pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
https://assumptionjournal.au.edu/index.php/Scholar

Factors Impacting Vocational Education' Satisfaction, Learning Engagement, and Continuance Intention of MOOCs

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Received: August 14, 2024. Revised: September 16, 2024. Accepted: Frebuary 18, 2025.

Abstract

Purpose: This study aims to enhance vocational school students' satisfaction, learning engagement, and intention to use MOOCs in Hangzhou, China. **Research design, data, and methodology:** The quantitative method (N=550) was used to distribute questionnaires to first-year students and collect sample data. The validity and reliability of the questionnaire were tested by project-objective consistency test and pilot test before delivery. Confirmatory factor analysis (CFA) and structural equation model (SEM) were used to analyze the data, verify the model's goodness of fit, the structure's validity, and research hypothesis testing. **Results:** The research results show that the Perceived Usefulness, Satisfaction, and Learning Engagement of conceptual models have a significant impact on Continuance interaction. Course material developers, course teachers, and senior managers of higher education institutions, when comprehensively evaluating the existing or upcoming MOOC platforms, should ensure that the human-machine interaction, human-machine system interaction, human-machine message interaction, and flow experience attributes are reasonable and practical and that students can indeed improve the efficiency of learning using the system. To further enhance students' satisfaction in using MOOCs and further Continuance Intention to Use MOOCs learning. **Conclusions:** MOOC platform managers should explicitly link the use of the platform to learner activities and positive learning outcomes.

Keywords: MOOCs, Vocational education, Satisfaction, Learning engagement, Continuance intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In 2008, the term MOOC emerged to describe courses accessible through online platforms. Since then, MOOCs have grown in popularity among students and educators. The low cost of education is considered an intermediary benefit achieved through online instruction. Massive open online courses (MOOCs) have enabled many worldwide to study and learn without geographical or time limitations (Sementelli & Garrett, 2015). These courses are designed for individuals who want to improve their professional skills or expand their knowledge (Spector, 2014). Many online courses typically last about four to six weeks, depending on the content, and can be completed using a learner's terminal device. The implementation and design of teaching materials are based on a simultaneous learning process involving top professors from some of the world's most prominent universities. The most important aspect of MOOCs is that they are completely free and open to the public (Joo et al., 2018). Key features of MOOCs include interactive forums, course content, and quizzes, which allow users to check their learning outcomes. MOOCs are interactive platforms that facilitate interaction between educators and learners (Pappano, 2012). With the help of individualized learning platforms, online students can modify their plans based on their objectives.

In China, the Education Ministry launched the country's first Massive Open Online Courses (MOOCs) in 2013. In

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2015, the agency noted the need to improve the management and development of online learning platforms. It also proposed creating many new MOOCs to enhance their quality. The ministry aimed to produce high-quality education courses by 2020. The COVID-19 pandemic, which had a profound global impact in the spring of 2020, also significantly affected various sectors, including education in China. In response to the pandemic, many educational institutions in the country were suspended (UNESCO, 2020a).

In response, the Education Ministry of China directed educational institutions to implement online teaching programs. Jiangnan University utilizes online platforms to enable its learners to pursue independent education. The Law and Economics Department of Zhongnan University employed various online learning resources to provide high-quality education. The university also used Multiple online platforms to maintain its teaching standards during the epidemic. Students at Nanjing University of Telecommunications must participate in designated class groups to ensure their academic progress during the pandemic. Tsinghua University urged its faculty members to deliver its spring 2020 theory courses online to provide the best possible education for its students. In addition to conducting online studies, many universities provided students with free information about Massive Open Online Courses (MOOCs). MOOCs differ from the online courses previously offered by universities during the pandemic. Students can choose whether or not to study on these platforms. Unlike mandatory online courses, MOOCs allow students to enroll at their discretion, while traditional online courses generally require participation according to the curriculum.

The evolution and rapid emergence of online learning have provided various educational institutions with new opportunities, including learning management systems and multiple online courses (UNESCO, 2020b). In China, numerous educational institutions and universities offer online learning programs using audio and video lectures. These programs can be delivered by teachers and are designed to meet the diverse needs of students (Hodges et al., 2020). While some institutions and universities in China provide online programs through video-based methods, other platforms enable students to interact with instructors.

This study investigates the issue of behavioral intention using Hangzhou, China, as a case study. In the internet era, it is crucial to encourage higher education institutions to use MOOCs in their teaching processes. Therefore, this research explores the factors that stimulate students' intention to continue using MOOCs for learning. University administrators can benefit from this study by developing course content and teaching processes that meet students' needs, promoting their intention to use MOOC systems for learning. The findings can provide valuable insights and strategic support for higher education institutions and learning management system course developers who aim to expand into the online education field or seek to transform traditional courses into blended learning models.

2. Literature Review

2.1 Human-Human Interaction

Through human-to-human interactions, students and teachers can enhance their communication and deepen their learning by leveraging the various features of an e-learning platform (Chen et al., 2017). The interactions between students and teachers are regarded as the most important factors affecting the outcome of a learning session. Eom et al. (2006) revealed that the interaction between educators and students can significantly impact satisfaction among online learners. You (2015) found that interactions between students and teachers reinforce learning tasks' social and emotional security and help students share relevant information. A study on students revealed that those who had favorable peer interactions performed better in their studies (Omar et al., 2015). The study also found that interactions between students and teachers are crucial factors influencing the satisfaction of online students. Besides the delivery of textbooks, interactions between students and teachers play a vital role in e-learning environments (Islam & Azad, 2015; Lam et al., 2014).

According to Badia et al. (2014), educators' teaching styles vary in e-learning environments. Different approaches can help improve the quality of teaching and assist students in completing their assignments (Lin et al., 2017). In e-learning research, student-teacher interactions are important factors contributing to user satisfaction. Based on the findings of previous studies, this paper develops the following hypothesis:

H1: Human-human interaction has a significant impact on satisfaction.

2.2 Human-System Interaction

Massive open online courses (MOOCs) enable learners to engage with the system through various features, including text, images, and multimedia capabilities (Chen et al., 2017). Harris et al. (2016) state that human-system interaction within e-learning environments can significantly affect user satisfaction. The concept of interactivity pertains to how participants communicate their needs and desires. Hsu et al. (2015) studied users' willingness to use social media in e-learning environments. They found that the ability to express ideas and views through various forms of media greatly contributes to user satisfaction. Interactivity plays a crucial role in shaping satisfaction. DeLone and McLean (2003) updated the success model to explain various behaviors after adopting an information system. The success of a system can be evaluated based on factors such as service quality, information quality and quantity, and the likelihood of its use. These factors influence both user satisfaction and the probability of continued system use.

The study identified that the availability of resources and the ability to share views and ideas are key factors influencing students' willingness to use social media. The interactions between students and the system significantly impact their satisfaction (Hsu et al., 2015). The updated success model for information systems can explain various behaviors following adopting new technology (DeLone & McLean, 2003). This model evaluates an information system's efficacy by considering the quality of its output, service, and information, affecting user satisfaction and system usage frequency. Based on the findings of previous studies, this paper develops the following hypothesis:

H2: Human-system interaction has a significant impact on satisfaction.

2.3 Human-Message Interaction

The level of human interaction with the system should also be considered to ensure users can easily access and study the course content (Chen et al., 2017). According to Hollender et al. (2010), interactions between people and information are core factors influencing the success of an information system. Researchers can leverage the various functions of information systems to expand their understanding of cognition (Harder et al., 2016), which can affect user satisfaction. Bharatia and Chaudhury (2004) found that the quality of the information and the information's quality are critical factors influencing user satisfaction with an information system. Saeed and Abdinnour-Helm (2008) noted that a high-quality information system can benefit users by enabling them to make more informed decisions. They emphasized that the quality of transmitted information affects users' satisfaction and perception of value.

Shyu and Chou (2008) suggested that effective learning design is essential for organizing online course content. Through e-learning platforms, students can easily browse course materials, explore platform features, and create learning materials (Harder et al., 2016; Materia et al., 2016). The quality of the information and user interactions influence users' willingness to return to and satisfaction with the e-learning platform (Ranganathan & Ganapathy, 2002). It is theorized that the quality of information presented in online courses affects students' satisfaction. Well-organized course materials can enhance students' enjoyment of learning activities and group discussions within an e-learning setting (Badia et al., 2014). Based on the findings of previous studies, this paper develops the following hypothesis:

H3: Human-message interaction has a significant impact on satisfaction.

2.4 Flow Experience

Developing a strong emotional attachment to a particular activity can be driven by flow experiences (Chang & Zhu, 2012; Liu et al., 2009). Studies have shown that the satisfaction of online students is influenced by the type of learning environment they are in, including the accessible content and the group discussions they participate in (Rose et al., 2012). The flow experience provided by Massive Open Online Courses (MOOCs) can significantly determine the level of satisfaction learners experience.

Rossin et al. (2009) conducted a study on 45 MBA students and found that the data flow during a course affected their learning outcomes, enhancing their perceptual knowledge and overall satisfaction. Similarly, a study involving 462 South Korean online learners revealed that the flow experience significantly impacted their satisfaction with the course (Joo et al., 2013). Cheng (2014) conducted a related study with 378 nurses from Taiwan and found that the flow of experiences could positively or negatively impact participants' satisfaction.

Other factors, such as motivation levels and the flow of information, also affect user satisfaction with e-learning platforms (Alraimi et al., 2015). MOOCs can stimulate a learner's flow experience, improving overall satisfaction and developing perceptual skills and knowledge mastery. Based on the findings of previous studies, this paper develops the following hypothesis:

H4: Flow experience has a significant impact on satisfaction.

2.5 Learning Engagement

Wegmann and Thompson (2014) define interpersonal communication as the quality of participation in learning activities that involve interactions with other people. Through an e-learning platform, individuals can engage and search for the information they require, with immersion in the process enhancing their satisfaction (Leong, 2011). Various factors, such as the design, quality of content, and the overall experience, can enhance the immersion students feel while using an e-learning platform. One positive effect of immersion is increased satisfaction among students (Goel et al., 2013). Studies have shown that more engaging e-learning platforms are more likely to be used over time.

A study revealed that users' trust in a blog system is related to their desire to continue using it (Shiau & Luo, 2013). Medical professionals' willingness to use blogs may also be affected by their overall experience with them (Cheng, 2014). Based on the findings of previous studies, this paper develops the following hypotheses:

H5: Learning engagement has a significant impact on satisfaction.

H10: Learning engagement has a significant impact on continuance intention.

2.6 Perceived Usefulness

A method or program's perceived effectiveness is also considered when assessing its usefulness (Davis et al., 1989). A learner's satisfaction can be enhanced by the learning platform's ability to fulfill a particular role (Cheng, 2014). Studies have proven that the perceived value of e-learning systems can significantly impact users' satisfaction (Al-Sabawy et al., 2011; Islam, 2013). In mobile commerce, research has shown that people are more likely to use a platform they perceive as useful when finding information about products they purchase. Users can interact with one another through online comments or live chat (Xue et al., 2020). The perceived usefulness of mobile commerce applications can affect user engagement levels (McLean, 2018). Individuals who believe e-learning is useful to use it (Cheng, 2012; Lwoga & Komba, 2015). The perceived value of MOOCs can influence platforms' willingness to continue offering educational content (Alraimi et al., 2015; Wu & Chen, 2017). The perceived worth of technology can also influence individual engagement. Based on the findings of previous studies, this paper develops the following hypotheses:

H6: Perceived usefulness has a significant impact on satisfaction.

H7: Perceived usefulness has a significant impact on learning engagement.

H9: Perceived usefulness has a significant impact on continuance intention.

2.7 Satisfaction

Satisfaction is a psychological state that arises from cognitive evaluations of outcomes and expectations (Bhattacherjee, 2001). According to the confirmation theory, consumer satisfaction with a product or service has positive effects (Oliver, 1980). A satisfactory experience is crucial for determining whether individuals will continue using an electronic system (Horzum, 2015). Research has shown that satisfaction is closely linked to an individual's desire to continue using a system (Hsiao et al., 2016). Danaher and Rust (1996) found that higher customer satisfaction is associated with a greater likelihood of continued service use.

This notion aligns with the adaptive expectation theory (Oliver & Winer, 1987), which predicts that individuals' preferences will remain unchanged even if the products or services they use change. Satisfaction is believed to impact the success of an information system significantly. Given the similarities in how people use and purchase services and goods, high satisfaction is considered a critical factor for the success of information systems (DeLone & McLean, 2003; Rai et al., 2002).

One key factor influencing technology's future use is customer satisfaction with e-learning initiatives (Barbour, 2010). Cronin et al. (2000) noted that the perceived value of an information system can also affect an individual's intent to continue using it. Researchers conducted a study to determine if satisfaction influences individuals' intent to continue using an information system. The study found that increasing satisfaction among students participating in Massive Open Online Courses (MOOCs) boosts their likelihood of continuing to use the technology. Based on the findings of previous studies, this paper develops the following hypothesis:

H8: Satisfaction has a significant impact on continuance intention.

2.8 Continuance Intention

The continuance intention refers to users' behavior of using a service after receiving it (Bhattacherjee, 2001). An individual's behavioral intention is influenced by their perception that the specific item they are using is beneficial, which affects their readiness to continue a particular action (Ajzen, 1991). Chiu et al. (2007) describe continuance intention as a subjective feeling related to users' perceptions of using a learning network. On the other hand, continuance intention refers to the willingness to take action in a satisfactory context. It describes the level of commitment an individual has to continue using a technology (Amoroso & Chen, 2017). The behavior of individuals after acquiring new technology can be used to determine their intent to continue using that technology (Park, 2014). The concept of continuance intention can also be used to describe changes in engagement during ongoing learning, potentially influencing the decision to continue using the technology (Bansal et al., 2005).

3. Research Methods and Materials

3.1 Research Framework

The researcher has developed a research model based on the Expectation-Confirmation Model (ECM), Uses and Gratification Theory (UGT), Technology Acceptance Model

(TAM), and the DeLone and McLean Information Systems Success Model (ISS). TAM explains the acceptance and adoption of Information Systems (IS) and analyzes user adoption factors. It provides a theoretical foundation for understanding external factors influencing user attitudes and intentions and is widely used to predict information technology usage. Drennan et al. (2005) noted that while TAM was created to study technology acceptance in business environments, it has since proven to be a versatile model applicable in educational settings.

The research model incorporates insights from three theoretical frameworks. The first framework, proposed by Chen et al. (2017), examines how interactivity and openness impact university students' intention to continue using Massive Open Online Courses (MOOCs). The study found that satisfaction significantly directly impacts continuance intention, with human-information interaction being the most important factor influencing satisfaction. In contrast, perceived openness has a lesser effect on usage intention. The second framework, developed by Mulik et al. (2019), investigates the flow experience of MOOC users and its impact on their intention to continue using the platform. The results indicate that a positive flow experience significantly enhances user satisfaction and continuance intention. The third framework, proposed by Cheng (2022), explores factors affecting students' willingness to continue using MOOCs. It finds that interface design quality, teaching quality, collaboration quality, perceived usefulness, learning engagement, and expectation confirmation positively impact students' learning outcomes, satisfaction, and intention to continue using MOOCs.

This study aims to identify key factors influencing satisfaction and learning engagement among vocational college students in Hangzhou, China, and to examine the causal relationships between these factors and their intention to continue using MOOCs, as outlined in the research conceptual framework. The research conceptual framework is proposed as follows: Figure 1.

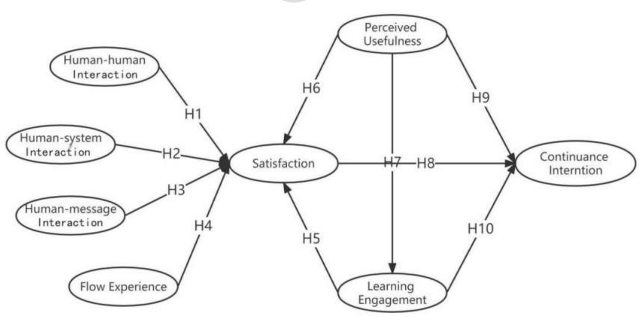

Figure 1: Research Conceptual Framework

H1: Human-human interaction has a significant impact on satisfaction.

H2: Human-system interaction has a significant impact on satisfaction.

H3: Human-message interaction has a significant impact on satisfaction.

H4: Flow experience has a significant impact on satisfaction.

H5: Learning engagement has a significant impact on satisfaction.

H6: Perceived usefulness has a significant impact on satisfaction.

H7: Perceived usefulness has a significant impact on learning engagement.

H8: Satisfaction has a significant impact on continuance intention.

H9: Perceived usefulness has a significant impact on continuance intention.

H10: Learning engagement has a significant impact on continuance intention.

3.2 Research Methodology

In this study, empirical analysis and quantitative methods were employed. First, sample data were collected from the target population using a questionnaire. Before large-scale data collection, the content validity and reliability of the questionnaire were verified through Item-Objective Congruence (IOC) tests ($\geq$ 0.67) and a pilot test of Cronbach's Alpha ($\geq$0.7). After ensuring reliability, electronic questionnaires were distributed to first-year students from four majors at Zhejiang Business College who had more than one year of experience with MOOCs.

Two quantitative methods were used: Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The first step involved using SPSS and AMOS for CFA to examine convergent validity. The second step employed SEM to explore causal relationships between all constructs in the conceptual model and to test the significance of the influences and proposed hypotheses.

3.3 Population and Sample Size

This study's target population comprised first-year students from Zhejiang Business College with over a year of experience using MOOCs and proficiency in multiple MOOC platforms. This selection criteria ensured that participants were familiar with MOOCs and had substantial usage experience. According to Soper (2006), a priori sample size calculator for Structural Equation Modeling (SEM), the recommended minimum sample size is 444 for eight latent variables and 28 observed variables, with a probability level 0.05. Consequently, 550 questionnaires were distributed, and valid responses were subsequently screened.

3.4 Sampling Technique

The sample was selected using a multistage sampling technique, including judgment, stratified random, and convenience sampling. Initially, judgment sampling was used to choose first-year students from four majors at Zhejiang Business College. Subsequently, stratified random sampling determined the sample size for each department or stratum, as shown in Table 1.

Table 1: Sample Units and Sample Size

Majors	Population Size	Proportional sample size
E-commerce students	776	183
Culinary Arts students	480	113
Finance students	306	72
Art and Design students	765	182
Total	**2,327**	**550**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic information collected from the respondents included their gender. Questionnaires were distributed to first-year students in four selected majors that frequently use MOOCs. Five hundred fifty questionnaires were distributed, ensuring a broad representation across these key academic areas. The respondent pool comprised 199 males, accounting for 36.1 percent of the total, and 351 females, making up 63.9 percent. This distribution reflects the gender balance within the selected majors and provides a robust basis for analyzing the usage and perceptions of MOOCs among students. The comprehensive data collection aimed to ensure that the study's findings would be representative of the broader student population engaging with MOOCs. The demographic profile is proposed as follows: Table 2.

Table 2: Demographic Profile

Demographic and Behavior Data (N=550)		Frequency	Percentage
Gender	Male	199	36.1%
	Female	351	63.9%

4.2 Confirmatory Factor Analysis (CFA)

When assessing SEM models, the structure of the variables and factors influencing the continuous use of an information system is analyzed using the Confirmatory Factor Analysis (CFA) method (Lei & Wu, 2007). CFA has distinct advantages compared to other techniques, allowing for measuring reliability and validity between variables (Byrne, 2010). Convergent validity can be assessed through metrics such as Cronbach's Alpha, factor loading, and average variance extracted (Fornell & Larcker, 1981).

A factor loading greater than 0.50 is considered significant (Hair et al., 1998). In this study, factor loadings for all individual items were greater than 0.50, with most being above 0.70, ranging from 0.526 to 0.839, as shown in Table 3. Researchers recommend using composite reliability (CR) values of 0.70 and above and average variance extracted (AVE) values greater than or equal to 0.4 (Fornell & Larcker, 1981; Hair et al., 1998). Table 3 demonstrates that the CR values in this study were all above the threshold, ranging from 0.774 to 0.859. The AVE values were also greater than 0.4, ranging from 0.507 to 0.671.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Human-Human Interaction (HHI)	Chen et al. (2018)	3	0.852	0.789-0.839	0.852	0.658
Human-System Interaction (HSI)	Chen et al. (2018)	3	0.837	0.770-0.814	0.837	0.632
Human-Message Interaction (HMI)	Chen et al. (2018)	3	0.859	0.795-0.831	0.859	0.671
Flow Experience (FE)	Cheng (2021)	5	0.832	0.526-0.794	0.835	0.507
Continuance intention (CI)	Chen et al. (2018)	3	0.839	0.781-0.822	0.840	0.637
Satisfaction (SS)	Chen et al. (2018)	3	0.770	0.671-0.790	0.774	0.535
Perceived usefulness (PU)	Cheng (2022)	4	0.816	0.691-0.769	0.818	0.529
Learning engagement (LE)	Cheng (2022)	4	0.806	0.626-0.781	0.809	0.516

The goodness of Fit indicators was measured and shown in Table 4, including indices such as CMIN/DF, GFI, NFI, RMSEA, and TLI, all within acceptable statistical values.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012;)	1.674
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.936
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.919
NFI	≥ 0.80 (Wu & Wang, 2006)	0.922
CFI	≥ 0.80 (Bentler, 1990)	0.967
TLI	≥ 0.80 (Sharma et al., 2005)	0.961
RMSEA	< 0.08 (Pedroso et al., 2016)	0.035
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Discriminant validity was found to be satisfactory, as presented in Table 5, with significance determined by comparing the square root value of AVE to the correlation factor.

Table 5: Discriminant Validity

	HHI	HIS	HMI	FE	CI	SS	PU	LE
HHI	**0.811**							
HSI	0.406	**0.795**						
HMI	0.146	0.110	**0.819**					
FE	0.359	0.382	0.111	**0.712**				
CI	0.131	0.213	0.198	0.187	**0.798**			
SS	0.414	0.496	0.211	0.485	0.309	**0.731**		
PU	0.294	0.211	0.149	0.199	0.285	0.305	**0.727**	
LE	0.149	0.205	0.132	0.130	0.210	0.260	0.204	**0.718**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

In Wanichbancha's (2014) article, the author defines the Structural Equation Model (SEM) method as a multivariate analysis technique. This method can study the relationships among latent and observed variables. SEM can test the causal relationships between discrete or continuous variables (Ullman & Bentler, 2013). SEM is not a descriptive but a confirmatory method for testing theoretical models (Hossain et al., 2021). Hair et al. (2006) pointed out that SEM is a powerful statistical technique. While general statistical techniques can only analyze the relationship within a single structure, SEM can simultaneously test the relationships between different variables. Due to its flexibility and versatility, SEM is commonly used in various scientific research fields (Lei & Wu, 2007).

Table 6 measures and demonstrates the goodness of fit for the structural model. The statistical values are CMIN/DF = 2.554, GFI = 0.892, AGFI = 0.871, NFI=0.860, CFI = 0.919, TLI = 0.910, and RMSEA = 0.053. All fit indices values were greater than the acceptable values, confirming the model's fitness.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012;)	2.554
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.892
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.871
NFI	≥ 0.80 (Wu & Wang, 2006)	0.860
CFI	≥ 0.80 (Bentler, 1990)	0.919
TLI	≥ 0.80 (Sharma et al., 2005)	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.053
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

As suggested in the hypothesis, the strength of the correlation between the dependent and independent variables is measured using standardized path coefficients or regression coefficients.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: HHI→SS	0.205	4.318*	Supported
H2: HSI→SS	0.373	7.399*	Supported
H3: HMI→SS	0.140	3.002*	Supported
H4: FE→SS	0.405	7.993*	Supported
H5: LE→SS	0.155	3.060*	Supported
H6: PU→SS	0.169	3.362*	Supported
H7: PU→LE	0.252	4.679*	Supported
H8: SS→CI	0.251	4.575*	Supported
H9: PU→CI	0.203	3.839*	Supported
H10: LE→CI	0.114	2.187*	Supported

Note: * $p<0.05$
Source: Created by the author

The strongest impact on Satisfaction is the Flow experience. The path relationship between Satisfaction and Flow experience has a standardized path coefficient of 0.405 and a t-value of 7.993 in H4. This supports the previous studies of Cao et al. (2005), Harris and Goode (2004), Lao and Pupat (2020), and Lee (2010). Flow experience regarding reliance, response capability, and individualization is another vital attribute of MOOCs' Satisfaction.

Human-system interaction significantly impacts Satisfaction with a standardized path coefficient of 0.373 and a t-a value of 7.399 in H2. Human-system interactions such as accessibility, timeliness, accuracy, and relevance can influence the degree of MOOC satisfaction by students Al-Omairi et al. (2021), Lin (2007), and Perkowitz and Etzioni (1999).

Another significant factor impacting perceived Usefulness is learning engagement with a standardized path coefficient of 0.252 and a t-value of 4.679 in H7. So, the features of LMS, such as controllability and flexibility, are important for students to consider and accept the system as a useful tool Kim et al. (2008), Rui-Hsin and Lin (2018).

Satisfaction was mainly contributed by continuance intention. The direct impact of Satisfaction on continuance intention is significant at a standardized path coefficient of 0.251 and t-value of 4.575 in H8, which is supported by the studies of Arteaga Sanchez et al. (2013) and Camarero et al. (2012). These studies show that students perceive the more useful MOOCs, the more likely they are to be of positive interest in learning with MOOCs.

Human-human interaction also significantly impacts Satisfaction with using the MOOCs service, with a standardized path coefficient of 0.205 and a t-value of 4.318 in H1. When students believe in the MOOCs service's reliability and independence, they are likely to have a positive impression or attitude toward using the system (Agag & El-Masry, 2016; Chawla & Joshi, 2019; Kim & Tadisina, 2007).

Perceived Usefulness has a significant direct impact on continuance intention to use, with a standardized path coefficient of 0.203 and a t-value of 3.839 in H9. This is consistent with the studies of Benjangjaru and Vongurai (2018), Bhattacherjee (2000), and Perry (2017). The Usefulness of the system to the extent that it enhances the performance of their learning is the strongest determinant of intention to use or participate in MOOCs.

Perceived Usefulness has a significant direct impact on Satisfaction with use, with a standardized path coefficient of 0.169 and a t-value of 3.362 in H6. The finding was consistent with Jaiyeoba and Iloanya (2019), Lau and Woods (2008), and Lee (2009). Hence, students are likely or intent to use MOOCs when they have a positive or favorable impression of them.

Learning engagement has a significant direct impact on Satisfaction with use, with a standardized path coefficient of 0.155 and a t-value of 3.060 in H5. This finding is consistent with previous studies by Gefen and Heart (2006), Lee et al. (2015), and Tarhini et al. (2017). They claim that when students are more engaged in learning during the relearning process, they will be Satisfied and use MOOCs to learn.

Human-message interaction significantly impacts Satisfaction with a standardized path coefficient of 0.140 and a t-value of 3.002 in H3. This is consistent with studies by Benjangjaru and Vongurai (2018), Bhattacherjee (2000), Lin (2003), and Perry (2017). The quality of human interaction was known to increase people's Satisfaction with learning. This was the most important factor that prompted them to participate in or use Massive Open Online Courses.

Learning engagement has a significant direct impact on continuance intention to use, with a standardized path coefficient of 0.114 and a t-value of 2.187 in H10. This is supported by the studies of Arteaga Sanchez et al. (2013) and Camarero et al. (2012). Students find that the more involved and active they are in learning, the stronger and more useful their Satisfaction will be.

5. Conclusion and Recommendation

5.1 Conclusion

This study aims to comprehensively analyze the important factors that affect students' satisfaction, learning engagement, and continuance intention in Hangzhou, China, when using MOOCs for learning. The rapid emergence and evolution of the internet have greatly impacted various facets of our daily lives. Understanding the factors influencing students' satisfaction and engagement with Massive Open Online Courses (MOOCs) is crucial for effectively promoting learning. The researchers proposed ten hypotheses to investigate the direct or indirect impacts on the defined research questions. The survey targeted first-year students from four Zhejiang Business College majors with at least one year of experience using MOOCs. A total of 550 questionnaires were distributed. After analyzing the collected data, the researchers used Confirmatory Factor Analysis (CFA) to measure and test the validity and reliability of the research conceptual model. Additionally, Structural Equation Modeling (SEM) was employed to analyze and discuss the factors influencing the continuance intention of students in vocational colleges to use MOOCs. All ten proposed hypotheses were supported, demonstrating the achievement of the research objectives.

The researchers were able to summarize their findings, with all 10 proposed hypotheses being supported. This validation instills confidence in the research's conclusions, providing a solid foundation for understanding the factors influencing student satisfaction, learning engagement, and continuance intention with MOOCs in Hangzhou, China.

First, the researchers found that satisfaction is the primary factor influencing a learner's decision to enroll in an online course. Horzum (2015) emphasized the importance of satisfaction in determining individuals' willingness to use information systems. Furthermore, the interactive nature of Massive Open Online Courses (MOOCs) significantly affects how satisfied students are with their learning experience. Therefore, enhancing system interaction is crucial for increasing learners' willingness to engage with MOOCs.

Secondly, the study ranked the antecedents significantly impacting satisfaction according to Human-Human Interaction, Human-System Interaction, Human-Message Interaction, and Flow Experience. Providing high-quality interactive services makes users perceive the system as valuable and useful. Eom et al. (2006) observed that increased interactions between students and teachers lead to higher user satisfaction. E-learning research has increasingly recognized the significance of these interactions. You (2015) stated that interactions between teachers and students enhance the social and emotional security of the learning process and provide relevant information for the students.

5.2 Recommendation

The researchers identified key factors influencing the use of Massive Open Online Courses (MOOCs) in four main subjects at Zhejiang Business College in Hangzhou. These factors include Human-Human Interaction (HHI), Human-System Interaction (HSI), Human-Message Interaction (HMI), Flow Experience (FE), Continuance Intention (CI), Satisfaction (SS), Perceived Usefulness (PU), and Learning Engagement (LE). These factors should be developed and promoted to enhance the adoption of MOOCs in vocational schools.

In this study, satisfaction was found to be the strongest predictor of continuance intention when using MOOCs. This underscores the importance of Satisfaction in determining whether users are willing to continue using the information system, making it likely they will continue to use MOOCs. Therefore, developers of curriculum materials, teachers, and senior managers of higher education institutions should ensure the availability of HHI, HSI, HMI, and Flow Experience when using MOOCs. The insights provided in this study can help MOOC platform designers and owners develop better promotion strategies. The results emphasize the importance of interactivity on the MOOC platform. Platform designers should seek to provide tools or features that maximize HSI and HHI. In this study, the effect of HMI was weak, suggesting that developers should optimize the logic for more effective interaction between users and information, facilitating users' access to learning-related materials. Providing these functions can enhance HMI. Flow experience is a key factor affecting satisfaction. MOOC platform managers should explicitly link the use of the platform to learner activities and positive learning outcomes. They should actively promote the platform through online word-of-mouth or existing online communities to increase the sense of flow experience. This can help learners engage more effectively with online courses, increasing their willingness to continue using MOOCs.Once interactive features are assured, the system's usefulness, operational processes, and other support facilities should be publicized to students through training or media communication to increase their awareness and acceptance. These measures can inspire a positive attitude and increase the likelihood of using MOOCs in the learning process.

In conclusion, this study details the impact of MOOCs on vocational school students' satisfaction, learning engagement, and continuance intention. It allows MOOC curriculum developers and senior managers of higher education institutions to identify variables that affect satisfaction, learning engagement, and continuance intention. These variables can be applied to projects, investments, and optimizing the use of MOOCs.

5.3 Limitation and Further Study

The study's limitations have been acknowledged, and further research is recommended. Firstly, this study focuses solely on vocational school students, specifically selecting participants from four majors within Zhejiang Business College. The sample size and scope were limited, indicating further research needed to validate and expand upon the findings. Secondly, the questionnaire used for the study included self-report scales, which could introduce bias. Additionally, the model did not account for certain variables.

Further studies are needed to analyze factors influencing a learner's use of online tools, such as reputation and satisfaction. Different types of online learning and study objectives can also yield varying results, making the model more general. Thirdly, the study was conducted exclusively on students. Including teachers could provide deeper insights into how their pupils perceive the effects of using online courses. As individuals become more familiar with online services, their perceptions of openness and interaction will likely evolve. Public perceptions of online learning can also change over time. Further research is needed to analyze the factors that affect college students' satisfaction and learning engagement using MOOCs. By addressing these limitations, future research can provide a more comprehensive understanding of the factors influencing the use and effectiveness of MOOCs in various educational contexts.

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