditional face-to-face instruction. Online learning can support students and schools and can create unique opportunities under emergency management. Educational institutions in various countries have launched large-scale online course modes in response to the pandemic. Additionally, online learning during a pandemic differs from traditional online learning modes. Through surveying students in higher education institutions, educational reform under emergency management can be explored. Therefore, university students were surveyed to investigate their continuance intention regarding online learning during the pandemic. Expectation confirmation theory was extended using the task-technology fit model to ascertain whether the technical support of promoting online learning helped student's complete course learning tasks during the pandemic and spawned a continuance intention to use online learning in the future. Data were collected through online questionnaires. A total of 854 valid responses were collected, and partial least squares structural equation modeling was employed to verify the research hypotheses. The results revealed that the overall research framework largely explained continuance intention. Concrete suggestions are proposed for higher education institutions to promote online learning modes and methods after the COVID-19 pandemic.

Keywords: COVID-19; expectation confirmation model; online learning; task-technology fit

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1. Introduction

The outbreak of COVID-19 has changed traditional teaching modes. By July 2020, more than 180 countries worldwide had closed schools due to the pandemic. The world is also reassessing online learning services to cope with the challenges faced by the global educational environment [1]. China uses online learning to maintain and promote learning activities to reduce the impact of school closures across the country as well as to reduce the spread of the virus. However, what to teach, how to teach, and how to meet the basic needs such as an education infrastructure are all questions faced by the country. The Ministry of Education of China provides various teaching platforms to enable students to participate in online learning through smartphones, desktop computers, or laptops [2].

For many researchers and online teachers, the online learning pursued during the pandemic can be used to address shortcomings of traditional face-to-face education. Online learning can support students and colleges through the creation of unique opportunities in an environment of crisis management. It has many advantages, such as enabling teachers and students to continue teaching and learning in any space without interference [3]. There is no doubt that online learning provides a new learning environment, making learning easier and supporting students to develop abilities, skills, and attitudes [4]. Since the beginning of 2020, when COVID-19 was first reported, many researchers have discussed the development opportunities and threats of online learning [3,5–9]. Other scholars have discussed teaching methods or teaching measures [10,11] and analyzed the adoption of a teaching system [12–14].

Looking at the development of online learning, its promotion is related to the willingness to continue using it and the satisfaction of students or teachers [15,16]. The success of online learning depends on student willingness to use and acceptance of the system [17]. Its use by students themselves is a key to the success of online learning. However, from the perspective of Chinese universities, online learning during the pandemic is a form of emergency management, especially when many university courses have changed from a single course to a form of the fully online course, and course content is mainly based on online learning resources provided by the Ministry of Education [18]. During the pandemic, students must spend time becoming familiar with and using the online platform, but the pandemic has increased students' willingness to learn online. The use of platforms will have an impact on learning, which in turn will affect the continuing use of online learning in the post-pandemic era.

In the past, the main theories on continuing willingness to use online learning tended to be based on expectation confirmation theory. This theory is also widely used to explain and predict the continuance intention of learners [19–21]. For example, Lee discussed the continuous use of online learning and integrated expectation confirmation theory (ECT), the technology acceptance model (TAM), the theory of planned behavior (TPB), and flow theory to explain the willingness of continuous use of learners. Zhou used social impacts to expand expectancy confirmation theory and replaced perceived usefulness with learning outcomes [22]. Cheng explored the continuous use of online learning of nurses and extended ECT and DeLone and McLean's information system (IS) success model and flow theory [23]. Dai et al. [19] took Chinese college students' willingness to continue to use massive open online courses (MOOCs) as the research topic and revised the initial structure of ECT by adding two variables: culture and attitude [19]. Although these studies proved that ECT has a sound research foundation on the continuous use of online learning, the higher education system is promoting the use of online learning platforms during the pandemic, which presents an environment of emergency management. The role of the pandemic in promoting the continued use of online learning in China in the future is a topic worth discussing.

From the perspective of schools, the aim of promoting online learning during the pandemic is to meet teaching needs created by the closure of the school. Especially when teachers are choosing online learning platforms or adopting various online courses, whether the form of the courses meets the needs of students is central to online learning during the pandemic and continuous learning in the future. In task-technology fit (TTF), "technology" refers to the computer system and the services required by users. They are tools that can help users complete specific tasks [24]. Therefore, when the task meets the requirements, efficiency can be maximized for information system users [25]. On the topic of online learning, studies of TTF have mainly integrated theories such as TAM and TPB [26–30], but few have integrated it with ECT [31].

For this reason, the current study used ECT as the informing theory and extended the model with TTF. These theories are used to understand whether the technical support promoting online learning in China during the pandemic helped students complete learning tasks and produced continuance intention. Continuance intention is also a key aspect for promoting online learning in Chinese universities in the future. Therefore, the research questions were as follows:

RQ 1: Is it meaningful to use TTF to explain the continuance intention of Chinese college students to use online learning after the pandemic?

RQ 2: Can the expanded ECT better explain the continuance intention of Chinese college students to use online learning after the pandemic?

The aim of the study is to construct an appropriate theoretical framework through the extension of the model. Chinese college students are the research objects, and understanding their views on online learning during the pandemic and their motivation and continuance intention regarding online learning in the future is the goal. This understanding may offer a new direction for the development of online learning in the post-pandemic era.

2. Literature Review

2.1. Expectation Confirmation Theory

Expectation confirmation theory (ECT) has become a widely accepted model for predicting and explaining satisfaction and continuance behavior [32,33]. Bhattacherjee presented a post-acceptance model of information system (IS) continuance (known as the ECT-IS model). The ECT-IS model, which modified ECT for the context of information system use, allows more reliable interpretations and predictions for IS continuance intention. In recent years, many scholars have adopted ECT-IS as a theoretical basis to explore the continuance behavior of a variety of information systems [32,34–36].

In ECT, user confirmation and expectations are the key predictors of satisfaction. Confirmation expresses user expectations, and lack of confirmation means that the user's expectations were not met. Thus, confirmation is positively correlated with satisfaction [37]. In the field of education, many studies have also used the ECT framework to explore student continuance intention [21,38,39]. Recent research using ECT to study online learning is summarized in Table 1.

Table 1. Research topics on ECT.

Authors	Research Contexts	Constructs	Fundamental Theories
Lee [20]	E-learning	Confirmation, Usefulness, Satisfaction, Continuance intention, Enjoyment, Concentration, Subjective norm, Behavior control, Ease of use, Attitude	ECT + TAM + TPB + Flow theory
Cheng [23]	Blended e-learning	Confirmation, Usefulness, Satisfaction, Continuance intention, Support service quality, Flow, Information quality, System quality, Instructor Quality	ECT + IS success model + Flow theory
Alraimi et al. [38]	MOOCs	Confirmation, Usefulness, Satisfaction, Continuance intention, Enjoyment, Openness, Reputation	ECT
Zhou [22]	MOOCs	Social influence, Satisfaction, Confirmation, Knowledge outcome, Performance proficiency, Continuance intention	ECT
Lu, Wang, and Lu [21]	MOOCs	Confirmation, Perceived, Usefulness, Satisfaction, Continuance intention, Intention to recommend, Flow, Perceived interested	ECT + Flow theory
Dai et al. [19]	MOOCs	Confirmation, Usefulness, Satisfaction, Continuance intention, Curiosity, Attitude	ECT

The literature suggests that ECT can be used to explain the influence of an online learning environment on the actual learning experience of students. Therefore, we employed ECT as the infrastructure to study factors that influence satisfaction and continuance intention in online learning.

2.2. Task-Technology Fit

The TTF model was proposed by Goodhue and Thompson [24]. They integrated two mainstream understandings of how information technology affects performance. In one understanding, attitude is regarded as the prediction index of technology use behavior. The other emphasizes that the degree of fitness of technology to task determines performance and explains the impact that technology and organizational fitness have on organizational performance. TTF is applied to the problem of how the technologies appearing in information systems fit the tasks of users, to improve performance [40,41]. Fitness between task and technology is the main component of the model; when technology provides functions and supports that are meant to "fit" task requirements, the degree of fitness determines individual performance [24,42]. Thus, if one provides better technology for a given task and fitness is high, then the user has higher personal performance in the task [43]. Many researchers have combined TTF with various theories to explain the online learning behavior of students and teachers. For example, Yu and Yu integrated TPB and TTF to explain the adoption of online learning [29]. Wu and Chen proposed a model that combines TAM and TTF models to explore the characteristics of and social motivations in MOOCs [41]. Sun and Gao integrated TAM and TTF models to explain the willingness to use online learning [44]. Wan et al. integrated TTF and UTAUT to explore continuance intention and MOOCs [45]. Also, for the architecture integrating TTF and ECT, Cheng [46] probed into the persistent impact of cloud online learning and believed that the integration of ECT and TTF could better explain the persistence of cloud online learning. You, Jong, and Wiangin [47] also found that the integration of TTF and ECT could better explain the antecedents and consequences of the impact of social media on consumers' choice of organic food. However, the outbreak of COVID-19 forced all Chinese universities to offer online learning in the hope of making up for the failure to complete offline teaching tasks in classrooms. Therefore, we believed that it is necessary and valuable to integrate the two theories to explain the phenomena during the epidemic.

3. Research Model and Hypotheses

3.1. Research Model

Based on ECT and TTF, we sought to construct a model of the continuance intention of Chinese college students regarding online learning during the pandemic. Figure 1 represents the study framework and hypotheses. According to ECT and the framework provided by TTF, four main constructs were identified, namely confirmation, perceived usefulness, TTF, and continuance intention.

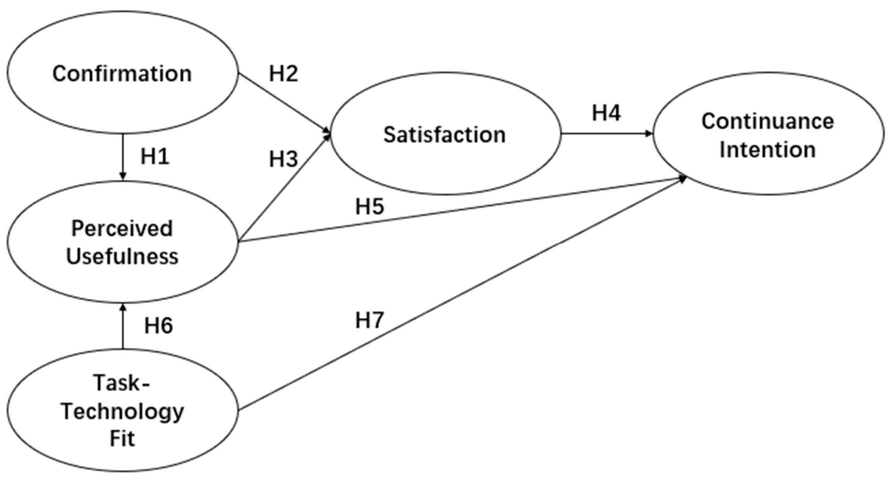

Figure 1. Research model.

3.2. Hypotheses

Bhattacherjee pointed out that the degree of user confirmation has a positive impact on perceived usefulness and used cognitive dissonance theory in support; when a new user of an information system does not have related experience, they cannot confirm whether using the system allows improved performance [32]. So the user would have low perceived usefulness to the new system and it is easy to confirm. Then, after the user starts operations, they gradually confirm whether the system can deliver benefits. Thus, they gradually adjust their original understanding toward post expectation (perceived usefulness). Bhattacherjee's results also confirmed that the degree of confirmation has a significant positive relationship with perceived usefulness. Subsequent studies have also confirmed the effect of confirmation on perceived usefulness [21,28,32,48]. In addition, the results of the study also confirmed that the degree of confirmation has a large impact on perceived usefulness and has good explanatory power [21,28]. In the context of the current study, the degree of confirmation (the comparison between expectation and experience) generated by students using online learning during the pandemic will modify the previous expectation and change it to post expectation (perceived usefulness). Thus, post expectation (perceived usefulness) increases with the degree of confirmation. Therefore, Hypothesis 1 is proposed:

Hypothesis 1 (H1). *The degree of confirmation has a significant positive relationship with the perceived usefulness of online learning.*

Satisfaction is affected by expectation and confirmation. The degree of confirmation derives from the difference between user expectations and actual use, and the degree of user satisfaction comes from the degree of confirmation [32]. According to the premise of ECT, user confirmation is a key prerequisite for satisfaction [20]. In the use of information systems, confirmation is regarded as the assessment of users achieving the expectations, and confirmation is proportional to satisfaction [37]. The influence of confirmation on satisfaction has been confirmed in the literature related to ECT [32,49–51]. For an online learning platform, the higher the degree of confirmation (comparison between expectation and post-experience) of students using online learning, the higher the feeling after the experience than the experience. Thus, the greater the confirmation, the more likely students are to have high satisfaction. Therefore, Hypothesis 2 is proposed:

Hypothesis 2 (H2). *The degree of confirmation has a significant positive relationship with satisfaction with online learning.*

In literature related to ECT, perceived usefulness has been proved to have a significant relationship with satisfaction [32,51–54]. For the present study, the higher the perceived usefulness perceived by students using online learning during the pandemic—which means that they agree with the usefulness and practicability of the online learning platform—the stronger the satisfaction they will have. Therefore, we put forward Hypothesis 3:

Hypothesis 3 (H3). *The degree of perceived usefulness has a significant positive relationship with satisfaction with online learning.*

According to the literature on ECT, satisfaction is a central factor affecting user intention to reuse [55,56]. Bhattacherjee, in discussing research on continuance intention and information systems, argued that continuance intention is mainly determined by the satisfaction generated after actual use [32]. Related research has verified that satisfaction has a sizeable impact on continuance intention [21,32,46]. In sum, ECT offers good explanatory power for the relationship between satisfaction and continuance intention. In the context of the current study, user likelihood to change the system decreases as satisfaction with the platform increases, and online learning continuance intention increases with satisfaction. Therefore, Hypothesis 4 is proposed:

Hypothesis 4 (H4). *Satisfaction with online learning has a significant positive relationship with online learning continuance intention.*

Bhattacherjee pointed out that when users believe that they can obtain benefits or useful help from a certain behavior, they continue performing the behavior and are not affected by the change of time [32]. The study also confirmed that perceived usefulness has a meaningful impact on continuance intention, and subsequent research confirmed that it has good explanatory power [22,51,57]. ECT-related studies have confirmed that perceived usefulness has an impact on continuance intention. For the present study, when students use an online learning platform and perceive its usefulness, they would be more likely to continue to use it. Therefore, Hypothesis 5 is proposed:

Hypothesis 5 (H5). *The perceived usefulness of online learning has a significant positive relationship with the online learning continuance intention.*

TTF level is determined by how well IS functions match the tasks users must execute. It is the main factor explaining work performance [58]. Tasks may be defined as activities executed to convert inputs into valuable outputs that satisfy human needs. Technology here is regarded as a combination of user support and information technology (e.g., software, hardware, and data [59]). Therefore, even if a technology is superior to currently adopted service mechanisms, the technology will not be adopted by users if it cannot satisfy user task requirements [60]. Many empirical studies have confirmed that the perception of whether a specific technology matches user values forms the cognitive basis for actual use of the technology. Therefore, when TTF is high, users tend to perceive the technology as useful [61].

Regarding online learning environments, when students use online learning with high TTF, they tend to perceive the learning platform as useful [41]. Moreover, from the perspective of technology and task characteristics, when students have a favorable experience with online learning, they will in turn have a greater intention to use the service [25]. Undoubtedly, learning goals represent tasks. When the task fits the technology (the online learning platform), users generate i) perception of the platform serves as useful and ii) continuance intention. Thus, Hypotheses 6 and 7 are proposed as follows:

Hypothesis 6 (H6). *The degree of TTF has a significant positive relationship with perceived usefulness with online learning.*

Hypothesis 7 (H7). *The degree of TTF has a significant positive relationship with continuance intention with online learning.*

3.3. Construct Operationalization

An associate professor and three doctors were asked to examine the questionnaire items for suitability to the study rationale, and then 38 students in a class were selected to assess the face validity of the questions [62]. A 7-point Likert scale was used to measure the items. To ensure the accuracy of the questionnaire design, the questions were translated from the original scales. Because the questionnaire was distributed in China, it was translated into Chinese and adjusted according to the circumstance of this study, so that the interviewees could easily read and fill in the questions. To ensure the correctness of the translations, two professors in the information systems field translated the items into Chinese, and then a translator trained in English–Chinese translation translated them back into English. A professional translator carried out the back translation to ensure the accuracy of the original translation. In terms of the choice of scales, the items of Isaac, Aldholay, Abdullah, and Ramayah were adopted and adjusted for TTF [26]; the items of

Gefen were used for perceived usefulness [63]; the items of Bhattacherjee were employed for confirmation [32]; the items of Isaac et al. were used for satisfaction; the items of Ashrafi et al. were used for continuance intention [46].

3.4. Data Collection

The survey was conducted with Chinese university students during the pandemic after 8 weeks of online learning. The questionnaire was distributed through the Internet, which was convenient with quick responses, low cost, and easy identification of respondents [64]. The main platform for the survey was wjx. The survey period was from May to June 2020. To ensure the quality of the sample, students were asked to confirm their understanding that the survey did not involve any academic assessment and was voluntary. The researchers sent the questionnaire to Chinese university instructors through Wechat and QQ and asked instructors at their university and at others to help forward it to their students. The sample was thus collected through the snowball method. To improve the quality of the responses, the students were provided a reward of RMB 3–5.

A total of 854 questionnaires from 18 universities in China were collected. To ensure the quality of the sample, three indicators were used to screen the responses [65]. First, according to the completion time of the initial pre-test, it took 5 to 15 min to complete the questionnaire. Therefore, according to the practice of previous studies, participants finishing the survey within 3 min would be regarded as not filling it in responsibly, and their questionnaire was regarded as invalid. Second, a reverse question was included in the questionnaire design. If a student gave a nonreversed answer, the questionnaire was regarded as invalid. Finally, those with repetitive results or extreme values were also regarded as invalid. Following this strict screening, 854 valid questionnaires were used for formal data analysis.

The valid responses were from 238 male, 616 female, 394 freshmen, 283 sophomores, 161 junior, 13 senior, and 3 graduate students. Among them, 395 learners used online learning 1 h every day, 201 learners 1 to 2 h every day, 131 learners 2 to 4 h every day, and 127 learners more than 4 h every day.

4. Results

The main analytic tool employed was partial least squares structural equation modeling (PLS-SEM). Compared with the conventional, covariance-based SEM method, PLS-SEM was more suitable because the goal of the study was to develop a theory. Moreover, PLS-SEM requires no consideration of multivariate normal distribution [66–68]. SmartPLS 3.28 software was used to analyze the structural model and the measurement model [69].

The common-method variance was excluded using the following method. First, at the stage of data collection, the questionnaire was intentionally designed in separate pages to enable the respondents to have an adequate break between pages. A pause reduces the common-method variance effect resulting from continuous use of the same scale [68]. Then, Harman's single-factor test was used to perform principal component analysis to verify whether the common-method variance existed [70]. According to the results, the first factor only explained about 36.5% of the variance and no factor explained more than 50% of the variance. Thus, no observable common-method variance was present; the result was in an acceptable range [64]. In addition, according to the indicators regarding collinearity recommended by Hair et al. [71], a variance inflation factor lower than 5 indicates the absence of a collinearity problem. All constructs had variance inflation factors between 3.18 and 4.8 and thus met the recommended level (See Table 2).

Table 2. Factor loading, Cronbach's alpha, composite reliability, and AVE.

Construct	Factor Loading	α	Composite Reliability	Average Variance Extracted (AVE)	VIF
Confirmation	0.92 *** 0.96 ***	0.93	0.95	0.94	3.18
Continuance Intention	0.97 *** 0.95 *** 0.96 ***	0.97	0.98	0.94	3.53
Satisfaction	0.96 *** 0.95 ***	0.91	0.96	0.92	3.66
Perceived Usefulness	0.93 *** 0.94 ***	0.93	0.95	0.93	3.98
Task-Technology Fit	0.95 *** 0.96 *** 0.93 ***	0.94	0.96	0.90	4.80

Note: $p < 0.001$ ***.

4.1. Measurement Model

Henseler et al. [72] demonstrated that SRMR was the square root of the sum of the square variance between the model and the empirical correlation matrix, and a value under 0.10 indicated a good fit. In this study, the overall result of SRMR was 0.037, indicating that the model was acceptable. In reliability and validity analyses of the measurement model, the main indicators for assessment were factor loading, composite reliability, convergent validity, and discriminant validity. 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 [73]. Regarding composite reliability, studies have suggested that the indicator value be greater than 0.7 [71]. The average variance extracted (AVE) should be greater than 0.5 [73]. The overall statistical results are presented in Table 2.

The goal of determining 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 [74]. 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 exhibited discriminant validity.

Table 3. Analysis of discriminant validity (Fornell–Larcker criterion).

	TTF	CINT	PU	SAT	CONF
TTF	0.947				
CINT	0.735	0.969			
PU	0.706	0.616	0.946		
SAT	0.860	0.779	0.731	0.959	
CONF	0.673	0.472	0.647	0.820	0.955

Notes: Perceived usefulness (PU); task-technology fit (TTF); continuance intention (CINT); confirmation (CONF); satisfaction (SAT).

Hair et al. [71] presented an alternative method, namely the HTMT correlation ratio, which was the value generated by comparing the mean value of each construct (based on uniform load) with its square uniform construct correlation, to assess discriminant validity. An HTMT value under 0.90 indicated discriminant validity between the two reflective constructs. In this study, the HTMT value topped at 0.888, and its results showed that both student and practitioner samples met all of the criteria. As shown in Table 4, the model had good reliability and validity.

Table 4. Analysis of discriminant validity (HTMT).

	TTF	CINT	PU	SAT	CONF
TTF					
CINT	0.681				
PU	0.786	0.724			
SAT	0.838	0.727	0.804		
CONF	0.780	0.762	0.790	0.888	

Notes: Perceived usefulness (PU); task-technology fit (TTF); continuance intention (CINT); confirmation (CONF); satisfaction (SAT).

4.2. Structural Model

To test the hypotheses, the bootstrap resampling method in SmartPLS was used to evaluate the PLS results, with the responses resampled 5000 times [71]. The overall R^2 value of our results was 0.630. The R^2 for satisfaction was 0.877, and the R^2 value for usefulness was 0.733 (Figure 2). The results indicate that the research model proposed for the study has high explanatory power and provides valuable statistical results.

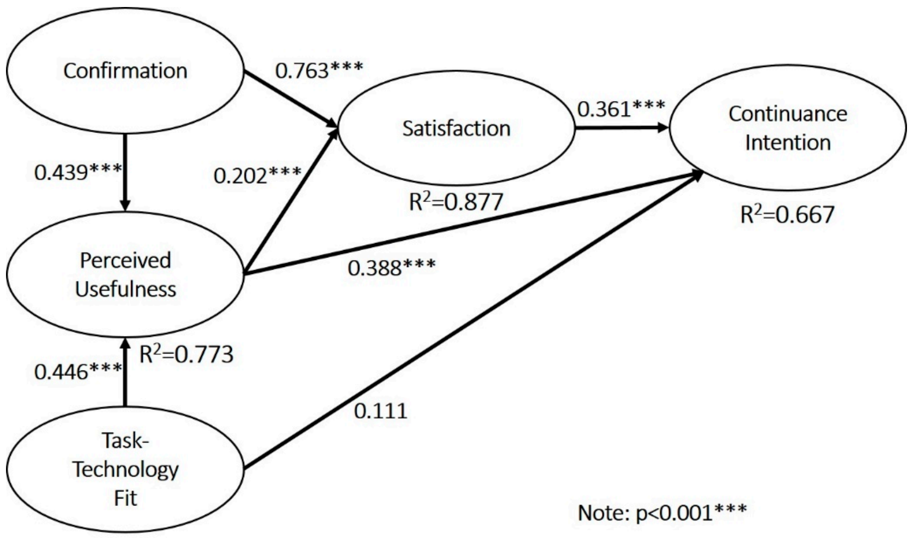

Figure 2. PLS results of the research model.

In terms of the hypotheses, for H1, confirmation has a significant effect on perceived usefulness (β = 0.439, $p < 0.01$). For H2, confirmation is also positively significant for satisfaction (β = 0.763, $p < 0.01$). For H3, usefulness is statistically significant for satisfaction (β = 0.202, $p < 0.01$). For H4, satisfaction is positively significant for continuance intention (β = 361, $p < 0.01$). For H5, usefulness is significant for continuance intention (β = 0.388, $p < 0.01$). However, for H6 (β = 0.446, $p < 0.01$) and H7 (β = 0.111, $p > 0.05$), TTF has a significant effect on perceived usefulness but no statistical significance for continuance intention. According to these results, the extended model constructed on the basis of ECT has favorable explanatory power for the online learning continuance intention of college students during the pandemic. The hypothesis testing results are summarized in Table 5.

Table 5. Results of hypotheses.

Hypothesis	Path Relationship	Beta	Result
H1	Confirmation →Perceived usefulness	0.439 ***	Support
H2	Confirmation → Satisfaction	0.763 ***	Support
H3	Perceived usefulness → Satisfaction	0.202 ***	Support
H4	Satisfaction → Continuance intention	0.361 ***	Support
H5	Perceived usefulness → Continuance intention	0.388 ***	Support
H6	Task-Technology Fit → Perceived usefulness	0.446 ***	Support
H7	Task-Technology Fit → Continuance intention	0.111	Not supported

Note: $p < 0.001$ ***.

5. Discussion and Conclusions

5.1. Discussion

Based on the empirical results for Hypothesis 1, confirmation has a significant impact on usefulness, which is consistent with the results of previous studies on online learning [21,22,46]. According to the results, due to the impact of the pandemic, teachers and school administrators should prioritize the quality of curriculum content when choosing between curriculum platform and content. In particular, the service provided by the platform and the materials provided by the platform are both very important indicators that affect whether students feel the platform is useful.

The results regarding Hypothesis 2 are also consistent with those previously reported [21,28]. If the experience of using the online learning platform exceeds the expectation before use, students are satisfied with the course content. Thus, for teachers and schools, if the selection of course content better fits the attributes of the school, the learning effect is stronger for students. The results regarding Hypothesis 3 are also significant, which is also consistent with previous conceptions of ECT [22,57]. According to the results, during the pandemic, although most university instructors temporarily selected online courses as emergency management, students felt the materials and the content of the system were useful and reported satisfaction in learning. This could show that schools need to adjust and design the standards of curriculum and methods to promote online learning in the future.

Hypothesis 4 was supported. Those with high satisfaction also have high continuance intention, which is consistent with the conclusions of previous studies [21,75]. Surely, during the pandemic, the time for course preparation is tight for Chinese college instructors. However, according to the analysis results, we should consider how curriculum design can be improved, to encourage students to feel satisfied with their learning and with themselves, which in turn will affect the willingness of colleges and universities to continue promoting online learning in the future. Regarding Hypothesis 5, usefulness is significant for continuance intention, which is consistent with previous studies [53]. Therefore, for online learning during the pandemic, finding suitable course content and useful platforms is essential to promote continuous use. For instructors, deepening the quality of course content is also to be considered in the period after the pandemic. Finally, according to the tests of Hypotheses 6 and 7, TTF is significant for usefulness but not for continuance intention. This is different from the research results of Sun and Gao [44]. The possible reason might be that during the pandemic students are forced by the policies of the colleges to use the online learning systems, so students would consider whether the learning systems would fit their learning needs for their college courses. Therefore they would also have an opinion on the usefulness of the system. However, to answer whether students' would continue using the online system, the main factors should be the curriculum arrangement made by colleges and the learning efficiency felt by students.

5.2. Practical Implications

This study mainly explored the continuance intention of students regarding the use of online learning during emergency management. With the popularization of the Internet, the concept of online learning has been widely applied and even widely promoted in university education [76,77]. From the perspective of school management, the online learning environment under emergency management is a good turning point in promoting the development of online learning. Due to the pandemic in China, colleges and universities have thoroughly adopted online learning platforms, and the overall learning satisfaction of students is meaningful. Therefore, whether schools will promote online learning or teachers choose an online learning platform as teaching material in the future will become a very important indicator of continuance intention to use. Especially, in response to the outbreak of COVID-19, the Ministry of Education of China has adopted the method of "suspending classes without stopping learning" to make students take online courses or tutoring at home [18,78]. However, due to time constraints, many Chinese teachers had to use existing online learning platforms such as MOOC platforms like icourses, Chaoxing, and zhihuishu [2]. Therefore, if we can strengthen the functions of online learning platforms and provide more customized teaching materials, we can strengthen them and attract students to online learning. For example, when a school sets up a course, instructors in that discipline could prepare relevant course materials and regional casework as supplementary learning materials to better meet local needs. They could also prepare more online face-to-face real-time interactive learning activities, as well as ways for students to interact with instructors in real-time through online learning and to provide feedback on course content. The pandemic has changed learning modes. Therefore, improving the fitness of learners still focuses on the selection of course platforms and teaching materials. When the curriculum meets the needs of students, learning tasks can be improved, and the continuance intention of students to use online learning services in the future can also be increased. During online learning after the epidemic, we believed that teachers should design different curriculum tasks according to the curriculum form. For example, online management courses may focus on case studies, online computer courses may focus on practical operations, and online science courses may focus on synchronous online learning and offline experiments. Effective course diversion can improve the learning efficiency of students, thus enhancing their learning motivation and encouraging them in online learning. Results of this study showed that when college students confirmed that online learning was helpful, they were more willing to engage in it continuously. This result suggests that teachers may choose existing platforms if they want to promote online learning, especially when the results suggest that users had good experiences with the platforms. This conclusion can also accelerate the promotion of online learning in the future.

5.3. Implications for Research

This study mainly explored the continuance intention to use online learning in a state of emergency management. Unlike previous studies, this study mainly focused on the current situation of online learning in Chinese universities during a pandemic. From a theoretical perspective, its main contributions are as follows. First, most previous studies of continuance intention to use online learning discussed universities or teachers promoting the continued use of online learning platforms under normal circumstances [21,22,57,75]. However, this study focused on online learning under emergency management during a pandemic and offered explanations of university student behavior in continuing to use online learning after the pandemic. Second, from the perspective of the pandemic, the mode of online learning during the pandemic itself is a type of technology, and learning during the pandemic was the task. When the technology fits the task, the expected performance in online learning by students will be better [41,79]. This differs from previous studies that integrated TTF with curriculum needs or characteristics. Therefore, the approach provides a new framework for exploring online learning in an environment of emergency management.

5.4. Limitations and Future Research

The questionnaires in this study were mainly collected through the snowball sampling method; thus the range of the collected samples was limited, especially as the sample did not include universities in each province of China. A follow-up study could assess whether the promotion of online learning and the continuance intention of students differ by area due to the impact of COVID-19. Second, the study was conducted when students had been using online learning during the pandemic for 9 weeks, and it was cross-sectional. Because COVID-19 persists, future researchers could conduct a longitudinal study and discuss the topic from different time points. This would further clarify whether the online learning mode caused by the pandemic will accelerate the promotion of online learning by universities. Third, sampling was carried out by survey, and the results are based only on statistical results, which may not allow for a deep discussion of the continuous use of online learning under emergency management. Therefore, future research can include qualitative methods [80–87], which could dig out more core factors of continuance intention, and the results might explain deficiencies in quantitative research. In this study, TTF and ECT were integrated to explain the online learning environment under emergency management. However, the data of this study were collected and carried out during the epidemic, so the results were limited to the context of emergency management, and might not apply to the studies on online learning in conventional cases, which is another limitation of this study.

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