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Factors Affecting the Continuance Usage Intention of MOOCs in Higher Education in China

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Abstract

Purpose: This study aims to enhance the intention of higher education students in Hangzhou, China, to continue using MOOCs. The key variables are human-human interaction, human-system interaction, human-message interaction, perceived usefulness, learning engagement, continuance usage intention, flow experience and satisfaction using Massive Open Online Courses. **Research design, data, and methodology:** A quantitative method (N=550) was employed to distribute questionnaires among sophomore students and collect sample data. Prior to distribution, the validity and reliability of the questionnaire were assessed through item-objective congruence (IOC)and pilot tests. Data analysis involved confirmatory factor analysis (CFA) and structural equation modeling (SEM) to evaluate the model's goodness of fit, assess structural validity, and test the research hypotheses. **Results:** The results reveal that the conceptual model successfully predicts the factors influencing students' continuance usage intention for e-learning in higher education in Hangzhou, China. The study's findings supported nine out of the ten proposed hypotheses. The research indicates that perceived usefulness, satisfaction, and learning engagement significantly impact continuance usage intention. **Conclusions:** The study identified several factors that can enhance students' flow experience and satisfaction using Massive Open Online Courses. Key among these is improving the quality of interaction between students and the system.

Keywords: MOOCs, Learning Engagement, Satisfaction, Flow Experience, Continuance Usage Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The rapid emergence of information technology has drastically changed how we live and has significantly affected teaching methods used in schools. Traditionally, teachers have been central figures in education, playing a crucial role in developing and implementing educational programs within physical classrooms (Khan & Qudrat-Ullah, 2021). These offline learning spaces are typically filled with regular students and teachers. However, with the rise of online classes, these traditional venues are losing their competitive edge (Nguyen, 2015). The use of technology has expanded the boundaries of learning beyond physical spaces. Modern learning software is becoming more prevalent, enabling schools to utilize advanced front-end technology. The rapid emergence of new teaching methods and the technological advancements over the past few years are key factors driving this transformation (Gilbert & Green, 1994). Consequently, various stages of education, from primary to higher education, are gradually transitioning from traditional offline methods to online instruction (Henrie et al., 2015).

MOOCs offer the advantage of providing high-level education at a low cost, making them a better alternative to traditional methods (Welsh & Dragusin, 2013). One of the main advantages of MOOCs over traditional methods is their ability to create a more flexible learning environment. This makes them ideal for individuals who prefer to study at their own pace (Bruff et al., 2013). Students can receive a credit certificate after completing the assessment requirements of a Massive Open Online Course (Fianu et al., 2020; Wu & Chen,

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2017). However, MOOCs also have their disadvantages. First, problem-based learning is becoming increasingly popular, yet there are still many obstacles that learners and educators face when using this method. When preparing for exams and utilizing learning materials, students must consider their ability to solve real-life problems (Kek & Huijser, 2011). Secondly, Geissler et al. (2012) note that many students struggle to succeed in today's competitive market due to a lack of essential skills, such as effective communication, critical thinking, and creativity.

MOOCs offer learners numerous educational advantages. Building on previous research, this study proposes an extended research model based on the Expectation Confirmation Model (ECM). It incorporates perspectives from learning engagement and DeLone and McLean's Information System Success Model to examine the quality antecedents affecting learners' continuance intention for online learning. This provides a theoretical foundation for assessing and improving the quality of sustained learning in MOOCs. Hence, the researcher expects an integrated model to be proposed in this study by introducing quality factors affecting the continuance usage intention of MOOCs in higher education in Hangzhou, China.

2. Literature Review

2.1 Human-Human Interaction

There are three types of human-to-human interactions in e-learning: learner-content, learner-teacher, and learner-learner (Moore, 1989). Through these interactions, students can better engage with their teachers and classmates on e-learning platforms using features such as message boards, bullet screens, and private chats (Chen et al., 2017). According to Goh et al. (2017), the quality of interactions between students and teachers is a crucial factor influencing the success of e-learning. These interactions enhance the student's learning experience and help develop social-emotional bonds (Omar et al., 2015). Besides the interactions between educators and students, other factors, such as instructors' competence and attitudes toward students, can also impact the success of online education (Bailey & Pearson, 1983). Online learning can be prone to feelings of loneliness, which can affect student satisfaction (Moore, 1989). Social presence can help alleviate these feelings of isolation and prevent loneliness. Numerous studies have shown that social interaction significantly boosts the satisfaction of online students (Arbaugh, 2001). From the findings of previous works, this paper develops the hypotheses as follows:

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

2.2 Human-System Interaction

Human-system interactions are defined as the level of interaction that individuals have with the functions of a system. These interactions suggest that people can easily study or take courses online using the system's various features (Chen et al., 2017). Researchers have found that users' first impression of a system is influenced by its appearance (Elfaki et al., 2013). The interface design can also affect the effectiveness of the relationships between teachers and students in e-learning environments (Schulz et al., 2014). User satisfaction can be enhanced by easy and simple systems (Davids et al., 2014). Although the network platform's interface is not usually an issue for students, its dependability and stability are crucial factors affecting their satisfaction (Yuen et al., 2009). Users must interact with a system to take advantage of its many features within an e-learning setting. The system should be able to provide the necessary information and respond to users' diverse needs (Ruiz et al., 2008). A study analyzing the various factors that affect the transfer of e-learning training found that a welcoming environment can improve the quality of instruction (Park & Wentling, 2007). From the findings of previous works, this paper develops the hypotheses as follows:

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

2.3 Human-Message Interaction

Human-system interactions are crucial for enhancing the user experience when buying goods and services online (Ahn et al., 2007). DeLone and McLean (2003) found that interactions between humans and machines can positively impact the perceived value of a product or service. The harmonious interaction between users and systems can significantly affect user satisfaction, either positively or negatively (Kurucay & Inan, 2017). To enhance the user experience and improve the perceived value of an e-learning course, providers should consider various strategies, such as introducing value-added features like bulletin boards and personalized web pages (Petrick & Backman, 2002). Massive Open Online Courses (MOOCs) make accessing course materials easier than traditional learning platforms. Interactions between people can improve the learning process by facilitating discussions and cooperation among students (Liu et al., 2016). One of the major disadvantages of e-learning systems is their static learning environment, where every student follows the same method. Designing effective MOOCs requires understanding the information gathered through interactions between learners and the content. From the findings of previous works, this paper develops the hypotheses as follows:

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

2.4 Flow Experience

The concept of flow experience, introduced by Csikszentmihalyi (1975), refers to the psychological processes that help individuals focus strongly on their goals (Liu et al., 2009). As more medical professionals enroll in e-learning, interactions will increase, making the cloud-based learning system more engaging and enjoyable (Cheng, 2022). An immersive learning experience can provide a deeper understanding of a learner's emotional state and learning level, increasing their willingness to take advantage of MOOCs (Zhao et al., 2020). People often feel a sense of timelessness during flow experiences, which can lead to a loss of self-awareness (Csikszentmihalyi, 1990). To experience flow, an individual must have a motivating factor (Shin, 2012). Flow experiences comprise nine dimensions: clear goals, immediate feedback, balance between challenge and skill, merging of action and awareness, loss of self-consciousness, sense of control, altered perception of time, intrinsic motivation, and intense focus (Csikszentmihalyi, 1990). Guo and Ro (2008) emphasized the importance of flow experiences for college students' studies. According to research, good communication, a balance of skills and interests, and effective teaching can enhance flow experiences. From the findings of previous works, this paper develops the hypotheses as follows:
H4: Flow experience has a significant impact on satisfaction.

2.5 Learning Engagement

Nkhoma et al. (2017) emphasized that individual student engagement results from case-based learning. Hu and Kuh (2002) defined participation as the learner's involvement in teaching activities and the substantial effort they put in, ultimately helping to achieve the desired outcomes. According to Kraus and Coates (2008), student engagement focuses on the quality of involvement in activities associated with superior learning outcomes, as reported by higher education studies. Student participation is crucial for mastering knowledge and skill goals during the learning process (Robinson & Hullinger, 2008). Previous research has shown that students attending MOOCs are less engaged in learning than those on university-sponsored e-learning platforms. On average, less than 10% of students who participate in MOOCs complete the course. The high failure rate and low student engagement in online courses are often due to user dissatisfaction with the system's design (Maloshonok & Terentev, 2016). A study revealed that teacher quality significantly impacts online students' satisfaction and engagement levels (Hamdan et al., 2021). While classroom learning should be student-centered, teachers play a vital role in enhancing online learners' engagement and satisfaction levels (Karakas & Manisaligil, 2012). Numerous studies show a significant correlation between learning engagement and expected educational outcomes (Joshi et al., 2021). From the findings of previous works, this paper develops the hypotheses as follows:
H5: Learning engagement has a significant impact on satisfaction.
H10: Learning engagement has a significant impact on continuance intention.

2.6 Perceived Usefulness

The perceived effectiveness of a method or program is an essential factor in evaluating its overall impact (Davis, 1989). Rose and Fogarty (2006) suggest that the perceived usefulness of a MOOC is determined by learners' confidence in achieving the expected outcomes through the learning process. The perceived usefulness of a service or product is also influenced by consumer feedback on review sites, which can be text or images (Mudambi & Schuff, 2010). Additionally, a technology's perceived ease of use and practicality can affect a user's decision to continue using it (Sahin & Shelley, 2008). A study revealed that perceived usefulness is linked to how people believe a product or service can improve their learning (Cui, 2021). Chang and Tung found that perceived ease of use, information quality, self-efficacy, and the usefulness of online courses were positively correlated to their use (Tung & Chang, 2008). Elkaseh et al. discovered that the perceived ease of use and usefulness of social networking platforms can enhance the willingness of teachers and students to use them for educational purposes. Mayer et al. highlighted that the perceived usefulness provided by service system providers can significantly boost users' trust and positive attitudes, making them more inclined to use the e-learning system (Teo, 2009). The perceived usefulness of Massive Open Online Courses is determined by individuals' confidence that these programs can help them improve their learning outcomes (Akbar, 2013). From the findings of previous works, this paper develops the hypotheses as follows:
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

The subjective or affective state of satisfaction can be linked to cognitive evaluations of different outcomes and expectations (Bhattacherjee, 2001). A person's satisfaction with a service or product is related to their emotional response to the experience (Oliver, 1980). Satisfaction levels are determined by how content individuals are with their experiences (Rust & Oliver, 1994). According to the Uses and Gratifications Theory (UGT), interactivity is the main factor influencing satisfaction (Wei et al., 2015). The level of satisfaction individuals experience when using Massive Open Online Courses (MOOCs) is crucial in determining their intention to continue using them (Horzum, 2015). Studies have shown that student satisfaction and the likelihood of success are related to various factors of learner preparation (Kirmizi, 2015). The responsiveness and quality of online course content are significant factors affecting the satisfaction of online instructors (Gay, 2016). Bailey and Pearson (1983) noted that interactions between students and teachers, as well as the competence of instructors, are important factors impacting user satisfaction. Harsasi and Sutawijaya (2018) reported that the quality of online education affects student satisfaction and performance. Being satisfied with the content of an online course can motivate learners to engage more deeply with the material (Gasiewski et al., 2012). From the findings of previous works, this paper develops the hypotheses as follows:

H8: Satisfaction has a significant impact on continuance intention.

2.8 Continuance Intention

The continuous intention of users refers to their behavior of continuing to use a service after initial use (Bhattacherjee, 2001). Individuals' behavioral intentions reflect their readiness to perform a particular action (Ajzen, 1991). Despite the importance of educational quality, studies still need to thoroughly analyze the effects of online learning quality on user behavior (Ozkan & Koseler, 2009). Research has shown that the quality of a learning system and the information it provides are key factors influencing a person's intention to use it (Yang et al., 2017). Evidence supports the idea that emotional engagement and behavioral intention are interconnected. Shiau and Luo (2013) found that individuals' continuous willingness to blog is linked to emotional engagement. Dai et al. (2020) discovered that the attitudes and curiosity of Chinese students significantly influence their continuous willingness to use a MOOC system.

3. Research Methods and Materials

3.1 Research Framework

The theoretical framework was proposed by Cheng (2022), who developed a research model integrating the Expectation Confirmation Model (ECM) and learning engagement (LE) perspectives based on the DeLone and McLean Information Systems (IS) Success Model. Cheng's study aimed to identify the factors influencing students' willingness to enroll in MOOCs. Previous studies have shown that the factors influencing students' willingness to continue using MOOCs must be more comprehensive. Cheng's study aims to analyze these factors thoroughly and proposes a model combining the features of the three main platforms to encourage the continued use of MOOCs. This integrated model offers a more holistic understanding of what drives students to persist in using Massive Open Online Courses.

The research conceptual framework is proposed as follows: Figure 1.

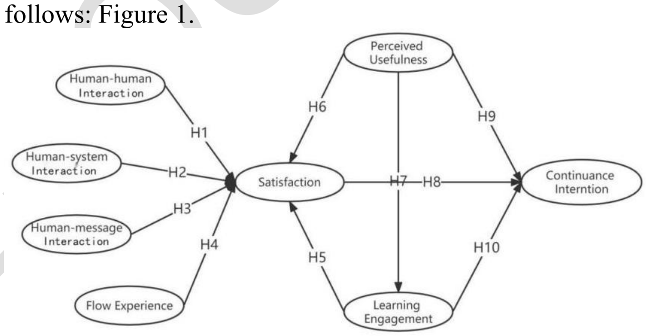

Figure 1: Conceptual Framework

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

The study employed a quantitative method and empirical analysis. The advantage of the SEM method is its ability to simultaneously explore various dependencies, particularly when the model includes indirect and direct influences between its structures (Hair et al., 2010). Data were collected from the target population through a questionnaire. Before large-scale data collection, the content validity and reliability of the questionnaire were verified using the Item-Objective Congruence (IOC) test and a pilot test for Cronbach's Alpha. After confirming reliability, the questionnaires were distributed online to sophomore students at Zhejiang Business College, covering four main subjects. Participants were required to have at least one year of online education experience. Anderson and Gerbing (1988) proposed two quantitative methods for analysis: 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 was conducting SEM to explore the causal relationships between all constructs in the conceptual model, testing the significance of influences and proposed hypotheses.

3.3 Population and Sample Size

This study collected data from a convenient sample of 550 sophomore students from four main majors at Zhejiang Business College. All participants had over a year of experience using MOOC platforms and could utilize multiple platforms, ensuring the validity of the data. According to Soper (2006), a priori sample size calculator for structural equation modeling (SEM), with eight latent variables and 28 observed variables at a 0.05 probability level, the recommended minimum sample size is 444. Therefore, 550 questionnaires were distributed, and valid responses were screened.

3.4 Sampling Technique

The sample was selected using a multi-stage sampling technique, including judgment, stratified random, and convenience sampling. First, judgment sampling was used to select sophomore students from four majors at Zhejiang Business College. Then, stratified random sampling determined the sample size for each department or stratum, as shown in Table 1.

Table 1: Sample Units and Sample Size

Main Subjects	Population Size	Proportional sample size
E-commerce students	776	183
Culinary Arts students	480	114
Finance students	306	72
Art and Design students	765	181
Total	**2,327**	**550**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Comprehensive data collection ensures that the research results are more representative and accurately reflect the characteristics and conditions of the broader student population participating in MOOCs (Massive Open Online Courses). Researchers selected sophomore students from four majors frequently using MOOCs and distributed 550 questionnaires to those with more than one year of MOOC usage experience. Demographic information collected from respondents included their gender. Among the respondents, 213 were male (38.7%) and 337 were female (61.3%). This distribution reflects the gender balance of the selected majors, providing a solid foundation for analyzing higher education students' use and perceptions of MOOCs. The demographic profile is proposed as shown in Table 2.

Table 2: Demographic Profile

Demographic and Behavior Data (N=550)		Frequency	Percentage
Gender	Male	213	38.7%
	Female	337	61.3%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is considered a key starting point of Structural Equation Modeling (SEM) and plays a crucial role in the data analysis process of SEM. Through the verification and optimization process of CFA, researchers can ensure the rationality and validity of the measurement model, thereby providing a solid foundation for subsequent structural model analysis (Hair et al., 2010). CFA measures the reliability and validity of the variables (Byrne, 2010). Convergent validity can be assessed through Cronbach's Alpha, factor loadings, and Average Variance Extracted (AVE) (Fornell & Larcker, 1981). Factor loadings above 0.50 are highly significant (Hair et al., 1998). In this study, factor loadings for all individual items were greater than 0.50 and mostly above 0.75, ranging from 0.526 to 0.847. Researchers recommend using a Composite Reliability (CR) value of 0.70 and above and an AVE value of 0.4 or higher (Fornell & Larcker, 1981; Hair et al., 1998). The CR values in this study were all above the threshold, ranging from 0.784 to 0.859. The AVE values were also above 0.4, ranging from 0.507 to 0.670. Cronbach's alpha is a technique used to assess the internal consistency of items within a construct

(Killingsworth & Gilbert, 2010). Cronbach's alpha values should be 0.7 or higher to indicate acceptable reliability (George & Mallery, 2003; Hair et al., 2010). All Cronbach's Alpha values exceed the 0.7 level. Refer to Table 3 for the above data.

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	0.859	0.792-0.847	0.859	0.670
Human-System Interaction (HSI)	Chen et al. (2018)	3	0.851	0.792-0.828	0.851	0.656
Human-Message Interaction (HMI)	Chen et al. (2018)	3	0.857	0.779-0.838	0.858	0.668
Flow Experience (FE)	Cheng (2022)	5	0.832	0.526-0.800	0.835	0.507
Continuance intention (CI)	Chen et al. (2018)	3	0.839	0.781-0.815	0.840	0.636
Satisfaction (SS)	Chen et al. (2018)	3	0.780	0.707-0.790	0.784	0.547
Perceived usefulness (PU)	Cheng (2022)	4	0.826	0.692-0.768	0.827	0.545
Learning engagement (LE)	Cheng (2022)	4	0.806	0.631-0.786	0.808	0.515

Hair et al. (2010) identified the confirmatory factor analysis (CFA) matrix as the most effective tool for evaluating and assessing variable performance. In their study, they employed seven criteria to assess the model's fit, including the relative Chi-square (CMIN/df), Goodness of Fit Index (GFI), root mean square error of approximation (RMSEA), Comparative Fit Index (CFI), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Adjusted Goodness of Fit Index (AGFI).

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012;)	1.748
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.934
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.916
NFI	≥ 0.80 (Wu & Wang, 2006)	0.920
CFI	≥ 0.80 (Bentler, 1990)	0.964
TLI	≥ 0.80 (Sharma et al., 2005)	0.958
RMSEA	< 0.08 (Pedroso et al., 2016)	0.037
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 confirmed to be satisfactory, as shown in Table 5, by comparing the square root of the AVE with the correlation coefficient.

Table 5: Discriminant Validity

	HHI	HIS	HMI	FE	CI	SS	PU	LE
HHI	**0.819**							
HSI	0.418	**0.810**						
HMI	0.122	0.109	**0.817**					
FE	0.383	0.399	0.089	**0.712**				
CI	0.121	0.206	0.189	0.185	**0.797**			
SS	0.419	0.510	0.199	0.493	0.305	**0.740**		
PU	0.302	0.190	0.138	0.179	0.253	0.276	**0.738**	
LE	0.147	0.203	0.116	0.108	0.189	0.251	0.210	**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)

This study employed Structural Equation Modeling (SEM) to analyze the collected data. According to Hair et al. (2006), SEM is a highly powerful statistical analysis tool that surpasses traditional statistical techniques limited to analyzing relationships within a single construct. SEM can simultaneously and systematically examine the intricate network of relationships among multiple variables, providing researchers with more comprehensive and in-depth insights. SEM allows for the exploration of dependencies, the analysis of causal relationships between latent and observed variables, the measurement of latent variables using multiple indicators, and the enhancement of measurement accuracy through random error. Additionally, it validates hypotheses at the construct level (Hoyle, 2011). The goodness of fit for the structural model was measured and demonstrated in Table 6. The statistical values were CMIN/DF = 2.669, GFI = 0.889, AGFI = 0.867, NFI=0.872, CFI = 0.916, TLI =0.906, and RMSEA =0.055. All values from fit indices were greater than the acceptable values, so they affirmed the model 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;)	2.669
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.889
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.867
NFI	≥ 0.80 (Wu & Wang, 2006)	0.872
CFI	≥ 0.80 (Bentler, 1990)	0.916
TLI	≥ 0.80 (Sharma et al., 2005)	0.906
RMSEA	< 0.08 (Pedroso et al., 2016)	0.055
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

The magnitude of the correlation between the dependent and independent variables in the hypothesis is calculated using standard path coefficients or regression coefficients.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: HHI→SS	0.188	4.041*	Supported
H2: HSI→SS	0.396	7.936*	Supported
H3: HMI→SS	0.150	3.248*	Supported
H4: FE→SS	0.402	8.001*	Supported
H5: LE→SS	0.159	3.158*	Supported
H6: PU→SS	0.128	2.598*	Supported
H7: PU→LE	0.258	4.819*	Supported
H8: SS→CI	0.264	4.827*	Supported
H9: PU→CI	0.176	3.358*	Supported
H10: LE→CI	0.095	1.795	Not Supported

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

As presented in Table 7, nine of the ten proposed hypotheses were supported. Factors Affecting the Continuance Usage Intention of MOOCs were strongly impacted by human-to-human intention. Human to system intention, Human to message intention, Flow Experience， Perceived Usefulness, and Satisfaction.

The strongest impact on Satisfaction is the Flow experience. The path relationship of satisfaction and Flow experience has a standardized path coefficient of 0.402 and a t-value of 8.001 in H4. Human-to-system interaction significantly impacted Satisfaction with a standardized path coefficient of 0.396 and a t-value of 7.936 in H2. Learning engagement is another significant factor impacting perceived usefulness, with a standardized path coefficient of 0.258 and a t-value of 4.819 in H7. Satisfaction was mainly contributed by continuance intention. The direct impact of Satisfaction on continuance intention is significant at a standardized path coefficient of 0.264 and a t-value of 4.827 in H8. Human-to-human interaction also significantly impacts Satisfaction toward using with a standardized path coefficient of 0.188 and a t-value of 4.041 in H1. Perceived usefulness significantly impacts continuance intention to use with a standardized path coefficient of 0.176 and t-value at 3.358 in H9. Perceived usefulness significantly impacts Satisfaction when used with a standardized path coefficient of 0.128 and a t-value of 2.598 in H6. Learning engagement significantly impacts Satisfaction when used with a standardized path coefficient of 0.159 and a t-value of 3.158 in H5. Human-to-message interaction significantly impacts Satisfaction with a standardized path coefficient of 0.150 and a t-value of 3.248 in H3. Learning engagement has no significant direct impact on continuance intention to use with a standardized path coefficient of 0.095 and t-value at 1.795 in H10.

5. Conclusion and Recommendation

5.1 Conclusion

This study aims to comprehensively analyze the factors affecting the continuance usage intention of MOOCs in higher education in Hangzhou, China, to use MOOCs. The researchers proposed ten hypotheses to explore these factors' direct or indirect impacts on the defined research questions. After meticulously designing and verifying the reliability of the questionnaire, the research distributed it online to sophomore students with long-term experience using MOOCs from four main majors—E-commerce, Culinary Arts, Finance, and Art and Design—across six schools of Zhejiang Business College. Using the collected data, this study employed Confirmatory Factor Analysis (CFA) to assess and validate the effectiveness and reliability of the research conceptual model. A total of 550 questionnaires were distributed. Additionally, Structural Equation Modeling (SEM) was utilized to thoroughly analyze and discuss the factors affecting the continuance intention of students in higher education in China to use MOOCs. Ultimately, nine out of the ten proposed hypotheses were validated, strongly demonstrating the achievement of the research objectives.

The findings indicate that satisfaction was confirmed as the key factor influencing learners' decisions to use MOOCs for learning, highlighting the central role of satisfaction in determining individuals' willingness to learn through MOOCs and increasing their continuance intention. Moreover, the human-to-human interaction, human-to-system interaction, and human-to-message interaction significantly affected users' satisfaction with their learning experience. Therefore, enhancing the interactivity of MOOC systems is crucial for motivating learners' engagement.

Further, the study ranked the antecedent's impacting satisfaction, revealing that human interaction had the most significant influence, followed by human-system interaction, human-message interaction, and flow experience. This indicates that providing high-quality interactive services enhances users' perceived value and usefulness and significantly boosts their satisfaction. Specifically, increased interactions between students and teachers directly lead to higher user satisfaction. This finding further emphasizes the importance of various types of interactions in e-learning. Effective interactions between teachers and students create a safer and more harmonious social and emotional learning environment and provide valuable information resources and learning support for students.

5.2 Recommendation

In this study, the researcher found that satisfaction is the strongest predictor of the continuance intention to use MOOCs. This underscores the importance of satisfaction in determining whether users are willing to continue using information systems. Satisfaction with MOOCs is significantly driven by human-human interaction, human-system interaction, human-information interaction, flow experience, perceived usefulness, and learning engagement. Therefore, stakeholders involved in MOOCs, such as students, course developers, instructors, or academic staff, should ensure the practicality of human-human interaction, human-system interaction, human-information interaction, flow experience, perceived usefulness, and learning engagement when choosing or using MOOCs. The findings further emphasize the importance of interactivity on MOOC platforms, highlighting that while human-system and human-human interactions are acceptable, human-information interaction needs the most improvement. Developers must further identify user needs to enhance logical access to knowledge.

In this study, the flow experience most influenced students' satisfaction. Therefore, designers or managers of MOOC platforms should focus on enhancing interactivity. Firstly, creating discussion forums and online communities where students can engage in real-time conversations with peers and instructors can stimulate interest and increase participation. Secondly, providing immediate feedback mechanisms, such as auto-graded quizzes and real-time assessments, can help students track their progress and identify areas for improvement. Additionally, interactive teaching tools, such as live polls, online Q&A sessions, and virtual group projects, can encourage active participation in course content, increasing student engagement. Lastly, incorporating gamified elements and reward systems can motivate students to participate more actively and gain a sense of accomplishment during their learning journey. These interactive methods help students gain a deeper understanding of the course material and allow them to experience a state of flow, thereby enhancing overall learning effectiveness and satisfaction.

Overall, this study thoroughly explores the factors influencing the intention to use MOOCs in higher education. The outlined measures can stimulate a positive attitude among students and increase the likelihood of their continued use of MOOCs for learning. Consequently, these recommendations can effectively enhance students' satisfaction and positive attitude toward the continuance usage intention of MOOCs in Higher Education.

5.3 Limitation and Further Study

This study should acknowledge several limitations, and further research is recommended. Firstly, the study's sample population was limited to students from four majors at Zhejiang Business College, constraining the sample size and scope. Future research could explore other majors or populations from different regions to enhance generalizability. Secondly, the research data was primarily collected through self-report questionnaires, which may introduce social desirability or recall bias. Students might provide responses they believe the researchers want to hear rather than their true feelings and experiences. Thirdly, this study employed a cross-sectional design, collecting data at a single point in time. This design cannot capture the dynamic changes in causal relationships between variables, nor can it reveal trends in student satisfaction, learning engagement, and continuance intention over time. Lastly, although multiple variables were selected for this study (such as satisfaction, learning engagement, and flow experience), there may still be other important factors that should be included. For instance, students' technical proficiency, the quality of course content, and teachers' teaching abilities also significantly influence the intention to use MOOCs.

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