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The Continuous Use Intention for the Online Learning of Chinese Vocational Students in the Post-Epidemic Era: The Extended Technology Acceptance Model and Expectation Confirmation Theory

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Abstract: In an attempt to prevent and control the outbreak of COVID-19, education systems worldwide have comprehensively implemented online courses to fulfill the educational goal of the suspension of classes without suspending school. Numerous online courses have been developed under these circumstances. From the perspective of sustainable development goals, these online courses should be continued. However, as the epidemic gradually eases, it is questionable whether or not students will still willingly participate in these courses. The method of teaching is a critical issue for schools to decide. Compared with other related educational research, the research on the vocational education system is still limited. To expand the understanding of this topic, this study adopted snowball sampling and invited students from Chinese vocational colleges to fill in a questionnaire to help understand the perceptions that affect students' expectations, attitudes, perceived effects, and satisfaction and the persistence of online learning. A total of 819 valid questionnaires were retrieved, with an effective questionnaire response rate of 81.9%. Meanwhile, under the framework of Expectation Confirmation Theory (ECT) and the Technology Acceptance Model (TAM), this study extended the theoretical model and proposed a sustainable model. The results of this study showed the following: 1. Expectancy belief and online learning attitudes had a positive impact on perceived ease of use and usefulness; 2. Perceived ease of use had a negative impact on practical class satisfaction but a positive impact on theoretical class satisfaction and perceived usefulness; 3. Perceived usefulness had a negative impact on practical course satisfaction but a positive impact on theoretical course satisfaction; and 4. Both types of course satisfaction had a positive impact on continuous use intentions for learning.

Keywords: continuous online learning; course satisfaction; expectation confirmation theory; online learning attitude; technology acceptance model; vocational colleges

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1. Introduction

COVID-19 undoubtedly had a severe impact on global higher education. Teachers and students suddenly had to change their learning styles from offline classrooms to online systems without notice or training sessions [1]. Both the general education system and the vocational education system faced this turning point. The rapid shift to online learning courses led to the instant development and implementation of educational technology in higher education, which forced faculty who were skeptical about or resisted adopting online learning courses in the past to consider the feasibility of online or blended teaching [2]. In this situation, of course, it is necessary to pay attention to the views of students as well.

Even though COVID-19 has greatly affected higher education, Liu argued that it has also contributed to meeting the Sustainable Development Goals (SDGs) [3]. In other words, the COVID-19 epidemic was an opportunity to promote sustainable teaching in higher education [4], as well as in higher vocational education. Online learning is seen as the trend for future education and has taken a firm foothold in higher education to support classroom learning and promote self-directed learning [5]. As a result, online learning has become an integral part of educational models, even though the epidemic may recede someday [6].

In the earlier stage of the pandemic, when learners were forced to adopt online technologies in their studies [7], the quality of online learning raised some concerns because it did not always meet the learning needs of students and thus caused a decline in their participation. It was doubtful whether students would continue to rely on online learning when their learning expectations were completely different from the real situation [8]. For example, the research by Toader et al. found that as many as half of students believed that the impact of online education was negative [9]. Before the epidemic, most of the online courses were categorized as general subjects (general knowledge) and basic subjects [10]. Thus, when online courses required hands-on practice, or when specific physical environments were required, students encountered learning difficulties. For example, the research by Han et al. pointed out that many vocational colleges faced issues and challenges with online learning in terms of practical training and internships and organizational and technological environments [11].

To sum up, even though school administrators have made various efforts to facilitate students' online learning during COVID-19, the sudden implementation of online learning still raised some unresolved issues. At the beginning of the epidemic, the factors affecting students' acceptance of online learning received little attention, but now the academic community is trying to measure the quality of online learning [12,13]. These related research topics are worthy of attention. Given the fact that online learning is most likely to persist even in post-epidemic times, relevant research is expected to promote the development of online course design [13]. Based on previous research on online learning, scholars have pointed out the related research gaps. Although the epidemic has eased a little, it is still occurring repeatedly and is still having a certain impact on the education scene. Therefore, in the post-epidemic era, discussing students' perspectives and their willingness to continue to participate in online learning will make some meaningful contributions to the sustainable development of online education.

The Technology Acceptance Model (TAM) has been widely used to investigate users' acceptance of different technologies in various situations [14]. Therefore, in this study, TAM was adopted as the theoretical framework for model construction. However, Koç et al. pointed out that the main variables in the original TAM model cannot fully reflect the specific effects of technology and environmental factors that may affect users' acceptance [15]. Hence, TAM has been extended several times to suit different technologies [16]. In this study, to better understand learners' acceptance of continuous online learning in the post-epidemic situation, it is also suggested that the TAM model be expanded to gain a more complete understanding of students' perceptions.

Another theory for continuous online learning is Expectation Confirmation Theory (ECT) [17], which works by assessing people's levels of satisfaction and expectations and adding some predictors to the model. More detailed exploration can generate a better understanding of people's continued willingness [18]. This theory is recognized as a stable theoretical model for understanding the continuous behavior of users in different information system environments [19], and it is used by marketing and information systems to understand users' perceptions of a product since the previous perceptions and satisfaction have a crucial effect on their behavior [20]. As a result, this study used this theory as one of the theoretical frameworks to gain a more complete understanding of students' perceptions of continuous online learning.

In the TAM model, external variables are important antecedents that affect the learning experience. Through the literature review, this study established expectancy belief and online learning attitudes as the external variables of the research model. Among them, expectancy belief was defined as students' confidence in achieving expected results in an academic environment [21]. During the COVID-19 epidemic, expectancy belief was described as the degree to which students believed that engaging in online learning would facilitate/improve their learning [22].

Attitude refers to evaluating people's tendencies and inclinations in a favorable or unfavorable reaction [23]. The study by Magen-Nagar and Shonfeld stated that students who participated in online courses first showed technophobia, and they were generally reluctant to use technology [24]. As such, attitudes toward technology were found to be one of the most important factors influencing the willingness of technology use intention. To bridge the gap from a research perspective, attitudes toward technology should be integrated into research models [25].

In addition, for school faculty to better implement online learning, they must understand the learning experience of learning before teaching. Otherwise, it will be difficult to achieve successful online education without a deep understanding of students' experiences in online learning. Perceived ease of use (PEU) and perceived usefulness (PU) are important variables in TAM and ECT [17,26], which can help to explain people's online learning experience. Therefore, PEU and PU were used as mediating variables in this study.

Furthermore, learning satisfaction represents whether the learner's needs are fulfilled [27]. Therefore, measuring satisfaction is essential because this variable can help in predicting people's behavior and then planning necessary strategies based on student satisfaction [20]. Scholars believe that more comprehensive, systematic, and in-depth research on online learning satisfaction should be performed, which will have great significance for improving the service quality of online learning courses and the online teaching quality evaluation system [28]. In this study, course satisfaction was subdivided into two types: course satisfaction for practical courses and course satisfaction for theoretical courses, as mediating variables.

In contemporary educational philosophy, students are active learners, and their enthusiasm for learning is a key indicator of education. Whether the implementation of online learning is successful or not depends on whether students accept it or not. Therefore, students' subjective willingness to participate in online learning is a critical factor of success [27]. In this study, the continuous use intention of learning was recognized as the dependent variable.

Based on the above, there is limited literature on the continuous use intention of online learning during the COVID-19 outbreak. Hence, there is an urgent need to identify the factors that influence students' continuous use intention for online learning by conducting relevant research during the epidemic and even in the future [8,29], especially when the epidemic still has an impact on the education system, and online learning is still ongoing due to the epidemic prevention measures in colleges in China. However, the current sustainable model cannot effectively or fully explain students' perspectives on their willingness (acceptance) to engage in online learning in vocational education. As a result, this study proposed an extended theoretical model under the framework of ECT and the TAM to determine the utility factors as the antecedents affecting vocational college students' continuous learning intention.

1.1. Expectancy Belief

An expected outcome is defined as an anticipation of a result. It is a judgment or belief that people hold regarding the likely consequences of performing a particular action or the expectation that an action will lead to a particular outcome [21,30]. It can be a prospective assessment or retrospective assessment involving causal attribution [31]. Most people expect certain results when they perform specific actions [32]. Therefore, expectancy belief is viewed as a motivating belief [33]. The previous findings suggested that, during the COVID-19 epidemic, students' expectations of using the learning system had a positive impact on their sustainable engagement [34]. In this study, expectancy belief was adopted as the independent variable, referring to participants' expectations about the learning performance that online learning brought to them.

1.2. Online Learning Attitude

Attitude refers to evaluating people's certain tendencies and reactions in a favorable or unfavorable way [23]. If attitudes toward learning are negative or dismissive, students have little opportunity to participate in any learning process [35]. In other words, a student's preference for a certain teaching/learning method implies a positive attitude towards that method [36]. Students themselves are considered as the most important factor in an online learning environment because their positive or negative attitude towards this learning environment will have a great influence on their own learning [37]. In sustainable online learning, students' attitudes towards online learning should be accountable, since online courses may replace offline classroom learning for a long period of time [38]. Therefore, this study discussed the influence of online learning attitudes on learning experience. Online learning attitudes could be the positive or negative evaluation perceptions that learners hold while participating in online learning.

1.3. Perceived Ease of Use (PEU)

Two variables, PEU and PU, represent people's cognitive responses [39]. PEU represents the degree to which an individual expects to use a particular system without much effort [14,40]. To be more specific, PEU is defined as the user's belief that adopting an e-learning system will not need a high level of complexity and that they can start using the system immediately without spending much time on learning how to use it, thereby reaping the benefits of learning such as saving time, money, and effort [16]. This is what the users recognize as the effort of learning required to adopt technology [41]. Only users who think the technology is easy to use can have positive feelings about this technology [39]. Therefore, this study adopted PEU to discuss the influence on learning experience.

1.4. Perceived Usefulness (PU)

PU represents the degree of perception that a technology can actually benefit the users [41], and it is usually defined as the user's perception of the value of digital systems that help them to improve their performance [14,42]. Therefore, PU is also described as the subjective probability that using a particular technology will improve their performance, according to people's beliefs [40]. In the field of teaching, learners must constantly evaluate their learning in an e-learning environment [43]. Students' perceptions of the learning environment are related to their perceived learning outcomes and may be related to the learning outcomes achieved [44]. This study included PU to explore the impact on learning experience.

1.5. Course Satisfaction

Evaluating learning satisfaction is critical to understanding students' perceptions of their learning experience [45]. Students feel satisfied when their learning experience (performance) matches the expected outcomes of the courses they took [46]. The degree of satisfaction is directly reflected in the learning process. It is a psychological reaction to the online learning content and learning environment, and a perception is formed after comparing the actual perceived rationality and emotion [28]. As a result, maintaining student satisfaction with the learning experience is a significant issue for educators [46]. Therefore, students' satisfaction with courses is used as one of the key elements in evaluating online courses. In other words, students' satisfaction during online classes should be investigated [47,48]. In addition, relevant research also showed that, due to the special circumstances caused by the epidemic, teachers and students who had never participated in online learning before had to mandatorily adopt the online learning and teaching mode, since this was an involuntary change from the traditional learning mode to this brand-new learning mode. Thus, it is necessary to understand the satisfaction of online learners [49]. This study used course satisfaction to explore the effect on continuous learning intention.

1.6. Continuous Use Intention to Learning

Continuous use intention is a subjective tendency to repeatedly choose something, which can be used to predict the persistent use behavior [50]. It is a behavioral intention which inclines to the willingness to use a product or service continuously after the initial use. It keeps occurring, which indicates that users accept the product or service and are likely to continue using it [8]. According to the TAM, acceptance depends on the use intention for a particular technology [26]. Therefore, the user's long-term continuous use is the key factor for the long-term survival and ultimate success of this technology [51]. In educational settings, the learning/teaching measures taken should remain welcoming and supportive for all learners, as well as for online learning modalities, as it is critical to maintain students' use intention to behave in any form of learning environment [22]. Moreover, persistence is an important indicator of people's continued use of e-learning technology after first trying e-learning technology [52]. This study used continuous use intention to learn to ensure students' acceptance of online learning.

2. Theoretical Basis and Research Assumptions

2.1. Expectation Confirmation Theory

Users often have expectations of what they are using. These expectations will be actualized once completed and become an internal experience which is identified and transformed into either positive feelings (satisfaction), apathy, or negative feelings (no satisfaction) [53,54]. The ECT states that the process of judgment and internal evaluation is an important factor in determining the user's continuous behavior [55]. This theory provides a valid theoretical perspective to explain how a product/system can improve its service quality to maintain user loyalty [56]. ECT describes user behavior from the perspectives of pre-behavior (expectation) and post-behavior (perceived performance) [57]. Therefore, ECT explains important shifts in human behavior in the use of technology, as the long-term viability of information systems depends on the user's continued use rather than initial use [55]. In terms of the digital realm, initial adoption is significant for the successful application of a product/system/service, and continued usage (acceptance) is more about the practical benefits of long-term usage. This study used ECT as one of the theoretical frameworks of an extended research model to help to explain students' continuous use intention for online learning (acceptance).

2.2. Technology Acceptance Model

The first TAM was proposed by Davis [26]. This is an intention-based model that was originally developed to predict users' initial adoption of new information systems [58]. According to TAM, once people believe that using a particular system will achieve the desired result or performance, they intend to reuse it [54]. Furthermore, from a general concept, the less effort required to learn a new technology, the higher the acceptance of the technology [39].

The TAM framework is composed of three dimensions: ease of use, usefulness, and willingness to act, and it has validated external factors based on personal belief [59,60]. However, in specific situations using TAM as a framework, ease of use and usability may not fully determine an individual's willingness to use these technologies, so additional variables should be included to better understand user perceptions on this basis [42]. This study used TAM as one of the theoretical frameworks of an extended research model to help explain students' continuous learning intention for online learning (acceptance).

2.3. Research Model

Under the framework of ECT and TAM, this study expanded the theoretical model, including seven variables: expected belief, online learning attitude, PU, PEU, theoretical course satisfaction, practical course satisfaction, and continuous use intention for learning. A sustainable model was proposed to explore the intention (acceptance) of students to continue online learning, as shown in Figure 1.

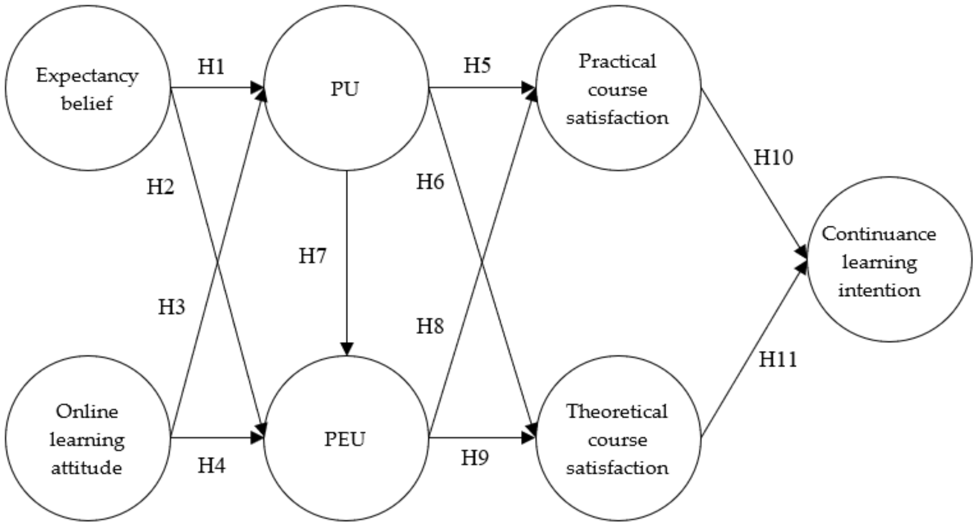

Figure 1. Research Model for learning.

2.4. Research Hypothesis

People believe that a particular behavior will generate the desired outcome. However, if individuals do not have confidence in their ability to accomplish the expected action, this message ultimately does not influence their performance [61]. The strong effect of expectancy belief on perception (perceptual performance) can be explained [62]. In addition, Davis also proposed that external variables can affect people's PEU and PU of technology [26]. It can be seen that expectancy belief can act as a motivational or inhibitory factor for perceived outcomes. Based on the above literature review, the hypotheses proposed in this study are as follows:

H1. *Expectancy belief has a positive effect on PEU.*

H2. *Expectancy belief has a positive effect on PU.*

The TAM suggested that external variables can be used to explore the effects on PU and PEU [63]. Research has confirmed that domain-specific attitudes have a positive impact on PEU and usefulness [23]. In addition, some studies have pointed out that when participants have a better attitude towards using information communication technology for online distance learning, it may have a positive impact on their learning experience [35]. Based on the above literature review, the hypotheses proposed in this study are as follows:

H3. *Online learning attitude has a positive impact on PEU.*

H4. *Online learning attitude has a positive impact on PU.*

The decision-making process of using acceptance or adoption of a technique depends on specific psychological determinants [64]. For example, PEU and PU have been found to affect students' perceived satisfaction [64,65]. After people use a specific IT for a period of time, they will form a perception concept, which will be the most significant factor affecting their post-acceptance (satisfaction) regarding that particular IT [20]. Therefore, PU, as a reference benchmark for confirming judgments, has a positive impact on satisfaction [58,66].

Furthermore, the TAM indicates that PEU has a direct effect on PU [23,58,67]. People are more likely to develop a favorable opinion of a technology if it feels easy to use [65]. Therefore, when students find IT easy to use, they will use it better. Based on the above literature review, the hypotheses proposed in this study are as follows:

H5. *PEU has a positive impact on full satisfaction with practical lessons.*

H6. *PEU has a positive impact on full satisfaction with theoretical courses.*

H7. *PEU has a positive effect on PU.*

H8. *PU has a positive impact on practical course satisfaction.*

H9. *PU has a positive impact on theoretical course satisfaction.*

Compared with adoption behavior, continuous learning intention or post-adoption is a long-term exchange relationship [68]. When users are strongly motivated by perceiving the presence of necessary resources, it is reasonable to assume that this perception will also lead to better e-learning adoption [63]. In addition, studies have confirmed that when users are satisfied with an e-learning system, they will continue to use the system [20,51,69]. This is also consistent with ECT's viewpoint that the continuous use intention for IT mainly depends on the user's satisfaction with their previous experience [55]. Based on the above literature review, the hypotheses proposed in this study are as follows:

H10. *Practical class satisfaction has a positive impact on continuous learning intention.*

H11. *Satisfaction with theoretical courses has a positive impact on continual use intention.*

3. Research Methods

3.1. Research Methods and Implementation

This study used a quantitative approach based on a cross-sectional survey. For this type of study, questionnaires are considered to be the most reliable tool for measuring the relationship between variables in the research model [70]. Considering the school's epidemic prevention requirements, this study conducted an online questionnaire for data collection. In this study, snowball sampling was adopted, and the questionnaire web page was sent to teachers in vocational colleges for their assistance with recruiting students from vocational colleges to fill in the questionnaire and encouraging students to forward the link to their peers in other vocational colleges. The questionnaire distribution started on 15 May 2022 and continued until 1000 responses were collected.

3.2. Participants

A total of 1000 questionnaires were received in this study, from which incomplete questionnaires or those with a single response were deleted. The number of valid samples was 819, giving an effective recovery rate of 81.9%. The average age of the participants was 19.38 years old, and the standard deviation was 1.22 years. The background information is shown in Table 1.

Table 1. Participant Background Information.

Category	Content	
Gender	Male: 440 (53.7%)	Female: 379 (46.3%)
Grade	Freshman: 248 (30.3%)	Sophomore: 385 (47%)
	Junior: 186 (22.7%)	
Studying professional subjects	Hospitality: 41 (5%)	Architecture: 51 (6.2%)
	Mechanical: 59 (7.2%)	Mechatronics: 72 (8.8%)
	Electronic and electrical: 56 (6.8%)	Computer: 63 (7.7%)
	Chemical: 36 (4.4%)	Agriculture: 35 (4.3%)
	Finance and accounting: 54 (6.6%)	Marketing: 61 (7.4%)
	Fine arts: 67 (8.2%)	Physical education: 28 (3.4%)
	Hair and image: 22 (2.7%)	Video and film: 36 (4.4%)
	Clothing: 14 (1.7%)	Broadcasting and program hosting: 25 (3.1%)
	Dance and performance: 17 (2.1%)	Pre-school education: 82 (10%)
Had taken online courses before the epidemic	Yes: 547 (66.8%)	No: 272 (33.2%)
Type of online courses	Theoretical courses: 167 (20.4%)	Practical courses: 43 (5.3%)
	Cultural courses: 337 (41.1%)	None: 272 (33.2%)

3.3. Measurement

This research model consists of seven variables, namely, expectancy belief, online learning attitudes, PEU, PU, satisfaction with the two course types, and continuous use intention. To ensure the reliability and validity of the scale, all items were adapted from past studies and modified to fit the research background of online learning in vocational colleges. Meanwhile, all items were measured using a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). All participants filled in the questionnaire based on their situation. The content of the first draft of the questionnaire was reviewed and modified by three scholars in the field of vocational education with a digital learning background to construct expert content validity. Thus, the variables, item descriptions, and options of the questionnaire were revised and improved based on the feedback from the experts. Ten students from vocational colleges were recruited to fill in the questionnaire for a trial test. Based on the feedback of the trial test, we adjusted the content description of the questionnaire again so as to present a text description method that is closer to the participants' understanding. Finally, an online questionnaire survey was conducted through the Questionnaire Star platform.

3.3.1. Expectancy Belief

This study used the Expectancy Belief Scale of Ye et al. [71], with a total of eight items, to measure participants' perceptions of expectations regarding participating in online learning—for example: "I want to learn more professional knowledge through online courses". The original questionnaire had a Cronbach's alpha of 0.88, factor loading (FL) values of 0.69 to 0.76, a CR of 0.88, and an AVE of 0.51.

3.3.2. Online Learning Attitude

Online learning attitude refers to the positive or negative evaluation perceptions that learners hold when participating in online learning. According to this concept, this study designed a total of seven items in the online learning attitude scale to measure participants' views on participating in this learning method during online learning—for example: "After participating in an online course, I will spend more time studying for the course".

3.3.3. PEU and PU

This study referred to and modified the PU and usability dimensions of the technology acceptance scale of Hong et al. [72], each with seven questions for measuring participants' perceptions of the utility and convenience of online learning. Examples of PU are: "I feel that participating in an online course allows me to gain more information about my learning". A PEU example is: "I can easily interact with the teacher on the online course platform". The Cronbach's alpha for PEU was 0.88, the factor loading (FL) was 0.66 to 0.97, the CR was 0.86, and the AVE was 0.67. The Cronbach's alpha for PU was 0.90, the factor loading (FL) values were 0.63 to 0.77, the CR was 0.92, and the AVE was 0.75.

3.3.4. Course Satisfaction

The course satisfaction scale of Ye et al. had six items each for measuring participants' perceptions of satisfaction with the two types of courses [71]. An example of a professional course satisfaction question is: "I feel that in the online course of professional practice, I learned the professional skills I need." An example of theoretical course satisfaction is: "I think online courses in theory are a good tool for reviewing what I've learned." The original questionnaire had Cronbach's alpha values of 0.90 to 0.91, factor loading (FL) values of 0.74 to 0.78, CR values of 0.90 to 0.91, and AVE values of 0.64 to 0.68.

3.3.5. Continuous Learning Intention

This study referred to and modified the "willingness to participate in the continuous participation" scale designed by Hong et al. [73]—for example: "I hope to learn more professional knowledge through online courses". The original questionnaire had a Cronbach's alpha of 0.89 and a KMO of 0.80.

3.4. Statistical Analysis

One main goal of social science research is to explain and predict specific behaviors of individuals, groups, or organizations in an effective manner, in the context of identifying specific concepts and events, and to identify causal relationships between variables in research issues [74]. Structural equation modeling (SEM) is a set of statistical techniques and an effective tool for helping explain variable relationships, also known as causal modeling, causal analysis, path analysis, or confirmatory factor analysis [75]. Using a confirmatory (hypothesis-testing) approach to the multivariate analysis of aspects and theories, which constructs causal relationships between multiple variables, also helps to determine whether a hypothesized theoretical pattern is consistent with the collected data, thereby reflecting this theory [76]. The powerful effect of this statistical technique makes SEM one of the most prominent statistical methods in the social sciences [77]. Therefore, this study adopted SEM to verify the extended theoretical model.

4. Results and Discussion

The statistical tools used in this study were SPSS 23.0 and AMOS 20.0. Project analysis, external model evaluation, descriptive statistical analysis, overall fitness analysis, and model verification were carried out. The analysis results are described as follows.

4.1. Item Analysis

Before carrying out model verification, it is very important to confirm whether the measurement model has an acceptable degree of fit. Therefore, this study used item analysis to test the measurement model. Relevant criteria include that the χ^2/df value should be less than 5; the root mean square error of approximation (RMSEA) should be less than 0.10; the goodness of fit index (GFI) and adjusted goodness of fit index (AGFI) should be higher than 0.80; and items with factor loadings (FL) not higher than 0.50 should be deleted from the original questionnaire [78,79]. The results are shown in Table 1. According to these results, expected belief consisted of eight items but was reduced to five; online learning attitude was reduced from seven items to five; PU was reduced from seven items to five; PEU was reduced from seven items to five; practical class satisfaction was reduced from six items to four; theoretical course satisfaction was reduced from six items to four; and continuous use intention for learning was reduced from six items to four.

In this study, the external validity of the items was tested to confirm the inferential range of the research results [80]. In each item, the values answered by all participants were divided into the top 27% and the bottom 27%, and a *t* test was performed; when the *t*-value of the test result was greater than 3, it was regarded as the item with external validity. Table 2 shows that the *t*-values of the items in this study ranged from 35.25 to 59.17, which indicated that all items had a good external validity in this study [81].

Table 2. First-order confirmatory analysis.

Index	χ^2	*df*	χ^2/df	RMSEA	GFI	AGFI	FL	*t*
Threshold	—	—	<5	<0.10	>0.80	>0.80	>0.50	>3
Expectancy belief	17.72	5	3.54	0.05	0.99	0.98	0.82~0.94	41.65~59.17
Online learning attitude	14.87	5	2.97	0.05	0.99	0.98	0.84~0.92	39.57~40.07
PU	17.36	5	3.47	0.06	0.99	0.98	0.85~0.94	42.36~50.81
PEU	16.75	5	3.35	0.05	0.99	0.95	0.93~0.96	35.25~36.32
Practical course satisfaction	4.44	2	2.22	0.04	0.99	0.99	0.97~0.98	36.29~37.18
Theoretical course satisfaction	2.98	2	1.49	0.02	0.99	0.99	0.94~0.97	44.70~46.94
Continuous learning intention	3.45	2	1.73	0.03	0.99	0.99	0.91~0.95	51.67~54.63

4.2. Reliability and Validity Analysis

The external model process confirmed the reliability, convergent validity, and discriminant validity of the dimensions. Reliability analysis was performed using Cronbach's alpha and composite reliability (CR). Hair et al. suggested Cronbach's alpha and CR values higher than 0.70 as acceptable [78]; the Cronbach's alpha and CR values in this study were both between 0.95 and 0.99, which met the recommended standards, as shown in Table 3.

Table 3. Reliability and validity analysis.

Constructs	*M*	*SD*	α	CR	AVE	FL
Threshold	—	—	>0.70	>0.70	>0.50	>0.50
Expectancy belief	3.73	0.91	0.95	0.95	0.80	0.90
Online learning attitude	3.68	0.94	0.98	0.98	0.89	0.94
PU	3.70	0.98	0.98	0.95	0.89	0.94
PEU	3.44	1.19	0.98	0.97	0.88	0.94
Practical course satisfaction	3.45	1.16	0.99	0.99	0.95	0.98
Theoretical course satisfaction	3.65	0.84	0.98	0.98	0.91	0.95
Continuous learning intention	3.75	0.92	0.96	0.96	0.85	0.92

Convergent validity was judged by factor loading (FL) and average variance extracted (AVE). Hair et al. pointed out that the FL value should be higher than 0.50, and the items below this value should be deleted [78]. All the items retained in this study met the standards recommended by scholars. The values ranged from 0.90 to 0.98, as shown in Table 2. Hair et al. suggested that the AVE value must be greater than 0.50 to indicate that the construct has convergent validity [82]. The AVE values were all between 0.80 and 0.95 in this study, as shown in Table 3.

It is important to confirm the discriminant validity of a construct, because it can distinguish constructs from each other and measure different concepts. When the AVE root value of each construct is greater than the Pearson correlation coefficient value of other constructs, it means that the construct has discriminant validity [83]. The analysis results showed that each construct in this study had discriminant validity, as shown in Table 4.

Table 4. Construct discriminant validity analysis.

Constructs	1	2	3	4	5	6	7
1. Expectancy belief	(0.89)						
2. Online learning attitude	0.60	(0.94)					
3. PU	0.43	0.49	(0.94)				
4. PEU	0.49	0.48	0.64	(0.94)			
5. Practical course satisfaction	0.03	−0.10	−0.29	−0.33	(0.97)		
8. Theoretical course satisfaction	0.45	0.40	0.49	0.39	0.18	(0.95)	
7. Continuous learning intention	0.33	0.25	0.11	0.11	0.33	0.42	(0.92)

Note: The value on the diagonal is the square root value of AVE, and the other values are the correlation coefficient values.

4.3. Model Fit Analysis

Before conducting research model validation, it is also necessary to confirm whether the overall fitness of the model meets the acceptance criteria. The standard values of each fitting index are: the chi-square degree of freedom ratio (χ^2/df) must be less than 5 [78], the approximate root mean square error (RMSEA) should be less than 0.10, and the Goodness of Fit Index (GFI), Adjusted Fit Index (AGFI), Normative Fit Index (NFI), Non-Normative Fit Index (NNFI), Comparative Fit Index (CFI), Value-Added Fit Index (IFI), and Relative Fit Index (RFI) should all be greater than 0.80 [84]. The parsimonious normative fit index (PNFI) and the parsimonious goodness of fit index (PGFI) should be greater than 0.50 [78]. The fitted index values in this study were χ^2 = 1873.22, df = 453, χ^2/df = 4.14, RMSEA = 0.06, GFI = 0.88, AGFI = 0.86, NFI = 0.96, NNFI = 0.96, CFI = 0.97, IFI = 0.97, RFI = 0.95, PNFI = 0.87, and PGFI = 0.75. The values of each fitting index were in line with the standards recommended by scholars, which indicated that they had an acceptable degree of model fit.

4.4. Path Analysis

Structural equation modeling analysis was performed using AMOS 20.0 in this study, and the structural model assessments included the path coefficient (β), significance level (*p*-value), coefficient of determination (R^2), and amount of effect (f^2). The study results showed that: expectancy belief had a positive impact on PEU (β = 0.25 ***) and a positive impact on PU (β = 0.22 ***). Online learning attitudes had a positive impact on PEU (β = 0.37 ***) and a positive effect on PU (β = 0.14 ***). PEU had a negative effect on practical class satisfaction (β = −0.12 **) but a positive effect on theoretical course satisfaction (β = 0.39 ***) and a positive effect on PU (β = 0.50 ***). PU had a negative effect on practical course satisfaction (β = −0.24 ***) but a positive impact on theoretical course satisfaction (β = 0.12 **). Practical course satisfaction had a positive impact on willingness to continue learning (β = 0.28 ***). Theoretical course satisfaction had a positive effect on continuous learning intention (β = 0.40 ***), as shown in Figure 2.

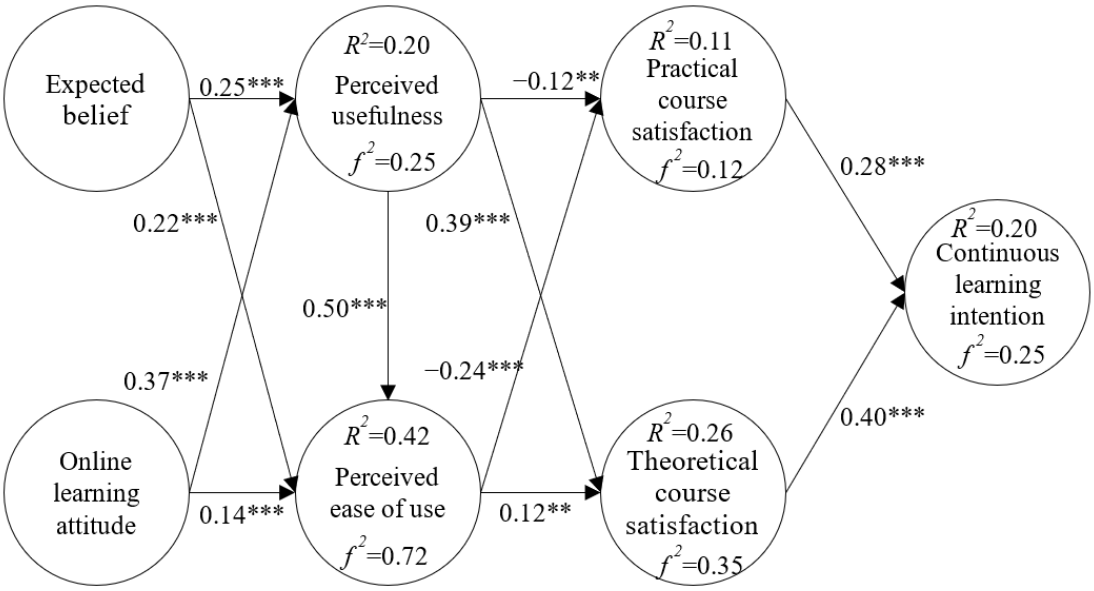

Figure 2. Research Model Validation. ** $p < 0.01$, *** $p < 0.001$.

In addition, the R^2 of expectancy belief and online learning attitude to PEU was 20%, and the f^2 was 0.25. The R^2 of expected belief, online learning attitude, and PEU to PU was 42%, and the f^2 was 0.72. The R^2 of PEU and PU for practical course satisfaction was 11%, and the f^2 was 0.12, while the R^2 of theoretical course satisfaction was 26%, and the f^2 was 0.35. The explanatory power of the willingness to learn was 20%, and the f^2 was 0.25, as shown in Figure 2.

4.5. Discussion

Although all 11 pathways in this study model were significant, two research hypotheses were overturned. In other words, when students had higher levels of expectancy belief and online learning attitudes, their PEU and PU were higher for online learning, and when they also had higher levels of PEU and PU, they were less satisfied with online learning. However, when students had higher levels of PEU and PU, they were more satisfied with theoretical courses. Finally, when students were more satisfied with the two types of courses, they wanted to continue their studies online. Most of the analysis results of this study were in line with the theoretical viewpoints proposed by Davis and Bhattacherjee [26,55].

The reason why PEU and PU cannot positively affect course satisfaction may be seen from past research results. Studies have pointed out that taking online courses may have a negative impact on student satisfaction compared with traditional courses [85]. The research of Zhang and Duan pointed out that, during the epidemic, vocational colleges responded to the call of the state to suspend classes and continue to study, and they conducted a preliminary exploration of online teaching, but due to the lack of experience, many problems and deficiencies were exposed [86].

The learning of skill subjects, such as remote teaching, will encounter the limitations of equipment and instruments, as well as time and space, because when learning the most basic skills, students need to experience them by themselves [10]. In terms of teaching materials, especially in higher vocational education, with many practical courses, it is more difficult for students to express the obstacles encountered when conducting practical courses online. Practical courses often cannot be completed through online learning [87]. Han et al. pointed out that this also led to problems and challenges faced by vocational colleges [11]. For example, during online learning, practical training courses and internships were significantly affected; their survey found that more than a quarter of schools' online practical training courses were not implemented, and more than one-third of schools had not implemented online internships at all.

Mushtaque et al. stated that although the use of online learning has become an important learning tool, the biggest learning challenges are inappropriate learning environments and students not being able to meet the educational requirements [88]. In their study, 55.9% of students thought that online learning was not suitable for all types of subjects. From the literature review, it was well illustrated that when vocational colleges tried to implement online education, it was difficult to meet the learning needs of students.

5. Conclusions and Recommendations

5.1. Conclusions

Since the outbreak of the epidemic, the global education system has invested a great deal of money and manpower in the construction of online courses for epidemic prevention and control so as to achieve the educational goal of suspending classes without stopping. This also means that a large number of online courses have been developed, and the improvement of online education has also been accelerated. From the perspective of sustainable development, these resources should be put to good use. However, as the epidemic gradually eases, all online courses under epidemic prevention measures have been gradually converted into hybrid courses, or offline courses have been fully resumed. Whether students will be willing to use the resources of the originally established (developed) online learning courses is an important issue that needs to be paid attention to. Compared with other education disciplines, studies on the vocational education system are still in the minority. Therefore, in order to expand the understanding of this topic, this study was carried out. This study aimed to explore vocational college students' perceptions of the use, implementation, and acceptance of online emergency learning as a source of sustainability in the post-epidemic era.

Under the framework of ECT and the TAM, this study extended the theoretical model and proposed a sustainable model, which effectively explained the continuous use intention for the learning of distance vocational education including skills learning. The extended TAM was empirically validated as a theoretical model for future research on the use of technology in educational settings.

The research results showed that, first, expectancy belief and online learning attitudes had a positive impact on PEU and usefulness; second, PEU had a negative impact on practical class satisfaction but a positive impact on theoretical class satisfaction; third, PU had a negative impact on practical course satisfaction but a positive impact on theoretical course satisfaction; fourth, both types of course satisfaction had a positive impact on continuous use intention for learning. The results of the SEM indicated that even though not all the hypothesized relationships of the variables could be supported, the role of the external variables was still confirmed to be significant.

Additionally, descriptive analysis showed that vocational college students generally had a neutral-biased view of online learning during the epidemic (*M* ranged from 3.44 to 3.75), and most of them still wanted to continue online learning in the post-epidemic time (M = 3.75), while the level of satisfaction with hands-on courses was a little lower (M = 3.45). The contribution of this study was to provide empirical evidence in higher vocational education, and the results of this study show how to ensure the quality and sustainability of education during the mandatory transition from traditional learning models to online learning after campus shutdowns (i.e., suspension of classes without suspending school).

5.2. Recommendations

Although countries (regions) around the world have gradually lifted their lockdowns after the outbreak of the epidemic, students in China are still required to participate in online learning for 3 consecutive years to ensure that the epidemic will not endanger their health. From the point of view of contemporary education, only if students are willing to participate actively in online learning will the passive acceptance of online learning diminish. All hypotheses confirmed that both types of course satisfaction had a positive effect on persistence intentions; however, the study also found that, in the vocational education system, online learning only seems to bring good results for theoretical courses. Therefore, teachers should seek to use multiple approaches to meet the needs of a wide range of students [6]. Vocational colleges should carry out teaching workshops or seminars for practical teachers to improve their online teaching capability so as to allow students to have a better online learning experience to meet students' learning needs.

In order to realize the sustainable development of online education, vocational colleges should also pay attention to the limitations of the online environment of practical courses by using the immersive and simulation characteristics of Metaverse technology to build virtual factories, thereby providing vocational college students with an immersive learning experience. Furthermore, for students who do not study well in practical courses, schools should also actively arrange for tutoring time after resuming offline courses to enhance and complement students' learning experience.

5.3. Contributions

This study makes several contributions to the literature. First, the level of satisfaction among vocational school students regarding online courses during the pandemic was confirmed in this study. Since strong practicality is still required during the learning process of vocational college students, it was confirmed in this study that the current online learning method is not so suitable for learners in the vocational education system. Using the data can help front-line lecturers in improving their online course teaching methods, especially for practical courses. Second, for educational managers, it is very important to keep track of learners' learning statuses. Although there are many acceptance models, the acceptance model proposed in this study discusses the usability of system software, the content of different types of courses, satisfaction, and continuous use intention to better confirm students' learning experience, which is undoubtedly a very important part of the learning process. Since online learning or blended learning will be the future educational trend, the extended acceptance model proposed in this study can also be used by teaching administrators to investigate students' online learning in the vocational education system.

5.4. Research Limitations and Recommendations for Future Research

This study has some limitations which need to be overcome. First, this study employed the snowball sampling method to survey students in Chinese vocational colleges with online learning experience. However, Sun et al. stated that respondents may not be actively participating in online courses when completing questionnaires, which may lead to their previous online learning experiences not being completely clear [89]; this issue needs to be promptly addressed. In future studies, intentional sampling can be adopted instead, and the surveys of students who have actively participated in online courses can be retested to verify the relationship between the variables in this study.

Second, this study used a cross-sectional design for questionnaire data collection, so only participants' feelings about the present moment could be understood during a specific time period. However, the theoretical view of ECT is that people's expectations change over time, and this often occurs with the use of information technology. Therefore, in the future, it would be possible to track different time periods (different epidemic situations) for a long time, as well as the opinions and willingness of vocational college students regarding participating in online learning. At the same time, a more in-depth understanding of the specific factors that make learners have these ideas after participating in online learning can be obtained from participants who have positive and negative attitudes and high levels of satisfaction and dissatisfaction so as to put forward relevant feedback more deeply, which can correspond with improvement strategies. It would also be possible to explore the difficulties encountered by vocational college teachers when they teach online and to make suggestions for teaching improvement.

In this study, the effectiveness of online learning was judged by participants' self-reported PU and satisfaction. To increase the objectivity of the study results, follow-up research can also consider other objective data such as formative or summative assessments to explore the effectiveness of online learning.

Finally, although the participants in this study represented a wide range of professional disciplines and experiences, the study was unable to demonstrate the unique characteristics of discipline-specific learning experiences and participation in online learning [6]. Each e-learning success factor and the relationships between them may vary across disciplines. Although 819 questionnaires were collected in this study, the proportions of participants' fields of study were unevenly distributed and disparate. Unfortunately, the results of the analysis could not reach statistical significance. In future research, it is suggested that the collection of questionnaires be expanded so as to explore whether the online learning experience of different professional disciplines in vocational colleges will be different.

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