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Impacting Factors of Higher Vocational Students' Continuance Intention toward MOOCs in China

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Abstract

Purpose: This study aims to explore the factors that impact higher vocational students' continuance intention of massive open online courses (MOOCs) to provide insights that can enhance the e-learning experience and ensure long-term engagement. Seven variables were presented in the conceptual framework, which were system quality, interface design quality, learner-instructor interaction quality, perceived usefulness, flow experience, satisfaction, and continuance intention. **Research design, data, and methodology:** Quantitative research focused on students with experience in MOOCs from Zhejiang Business College in Hangzhou, China. Item Objective Congruence (IOC) method. Additionally, a pilot test was conducted with fifty randomly selected respondents to collect data and evaluate the questionnaire's reliability using Cronbach's alpha approach. A combination of probabilistic and non-probabilistic sampling methods was utilized to gather 500 valid responses. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were conducted to assess the model's validity, reliability, and fit. **Results:** PU significantly impacted CI, whereas IDQ and LIIQ also significantly impacted PU. SQ had no significant impact on PU, while SF had a significant impact on CI, and FE impacted SF. **Conclusions:** Five expected hypotheses aligned with the research objectives, highlighting the importance of considering external factors and intrinsic motivation in MOOCs' continuance intention theoretical framework.

Keywords : MOOCs, Continuance Intention, Higher Vocational Student, Continuance Intention, System Quality

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The emergence and development of information technology have enabled new modes of living and working that are no longer bound by traditional constraints such as time, space, or location. Consequently, online education has emerged as a means of facilitating teaching and learning flexibly, free from the limitations of physical boundaries. In addition to traditional education, online education offers flexible and diverse access to knowledge, promoting equality

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of educational opportunities. Massive Open Online Courses (MOOCs) have recently gained significant popularity and are utilized by many educators and learners (Pouezevara & Horn, 2016). MOOCs set off a tsunami of technology integration into education, rapidly changing the face of higher education globally.

MOOCs are online courses that are accessible to all individuals without any prerequisites (Chaplot et al., 2015), such as university affiliation, enrollment timelines, or access qualifications (DeBoer et al., 2014), and offer a free and comprehensive online course experience (Jansen et al., 2015). MOOCs are acknowledged for helping individuals gain competencies and knowledge (Karnouskos, 2017). Nonetheless, the absence of pedagogical interaction between instructors and learners (Freitas et al., 2015), a standardized method for evaluating the quality of education and learning (OBHE, 2013), and coupled with low completion rates (Kopp & Lackner, 2014), have raised significant concerns regarding the effectiveness of MOOCs. Despite all these, with the underlying philosophy of providing quality educational resources for free and promoting sharing among learners (Baturay, 2015), MOOCs have a unique ability to democratize education, improve access to knowledge, and offer learning opportunities to a diverse global audience. This has contributed to the ongoing application of MOOCs (Kineber et al., 2023).

In 2013, MOOCs were introduced to China, establishing and operating various MOOC platforms. The China MOOC Action Declaration was then implemented to provide norms and technical support for MOOCs to set standards for their development, usage, and guarantee (Zheng et al., 2018). By February 2022, the number of MOOCs in China had surpassed 50,000, with over 300 million students earning MOOC credits. According to China Education News, China is currently the global leader in MOOC learners, and this number continues to grow rapidly.

MOOCs have played a significant role in higher education, complementing traditional courses (Montgomery et al., 2015). Previous literature has demonstrated a link between continuance intention and the overall quality of MOOCs (Cheng, 2022). Moreover, studies on satisfaction with MOOCs have indicated that flow experience, satisfaction, and continuance intention are interconnected (Lee & Tsai, 2010; Oh & Yoon, 2014). Given the challenge of high participation but low completion rates in MOOCs, perceived usefulness is crucial in impacting learners' continuance intention towards MOOCs (Juhary, 2014). Therefore, this study aims to develop a replicable and valuable model that delineates the factors impacting students' continuance intention towards MOOCs, aiming to enhance teaching quality and social acceptance.

2. Literature Review

2.1 Continuance Intention

Bhattacherjee (2001) first introduced the concept of continuance intention, which was later applied to evaluate the success of an information system (IS) (Lin et al., 2017). Unlike other psychological intentions, continuance intention focuses on the user's behavior after adopting a system. Chiu et al. (2007) suggested that continuance intention reflects or predicts the individual's possibility of continuance intention for online learning in the future and indicates their willingness to recommend it to others (Chang, 2013).

The ability to effectively engage and motivate learners is essential in fostering a desire to continue learning through MOOCs (Alenezi, 2021). Numerous studies have confirmed that continuance intention is a key determinant of MOOCs' success (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Dai et al. (2020) found that students' continuance intention on MOOCs was driven by curiosity and attitudes, leading to specific emotions and behaviors. The study defines continuance intention towards MOOCs as the extent to which an individual is inclined to use MOOCs in the future and to recommend them to others, such as friends.

Continuance intention plays a crucial role in developing a model that explains the long-term success factors of an IS (Wang, 2015). Bhattacherjee (2001) was the first to incorporate continuance intention into the Expectation Confirmation Model (ECM). Building on this, Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) to forecast continuance intention. Various constructs from diverse theories and backgrounds can significantly impact continuance intention. Consequently, competitive information systems often leverage more technology, acquire new skills, and enhance user satisfaction and willingness to continue them (Hofstede & Minkov, 2010).

2.2 System Quality

System quality encompasses an IS's functionality, including hardware and software (Kim et al., 2008). It refers to a reliable, compatible, and stable IS (Yuen et al., 2019) characterized by convenience, access speed, flexibility, reliability, security, and responsiveness (Almaiah et al., 2020). Banu et al. (2024) defined system quality as the individual learner's perception of the system's performance and its impact on meeting the learner's needs. Therefore, an IS must be practical and user-friendly, providing user feedback and enhancing security, scalability, and standardization to improve the skills required for the e-learning environment (Seta et al., 2018).

Based on previous studies, it was discovered that system

quality is perceived by individual learners based on their assessment of system performance, which is influenced by factors such as secure access to course content (Chen et al., 2018) or the ability to quickly retrieve required material from an IS (Lin et al., 2011). Learners who view the network as reliable and secure are more likely to find the system useful, thus enhancing their perceived value in an IS (DeLone & McLean, 1992). This idea is shaped by usability, expectations, availability, and response time (Guimaraes et al., 2009). Hence, this study would like to posit the following:
H1: System quality has a significant impact on perceived usefulness.

2.3 Interface Design Quality

Interface design quality pertains to the structural design of an interface that showcases an IS's features and instructional support (Cho et al., 2009), which encompasses aspects such as website layout, content structure, and graphical appearance (Galitz, 2007). Previous studies have suggested that the interface design acts as a stimulus to engage and capture users' attention (Barrett & Hegarty, 2016; Bilro et al., 2018) and plays a crucial moderating role. Given the significance of helping users understand the functionality of an IS, emphasis should be placed on interface design quality to enhance users' perception of an IS functionality (Faulkner, 1998).

Farhan et al. (2019) further pointed out that a well-designed interface provides learners with convenient functional services and effectively resolves any queries that may arise during the learning process. The effectiveness of an e-learning tool can be significantly improved through high-quality interface design, as it offers various ways for learners to access different functions and enhances their perceived usability (Cho et al., 2009). A well-structured interface with clear instructions can lead learners to view the tool as more useful due to its graphical layout and content organization (Kumar et al., 2018). Hence, this study would like to posit the following:
H2: Interface design quality has a significant impact on perceived usefulness.

2.4 Learner-Instructor Interaction Quality

Moore (1989) categorized the interactions within online learning as learner-content, learner-learner, and learner-instructor. According to Martin et al. (2018), the learner-instructor interaction is the most significant among Moore's classifications; they highlighted how instructors can enhance student engagement and learning outcomes by offering diverse communication channels, support, motivation, and prompt feedback. When learners can engage with instructors and share knowledge and information effectively using the interaction tools provided in the e-learning system, their cognitive participation in utilizing the system can be boosted (Lin et al., 2017).

The significance of instructor-learner interaction in the success of e-learning has attracted attention from scholars. When learners can engage with instructors through an online learning platform, it enhances their comprehension of the material through asking and answering questions and facilitates knowledge sharing through discussion participation (Cheng, 2021). Such interactions are advantageous for fostering cognitive engagement in learners during the e-learning process (Zhao et al., 2020) and help learners recognize the system's usefulness (Paechter et al., 2010). Hence, this study would like to posit the following:
H3: Learner-instructor interaction quality has a significant impact on perceived usefulness.

2.5 Flow Experience

Flow experience was conceptualized by Csikszentmihalyi (1975); he describes it as a state in which an individual becomes entirely immersed in an activity, remaining uninterrupted, and fully focused on the task at hand (Csikszentmihalyi, 1997). This unique convective experience is further corroborated by research by Liu et al. (2009) and Chang and Zhu (2012). Flow experience, a psychological state characterized by a range of emotions, senses, and experiences, involves deep engagement in an activity (Csikszentmihalyi, 1990). It is a universal phenomenon that can be experienced by anyone, irrespective of the action's nature or cultural background (Ozkara, 2015).

According to research by Bakker (2008), the flow experience is a psychological state linked to exploratory behavior and positive subjective experiences. In e-learning, the flow experience refers to an optimal and pleasant experience resulting from complete engagement and concentration (Lee, 2010). Specifically, learners in a flow state will operate at their highest potential and make significant progress in their learning (Hong et al., 2016). Previous research suggests that the flow experience is crucial in understanding learners' satisfaction (Chhetri et al., 2004). Hence, this study would like to posit the following:
H4: Flow experience has a significant impact on satisfaction.

2.6 Satisfaction

As defined by Oliver (1980), satisfaction pertains to meeting consumer expectations regarding product and service performance. The experience of a pleasant feeling when acquiring something or accomplishing a desired action can be defined as satisfaction (Refae et al., 2021). In extension to online education, satisfaction reflects a learner's assessment of their educational experience, services, and facilities (Weerasinghe & Fernando, 2017). If learners find enjoyment and success in the online learning environment, it can impact their willingness to continue using an IS (Alraimi et al., 2015).

Satisfaction is incorporated into the expectation confirmation model (ECM) to forecast the ongoing usage of technology following the initial experience by Bhattacherjee (2001). According to this framework, satisfaction can be seen as emotional reciprocity. It can be achieved when customers are confident in fulfilling their expectations during an electronic service interaction (Bhattacherjee & Lin, 2015). When the user is content with the IS, whether it be the service quality, system functionality, or information provided, it will inspire them to use it consistently (Baranova et al., 2022; Rahi et al., 2022). Hence, this study would like to posit the following:

H5: Satisfaction has a significant impact on continuance intention.

2.7 Perceived Usefulness

The notion of perceived usefulness was introduced by Davis (1989) as the users' perceptions of the anticipated benefits of utilizing an IS; he articulated that it pertains to the extent to which an individual believes that engaging with a specific system would improve their job performance. Suppose the usefulness indicates the degree of utilization of any technology to execute a specific task (Natarajan et al., 2017). In that case, perceived usefulness is understood as the user's conviction that employing any given technology will aid in achieving their objectives (Luna et al., 2019).

Lei and So (2021) discovered that students exhibit a stronger propensity to engage in virtual classes when they perceive them as advantageous and valuable for learning. Therefore, perceived usefulness in online learning refers to a student's belief that digital education will enhance academic performance (Venkatesh et al., 2003). This perspective has garnered support from other academics who have underscored that an individual's willingness or behavior towards an IS is impacted by their experiential perceptions and tangible gains, particularly when they affirm the value of an IS, leading to a greater readiness to use and endorse it (Juhary, 2014; Jung & Lee, 2018). Hence, this study would like to posit the following:

H6: Perceived usefulness has a significant impact on continuance intention.

3. Research Methods and Materials

3.1 Research Framework

The study constructed a conceptual framework incorporating three previous significant theoretical frameworks for support. The first theoretical framework proposed by Cheng (2022) considered the impact of system quality, interface design quality, and learner-instructor interaction quality on perceived usefulness. The second framework, developed by Mulik et al. (2020), depicted the causal link between flow experience and satisfaction. The third framework, also supported by Cheng (2021), affirmed the positive association between satisfaction and continuance intention. In summary, the study's conceptual framework is illustrated in Figure 1.

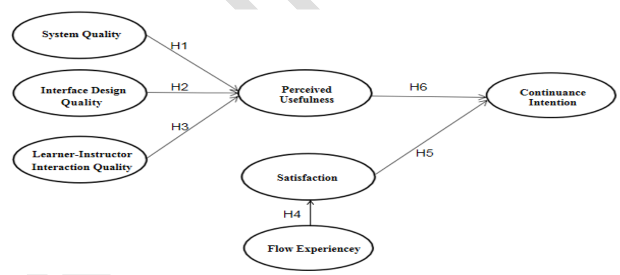

Figure 1: Conceptual Framework

H1: System quality has a significant impact on perceived usefulness.

H2: Interface design quality has a significant impact on perceived usefulness.

H3: Learner-Instructor interaction quality has a significant impact on perceived usefulness.

H4: Flow experience has a significant impact on satisfaction.

H5: Satisfaction has a significant impact on continuance intention.

H6: Perceived usefulness has a significant impact on continuance intention.

3.2 Research Methodology

The researchers utilized a non-probability sampling method to examine vocational college students in Hangzhou, China. An online questionnaire was distributed, and the collected data were analyzed to explore the factors impacting students' continuance intention to engage in MOOCs. The questionnaire comprised three sections: the first section screened questions to identify the study's specific population, the second section measured the seven variables and their relationships through a Likert scale, and the final section gathered demographic information from respondents, such as age, gender, usage frequency and device preferences of

MOOCs.

After designing the questionnaire, measuring its validity and reliability is essential to ensure its effectiveness. To evaluate the content validity, three experts with doctoral degrees and professional qualifications in online learning were invited to assess the questionnaire through the Item Objective Congruence (IOC) method. Additionally, a pilot test was conducted with fifty randomly selected respondents to collect data and evaluate the questionnaire's reliability using Cronbach's alpha approach.

The validity and reliability of the questionnaire used in this study were tested and confirmed to be suitable for measurement purposes. The researchers distributed the questionnaire online to 500 respondents and collected their responses. Statistical tools such as Jamovi and Amos were employed to analyze the cleaned sample data. Confirmatory Factor Analysis (CFA) and Goodness of Fit were utilized to assess and validate the convergence and fit among variables, ensuring their accuracy in reflecting the observed data. The Structural Equation Modeling (SEM) was then adopted to empirically test the relationship between the constructed conceptual framework and the hypothesized variables. Based on these analyses, the study's conclusions were drawn.

3.3 Population and Sample Size

The study focused on vocational college students in Hangzhou, China, who had at least one semester of MOOC learning experience. The researchers selected students from four majors at Zhejiang Business College as the sample group because these majors are widely represented in Hangzhou's higher vocational colleges. Following calculations from a sample size calculator, a minimum of 425 samples was deemed necessary, but the study collected 500 samples to ensure robust results. The research investigated the factors impacting students' continuance intention for MOOCs in Hangzhou.

3.4 Sampling Technique

The researchers employed a mix of probability and non-probability sampling techniques, such as judgment, quota, and convenience, to select students from four majors at Zhejiang Business College to achieve the required sample size. The sample size for each major was determined based on the proportion of the total number of students in each major. The details of the sample distribution are shown in Table 1.

Table 1: Sample Units and Sample Size

Four Main Majors	Percentage of total student population	Proportional Sample Size
Finance and Commerce	55.00%	275
Tourism	16.80%	84
Culture and Art	12.60%	63
Electronics and Information	15.60%	78
Total	**100%**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The researcher investigated the information of the screened 500 respondents, and the statistical information about their demographic characteristics is shown in Table 2. In terms of gender composition of the respondents, 41.60% were male and 58.40% were female. Regarding grade level distribution, 39.60% were first-year students, 32.80% were sophomores, and 27.60% were juniors. At the age level, 18 to 19 years old had the highest percentage of 47.40%, followed by 20-22 at 43.20%, and only 9.40% were over 22 years old.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	208	41.60%
	Female	292	58.40%
Grade	A freshman	198	39.60%
	A sophomore	164	32.80%
	A junior	138	27.60%
Age	18-19 years old	237	47.40%
	20-22 years old	216	43.20%
	More than 22 years old	47	9.40%

4.2 Confirmatory Factor Analysis (CFA)

Previous studies suggest using confirmatory factor analysis (CFA) to assess the reliability of all constructs (Hair et al., 1998; Holmes-Smith, 2001). The constructs demonstrated satisfactory CR and AVE values above 0.7 and 0.5, respectively (Nunnally, 1978), indicating high reliability. Furthermore, the reliability coefficients for all constructs, determined by factor loadings and Cronbach's alpha, exceeded the recommended thresholds of 0.5 and 0.7 (Hair et al., 1998). Table 3 illustrates that all construct values in this study met the necessary parameters and achieved an acceptable level. Moreover, the method outlined by Fornell and Larcker (1981) was applied to establish discriminant validity. The findings indicated that each construct's square roots of AVE exceeded the corresponding squared correlation, confirming distinctiveness (Table 3).

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
System Quality (SQ)	Cheng (2022)	4	0.794	0.593-0.756	0.800	0.502
Interface Design Quality (IDQ)	Cheng (2022)	4	0.838	0.734-0.790	0.841	0.569
Learner-Instructor Interaction Quality (LIIQ)	Cheng (2022)	4	0.839	0.741-0.781	0.84	0.568
Flow experience (FE)	Cheng (2022)	4	0.848	0.740-0.805	0.851	0.588
Perceived usefulness (PU)	Cheng (2021)	4	0.884	0.792-0.825	0.885	0.658
Satisfaction (SF)	Singh and Sharma (2011)	5	0.889	0.773-0.798	0.890	0.618
Continuance intention (CI)	Cheng (2021)	4	0.862	0.766-0.797	0.871	0.629

Moreover, the most commonly used rules in performing the CFA for the measurement model and testing the structural model include GFI, AGFI, NFI, CFI, TLI, and RMSEA. The CFA results from Table 4 indicate that the indices were above their respective common acceptance levels, indicating that the model achieved an ideal level of internal quality.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 Hair et al. (2006)	775.482/356 or 2.178
GFI	≥0.85 Hu and Bentler (1999)	0.907
AGFI	≥ 0.85 MacCallum and Hong (1997)	0.886
NFI	≥0.85 Schumacker and Lomax (2004)	0.896
CFI	≥ 0.90 Cheung and Rensvold (2002)	0.941
TLI	≥ 0.90 Bentler and Bonett (1980)	0.932
RMSEA	< 0.08 McDonald and Ho (2002)	0.049
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

The results showed that the values of all indices were within an acceptable range (see Table 5 for details), further proving the validity and adaptability of the model and providing a solid foundation for subsequent analysis.

As shown in Table 5, The square root of the AVE of all constructs in this study (on the diagonal) is greater than the correlation coefficient between the constructs. Therefore, it can be confirmed that discriminant validity has been confirmed.

Table 5: Discriminant Validity

	SQ	IDQ	LIIQ	FE	PU	SF	CI
SQ	**0.709**						
IDQ	0.016	**0.754**					
LIIQ	-0.008	0.231	**0.754**				
FE	0.042	0.151	-0.049	**0.767**			
PU	-0.011	0.391	0.370	0.267	**0.811**		
SF	0.067	0.037	0.022	0.338	0.165	**0.786**	
CI	0.033	0.209	0.205	0.228	0.489	0.361	**0.793**

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

4.3 Structural Equation Model (SEM)

Based on Hoyle (1995), structural equation modeling (SEM) is a powerful multivariate statistical technique that analyzes causal relationships between variables through hypothesis testing. The metrics of goodness of fit for SEM are listed in Table 6. The measurement of the structural equation model includes stipulating that CMIN/DF should be less than 3 (Hair et al., 2006), GFI should be greater than 0.85 (Hu & Bentler, 1999), AGFI should be greater than 0.85 (MacCallum & Hong, 1997), NFI should be greater than 0.85 (Schumacker & Lomax, 2004), CFI should be greater than 0.9 (Cheung & Rensvold, 2002), TLI should be greater than 0.9 (Bentler & Bonett, 1980), and RMSEA should be less than 0.08 (McDonald & Ho, 2002).

The overall fit indices of the measurement model calculated by Amos version 26 were: CMIN/DF=2.334, GFI=0.898, AGFI=0.880, NFI=0.884, CFI=0.930, TLI=0.923, and RMSEA=0.052. Thus, these results

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 Hair et al. (2006)	865.973/371 or 2.334
GFI	≥0.85 Hu and Bentler (1999)	0.898
AGFI	≥ 0.85 MacCallum and Hong (1997)	0.880
NFI	≥0.85 Schumacker and Lomax (2004)	0.884
CFI	≥ 0.90 Cheung and Rensvold (2002)	0.930
TLI	≥ 0.90 Bentler and Bonett (1980)	0.923
RMSEA	< 0.08 McDonald and Ho (2002)	0.052
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, RMSEA = root mean square error of approximation, CFI = comparative fit index, NFI = normalized fit index and TLI = Tucker Lewis index

4.4 Research Hypothesis Testing Result

The study's findings, as presented in Table 7, indicate that all hypotheses except H1 are supported with a p-value of 0.05. Contrary to expectations, SQ shows no significant association with CI, leading to rejecting H1. Regarding quality, IDQ (β = 0.389) has a more substantial impact on PU than LIIQ (β = 0.348). PU demonstrates the strongest influence on CI with a β = 0.504. Additionally, the β value for the impact of FE on SF is 0.387, while the impact of SF on CI is 0.339.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→PU	-0.024	-0.514	Not Supported
H2: IDQ→PU	0.389	7.655***	Supported
H3: LIIQ→PU	0.348	6.981***	Supported
H4: FE→SF	0.387	7.438***	Supported
H5: SF→CI	0.339	7.225***	Supported
H6: PU→CI	0.504	9.941***	Supported

Note: *** $p<0.001$
Source: Created by the author

The results obtained from Table 7 are specifically interpreted as follows: In contrast to the hypothesis, the SQ of MOOCs has no significant impact on CI. Thus, H1 is not adopted. Although previous research has established that system quality significantly influences learners' perceived usefulness (Bennetta et al., 2012; Molinillo et al., 2018). However, with advancements in online technology, the importance of system quality in determining learners' perception of usefulness has diminished, as indicated by other pertinent studies (Jo, 2022; Li et al., 2016).

Table 7 illustrated a significant relationship between IDQ and PU of MOOCs (β = 0.389, $p<0.05$), as well as a significant relationship between PU and CI of MOOCs (β=0.504, $p<0.05$), aligning with the proposed hypotheses H2 and H6. These findings support previous research (Kumar et al., 2018; Lwoga & Komba, 2015; Mouakket & Bettayeb, 2015; Shao, 2018) indicating that learners' perception of IDQ can significantly impact their continuance intention of an IS.

The study confirmed that learners' perceived LIIQ of MOOCs positively impacted their PU (β=0.348, $p<0.05$), consequently impacting their intention to continue using MOOCs. The positive relationship between LIIQ and PU and PU and continuance intention supports H3 and H6. Other researchers reinforced these concepts (Jiang & Ting, 2000; Kang & Im, 2013; Lin et al., 2017), who suggest that LIIQ played a crucial role in determining learners' continuance intention for an e-learning system based on its PU.

H4 about the relationship between FE and satisfaction with MOOCs was supported (β=0.387, $p<0.05$), suggesting that if learners experienced flow while using MOOCs, it could lead to their satisfaction (Ding et al., 2010). Furthermore, the relationship between MOOCs satisfaction and continuance intention, as indicated by H5 (β=0.339, $p<0.05$), has also been supported and is consistent with previous studies (Martin et al., 2015; Ranaweera et al., 2008).

The current result also found that satisfaction with MOOCs mediated the relationship between flow experience and continuance intention. This implied that when learners experienced flow for MOOCs, it impacted their continuance intention, partially due to their satisfaction with MOOCs. These results align with the conclusions drawn by Cheng (2014).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study delves into the factors influencing the continuance intention for MOOCs among vocational college students in Hangzhou, China. Drawing from existing research, the paper presents relevant hypotheses. It constructs a conceptual framework to examine the impact of system quality, interaction design quality, learner-instructor interaction quality, flow experience, perceived usefulness, and satisfaction on the continuance intention for MOOCs. Researchers developed a questionnaire to pinpoint the targeted group better and collect data. They distributed it to students from four majors at Zhejiang Business College who had completed at least one semester of MOOC learning. CFA was employed to assess the reliability and validity of the collected and screened data about the conceptual model. At the same time, SEM was used to analyze the factors above and their influence on the continuance intention for MOOCs among vocational college students in Hangzhou, China.

Based on data analysis, it was found that PU has the most significant impact on continuance intention, followed by satisfaction. Recent studies conducted during the COVID-19 pandemic further support the positive relationship between PU and satisfaction with continuance intention for online learning (Jiang et al., 2021; Mailizar et al., 2021). Additionally, PU and satisfaction directly impact continuance intention and serve as mediators of quality factors and flow experience, respectively, thereby positively impacting continuance intention. The direct impact of IDQ on PU and its indirect impact on continuance intention are more significant than that of LIIQ. Previous research has also emphasized that the effect of IDQ on PU is the most substantial (Molinillo et al., 2018; Mouakket & Bettayeb, 2015). Finally, the positive impact of flow experience on continuance intention was demonstrated through satisfaction, although it was not as strong as the direct effect of satisfaction.

5.2 Recommendation

The study highlights that factor such as IDQ, LIIQ, FE, PU, and satisfaction significantly influence the continuance intention for MOOCs. Therefore, it is essential to consider external factors and intrinsic motivations in the theoretical framework of MOOCs' continuance intention, as emphasized in Cheng's (2022) research. Particularly, PU and satisfaction emerge as the most influential factors on continuance intention, suggesting important implications for MOOC platform providers. This underscores the need for developers and course providers to implement strategies to enhance learners' academic performance and learning efficiency to foster positive expectation confirmation.

Quality factors, particularly factors like IDQ and LIIQ, play a crucial role in impacting the intention of learners to continue using MOOCs. To enhance learners' satisfaction and continuance intention for MOOCs, designers should create visually appealing elements such as different image titles, decorative fonts, colors, graphic buttons, and layouts to segregate content effectively. (Cho et al., 2009; Kumar et al., 2018). Regarding LIID, the course designers should aim to foster collaborative learning between students and teachers by utilizing mechanisms like discussion forums, peer assessment features, and video conferencing. These strategies can facilitate increased human interaction within the MOOC learning environment (Paechter et al., 2010).

The study also found that satisfaction was meditating on the flow experience and continuance intention of MOOCs, highlighting the impact of flow experience on continuance intention for MOOCs. Therefore, platform providers should create opportunities for learners to have a more flowing experience by offering unique and creative course content, services, and features (Nakamura & Csikszentmihalyi, 2009). Research of this kind will contribute to understanding how enrollment can be boosted by providing a flow experience for MOOCs.

5.3 Limitation and Further Study

This study should note some limitations, and further research is needed. While this study addresses key factors impacting the theoretical and practical of MOOCs, it does not encompass all relevant factors. Future studies should consider course reputation, platform service quality, and student trust. Secondly, the sample for this study was chosen from a higher vocational college in Hangzhou, China. Despite being considered to be highly representative, variations in results may occur due to differences in the subjects' majors, geographical locations, and the economic development of the respondents. For future research, expanding the sample to include a more diverse range of respondents from various cultural and economic backgrounds could enhance the universality of the findings. In addition, the impact of survey respondents' continuance intention on MOOCs has been primarily studied through online questionnaires. Future research could benefit from incorporating qualitative data, such as group discussions and in-depth interviews, to provide a more comprehensive understanding of continuance intentions towards MOOCs. With the advancement of technology and the growing experience of learners, there is a likelihood that learners' continuance intention for MOOCs will also evolve. Future studies could benefit from a longitudinal analysis to explore how this intention changes over time.

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