



## Students' Perceptions towards Using MOOCs Platform in Ideological and Political Courses

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### Abstract

**Background and Aim:** The integration of Massive Open Online Courses (MOOCs) in higher education has transformed traditional learning methods, particularly in ideological and political education (IPE). This study examines students' perceptions of using MOOCs for IPE courses at a vocational university, focusing on factors influencing satisfaction and continuance intention. Drawing on the Expectation Confirmation Model (ECM) and the Task-Technology Fit (TTF) model, the research investigates how perceived usefulness, confirmation, task-technology fit, and learning engagement affect students' satisfaction and their intention to continue using MOOCs. Moreover, the study advances theory by integrating the ECM and TTF frameworks, highlighting the mediating role of satisfaction and providing a nuanced explanation of continuance intention in the context of IPE.

**Results:** A quantitative approach was employed, surveying 248 students to analyze their experiences. Structural Equation Modeling (SEM) was used to test the hypothesized relationships between variables.

Results: The results indicate that perceived usefulness significantly influences satisfaction ( $\beta = 0.42$ ,  $p < 0.001$ ), and confirmation has a significant positive effect on satisfaction ( $\beta = 0.38$ ,  $p < 0.001$ ). Task-technology fit and learning engagement also positively impact satisfaction ( $\beta = 0.35$  and  $0.31$ , respectively,  $p < 0.001$ ). Additionally, satisfaction significantly affects students' continuance intention ( $\beta = 0.47$ ,  $p < 0.001$ ), with perceived usefulness, task-technology fit, and learning engagement playing crucial roles in shaping students' willingness to continue using MOOCs.

**Conclusion:** The findings underscore the importance of course design, interactive content, and platform usability in enhancing learning outcomes. The study provides empirical support for the theoretical integration of ECM and TTF in explaining MOOCs continuance, offering valuable insights for optimizing MOOCs in IPE.

**Keywords:** Students' Perceptions; MOOCs Platform; Ideological and Political Courses

### Introduction

The integration of technology in education has fundamentally transformed traditional learning environments, giving rise to platforms such as Massive Open Online Courses (MOOCs). MOOCs offer accessible, flexible, and scalable learning opportunities to a diverse audience, often free of charge (Yuan & Powell, 2013). In China, where governmental policies strongly promote technological integration to enhance educational accessibility and quality, MOOCs have rapidly gained traction in higher education (Li et al., 2017).

Ideological and Political Education (IPE) is a cornerstone of the Chinese education system, designed to instill values, ethics, and political awareness among students. Traditionally, IPE courses have relied on face-to-face instruction, which facilitates direct interaction between instructors and students. However, the transition to MOOCs for IPE delivery introduces both promising opportunities and significant challenges. While MOOCs can enhance accessibility and interactivity (Jordan, 2014), issues such as high dropout rates, variable course quality, and difficulties in maintaining engagement pose substantial obstacles (Margaryan et al., 2015; Ren et al., 2021). Despite the potential of MOOCs to improve learning outcomes, there remains a research gap in understanding how these challenges specifically impact IPE and how effective theoretical frameworks can address these issues.

This study addresses the gap by investigating the factors that influence students' satisfaction and continuance intention when using MOOCs for IPE. The research is guided by two complementary theoretical frameworks: the Expectation Confirmation Model (ECM) and the Task-Technology Fit (TTF) model. The ECM, based on Oliver's Expectation-Confirmation Theory (1980) and further developed by Bhattacharjee (2001), provides insights into why users continue using a technology over time. It does so by focusing on whether the technology meets users' initial expectations (confirmation) and how useful they





perceive the technology to be (perceived usefulness), ultimately influencing overall satisfaction and continuance intention (Foroughi et al., 2019; Huang, 2016).

Complementing the ECM, the TTF model emphasizes the importance of aligning the technological features of MOOCs with the specific learning tasks required in IPE (Goodhue, 1995). This model helps clarify how the compatibility between the MOOC platform's design and students' learning needs can enhance satisfaction and encourage long-term adoption. By integrating ECM and TTF, this study aims to provide a comprehensive understanding of the multifaceted factors that affect both the immediate satisfaction and the sustained use of MOOCs in IPE.

Thus, the current study is particularly concerned with identifying the determinants of satisfaction and continuance intention in the context of MOOCs for IPE. Understanding these constructs is essential for evaluating the long-term success and sustainability of MOOCs in delivering ideological and political education.

## Objectives

Building on the discussion presented in the introduction, the primary objective of this study is to comprehensively investigate the factors influencing students' satisfaction and their intention to continue using MOOCs for Ideological and Political Education (IPE). Specifically, the study aims to:

1. To explain the factors that affect students' satisfaction in using MOOCs in IPE.
2. To determine the factors that affect students' continuance intention in using MOOCs in IPE.
3. To identify the influence of students' satisfaction on their continuance intention in using MOOCs in IPE.

## Literature review

This review critically examines the literature across three key themes—MOOCs in Education, Student Engagement, and Technology Fit—to establish a theoretical and empirical foundation for the current study on MOOCs in Ideological and Political Education (IPE).

### MOOCs in Education

Massive Open Online Courses (MOOCs) have fundamentally altered the educational landscape by democratizing access to learning. MOOCs are designed to provide courses to a virtually unlimited number of learners through online platforms that often feature no-cost enrollment, although additional services such as certification may incur fees (Yuan & Powell, 2013). The MOOC model integrates diverse technological tools—such as video lectures, digital readings, quizzes, and interactive discussion forums—to create an engaging and flexible learning environment (Jordan, 2014). This multifaceted approach supports varied learning styles and promotes active participation among students.

One of the primary advantages of MOOCs is their accessibility. Learners from different socio-economic and geographic backgrounds can benefit from high-quality educational content without the barriers imposed by traditional classroom settings (Hew & Cheung, 2014). In addition, the flexibility inherent in MOOCs allows learners to progress at their own pace, thereby accommodating diverse schedules and learning needs. However, MOOCs are not without challenges. High dropout rates are a persistent issue, attributed in part to the lack of personalized support, the self-directed nature of learning, and the variable levels of prior knowledge among students (Reich, 2014). Furthermore, while MOOCs excel in disseminating information and fostering initial engagement, their impact on deep learning and skill acquisition remains contested, largely depending on course design and the extent of learner support (Margaryan, Bianco, & Littlejohn, 2015).

In the realm of Ideological and Political Education (IPE), MOOCs hold significant promise as well as pose distinct challenges. The multimedia-rich and interactive nature of MOOCs can enhance the delivery of complex ideological and political content, fostering critical thinking and ethical reasoning among students (Zheng, Han, Rosson, & Carroll, 2018). Yet, the shift from traditional face-to-face instruction to





online delivery necessitates rigorous pedagogical strategies to ensure that the educational objectives of IPE are effectively met.

The study focuses on students enrolled in ideological and political courses at a vocational university. These students typically specialize in vocational technology, with curricula that emphasize practical skills in fields such as engineering, information technology, and applied sciences (Li, 2017). This vocational focus often results in a predominantly analytical and pragmatic mindset, which may render the theoretical aspects of IPE less engaging or immediately relevant to these learners (Zheng, Han, & Rosson, 2018).

Moreover, vocational students often exhibit limited interest in theoretical coursework, frequently perceiving such subjects as monotonous or tangential to their primary area of study (Wang & Liu, 2020). Their engagement with theoretical content is further influenced by a tendency to view such courses as disconnected from the practical skills they prioritize. Nevertheless, the inherent demographic diversity within this population—including variations in age, gender, socioeconomic status, and prior educational experiences—provides a rich context for examining how MOOCs can be tailored to meet diverse learning needs (Li et al., 2017). By leveraging different modes of content delivery, such as videos, interactive modules, and readings, MOOCs have the potential to bridge the gap between practical training and theoretical knowledge.

### **Interplay Between Vocational Students and MOOC Technology in IPE**

The relationship between vocational students and the utilization of MOOCs in IPE is complex and multifaceted. Vocational students, whose education is primarily oriented toward practical applications, often encounter a disconnect when engaging with the theoretical dimensions of IPE. MOOCs, with their inherent flexibility and diverse content formats, offer a viable solution to this challenge. By integrating multimedia elements and interactive features, MOOCs can render abstract ideological and political concepts more tangible and accessible (Li et al., 2017).

The flexible nature of MOOCs aligns well with the demanding schedules of vocational students, many of whom balance academic pursuits with internships, part-time employment, or hands-on training (Jordan, 2015). This flexibility allows students to engage with course materials at their own pace, thereby facilitating a more harmonious balance between practical commitments and theoretical learning. Additionally, MOOCs can provide access to quality educational resources that might otherwise be unavailable due to geographic or institutional limitations, thus promoting educational equity (Yuan & Powell, 2013).

Interactive components, such as discussion forums and peer review assignments, further enhance the learning experience by fostering a sense of community and promoting active engagement with course content (Hew & Cheung, 2014). These interactive features are particularly valuable in IPE, where critical discussion and collaborative analysis are essential for understanding complex ideological and political issues.

### **Theoretical Foundations**

The current study is anchored in two robust theoretical models: the Expectation Confirmation Model (ECM) and the Task-Technology Fit (TTF) model.

#### **Expectation Confirmation Model (ECM)**

The ECM, as developed by Bhattacherjee (2001) and based on Oliver's Expectation-Confirmation Theory (1980), explains how users' continuance intention is driven by satisfaction. In the context of MOOCs, the model suggests that satisfaction is derived from two key constructs: Perceived Usefulness, which reflects the extent to which students believe that the MOOC platform enhances their learning performance (Davis, 1989; Venkatesh & Davis, 2000), and Confirmation, which assesses whether the platform meets the students' initial expectations (Bhattacherjee, 2008). Empirical research supports a strong positive relationship between these constructs and overall satisfaction, which in turn significantly influences the intention to continue using the technology (Lin, Wu, & Tsai, 2005).

#### **Task-Technology Fit (TTF) Model**





The TTF model, proposed by Goodhue and Thompson (1995), posits that the effectiveness of a technology depends on how well its features align with the tasks it is intended to support. In MOOCs, this means that the platform's multimedia content, discussion forums, and assignment tools must effectively facilitate the specific learning tasks required by IPE. A higher degree of fit is associated with enhanced satisfaction and increased continuance intention, as users are more likely to adopt technology that efficiently supports their educational activities (Goodhue & Thompson, 1995; McGill & Klobas, 2009).

### **Learning Engagement Theory**

Learning Engagement Theory further complements these models by emphasizing the role of active engagement in the learning process. Engagement is conceptualized as a multidimensional construct encompassing behavioral, emotional, and cognitive aspects (Newmann, Wehlage, & Lamborn, 1992; Fredricks et al., 2004). In the context of MOOCs, higher engagement—characterized by active participation in assignments, discussions, and interactive activities—not only directly improves satisfaction but also mediates the effects of perceived usefulness and task-technology fit on continuance intention.

### **Theoretical Integration and Research Gap**

While existing studies have individually examined MOOCs, student engagement, and technology fit, a critical research gap remains in understanding their interrelationships within the specific context of IPE. The current study bridges this gap by integrating the Expectation Confirmation Model (ECM) and the TTF model, supplemented by Learning Engagement Theory. The ECM, based on Oliver's (1980) work and extended by Bhattacharjee (2001), posits that satisfaction—driven by perceived usefulness and confirmation of expectations—is a key determinant of continuance intention. In parallel, the TTF model provides insight into how well the MOOC platform's capabilities align with the learning tasks of IPE. Integrating these frameworks offers a more comprehensive explanation of how the interplay between perceived utility, technology fit, and active engagement drives both satisfaction and the intention to continue using MOOCs. This integrated approach addresses the literature's shortfall in exploring these constructs in tandem, particularly within IPE.

### **Critical Evaluation**

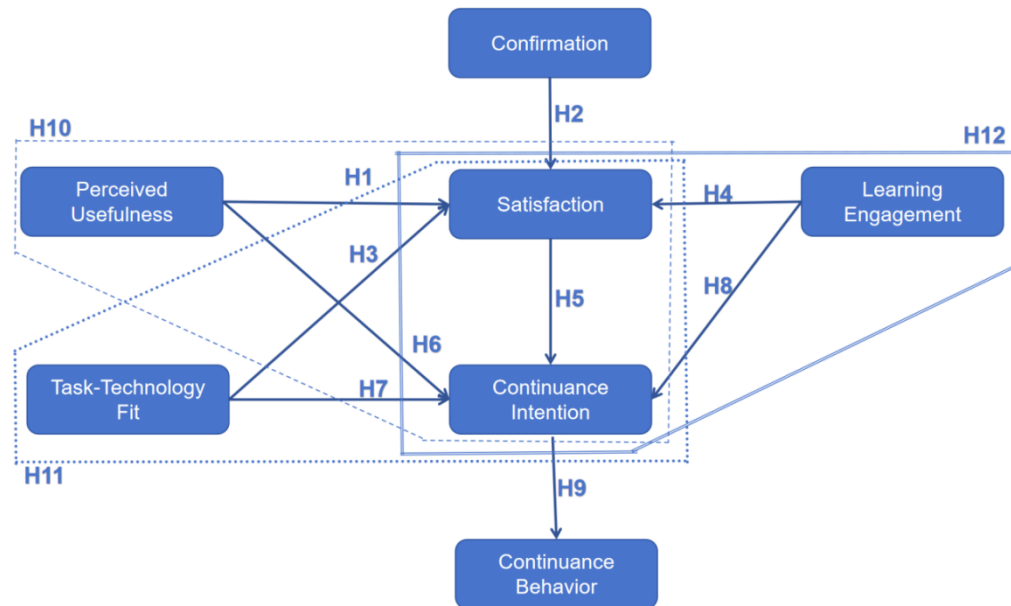
Critically, while MOOCs have been lauded for their potential to enhance accessibility and engagement, the mixed empirical findings regarding dropout rates and learning depth indicate that significant refinements in course design and support are necessary. Moreover, while the benefits of active engagement are well documented, the specific strategies required to engage students in the context of IPE remain underexplored. Similarly, although the TTF model has proven valuable in assessing technological alignment, its application to the nuanced requirements of IPE delivery through MOOCs warrants further investigation. By addressing these gaps, the current study not only advances theoretical understanding but also provides practical implications for optimizing MOOC design in IPE.

Together, these theoretical perspectives provide a comprehensive framework for understanding the dynamics of MOOC usage in IPE. They offer validated measurement approaches for key variables—including perceived usefulness, confirmation, satisfaction, task-technology fit, and learning engagement—which are crucial for evaluating both the immediate and long-term effectiveness of MOOCs in fostering educational success.

### **Conceptual Framework**

This study integrates the Expectation Confirmation Model (ECM) and the Task-Technology Fit (TTF) model, supplemented by Learning Engagement Theory, to comprehensively explain the determinants of students' satisfaction and continuance intention in using MOOCs for Ideological and Political Education (IPE). The ECM and TTF models are particularly well-suited for this research as they address both the attitudinal and functional dimensions of technology use—two aspects that are critical in the context of IPE delivered through MOOCs. Figure 1 shows the conceptual framework of the study.





**Figure 1** Conceptual Framework

The Expectation Confirmation Model (ECM), originally developed by Bhattacharjee (2001) and rooted in Oliver’s (1980) Expectation-Confirmation Theory, posits that a user’s decision to continue using a technology is primarily driven by their satisfaction. In the context of MOOCs, satisfaction is shaped by whether the platform meets students’ initial expectations (confirmation) and how useful they perceive the platform to be (perceived usefulness) (Davis, 1989; Venkatesh & Davis, 2000). This model is an excellent fit for the current study because IPE traditionally relies on direct, interactive instruction, and the shift to a digital environment poses unique challenges in managing expectations and demonstrating utility. By applying ECM, this study can evaluate how well MOOCs meet the expectations of IPE students and thereby determine the factors that influence their satisfaction and subsequent continuance intention.

Complementing ECM, the Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995) provides a framework for assessing the functional compatibility between the MOOC platform’s features and the specific learning tasks required in IPE. IPE courses often involve complex, nuanced content that demands effective digital delivery mechanisms. TTF is particularly relevant in this context as it allows researchers to examine how the alignment of technology features—such as multimedia content, interactive discussion forums, and assignment tools—with students’ learning needs contributes to overall satisfaction and sustained usage (McGill & Klobas, 2009). Given that IPE requires both the transmission of detailed ideological content and the facilitation of critical discussion, TTF helps illuminate whether MOOCs are adequately designed to support these dual demands.

Additionally, Learning Engagement Theory is incorporated to capture the behavioral, emotional, and cognitive dimensions of student involvement. Engagement is a critical precursor to both satisfaction and continuance intention (Fredricks et al., 2004; Newmann, Wehlage, & Lamborn, 1992). In the MOOC environment, especially in IPE where content can be abstract and challenging, active engagement—through participation in discussions, collaborative projects, and interactive activities—can enhance satisfaction and encourage continued use. Integrating learning engagement with ECM and TTF not only strengthens the theoretical framework but also provides a more holistic view of the factors driving MOOC adoption in IPE.

Together, these models offer a robust framework that addresses both the psychological determinants (via ECM) and the functional appropriateness (via TTF) of MOOCs in IPE. This integration allows the study to investigate how the interplay between expectation confirmation, perceived usefulness, and



technological alignment, moderated by learning engagement, influences overall satisfaction and the intention to continue using MOOCs.

Based on the integration of these theoretical perspectives, the study hypotheses are listed in Table 1.

**Table 1** List of Hypotheses in the Study

Hypotheses	Statement	Literature Support
H <sub>01</sub>	Perceived usefulness does not influence Satisfaction.	Ouyang et al. (2017)
Ha1	Perceived usefulness influences Satisfaction.	Wang, Lin & Su (2021)
H <sub>02</sub>	Confirmation does not influence Satisfaction.	Ouyang et al. (2017)
Ha2	Confirmation influences Satisfaction.	Wang, Lin & Su (2021)
H <sub>03</sub>	Task-technology fit does not influence Satisfaction.	Fu et al. (2020)
Ha3	Task-technology fit influences Satisfaction.	
H <sub>04</sub>	Learning engagement does not influence Satisfaction.	Cheng (2022)
Ha4	Learning engagement influences Satisfaction.	Liu et al. (2023)
H <sub>05</sub>	Satisfaction does not influence Continuance intention.	Ouyang et al. (2017)
Ha5	Satisfaction influences Continuance intention.	Alyoussef (2021) Wang, Lin & Su (2021)
H <sub>06</sub>	Perceived usefulness does not influence Continuance intention.	Ouyang et al. (2017) Wang, Lin & Su (2021)
Ha6	Perceived usefulness influences Continuance intention.	
H <sub>07</sub>	Task-technology fit does not influence Continuance intention.	Fu et al. (2020) Wang, Lin & Su (2021)
Ha7	Task-technology fit influences Continuance intention.	
H <sub>08</sub>	Learning engagement does not influence Continuance intention.	Cheng (2022)
Ha8	Learning engagement influences Continuance intention.	
H <sub>09</sub>	Continuance intention does not influence Continuance Behavior.	Liu et al. (2019)
Ha9	Continuance intention influences Continuance Behavior.	
H <sub>010</sub>	There is no mediation effect of satisfaction in the influence of perceived usefulness on Continuance intention.	Ouyang et al. (2017) Cheng (2022)
Ha10	There is a mediation effect of satisfaction in the influence of perceived usefulness on Continuance intention.	
H <sub>011</sub>	There is no mediation effect of satisfaction in the influence of Task-technology fit on Continuance intention.	Ouyang et al. (2017)
Ha11	There is a mediation effect of satisfaction in the influence of Task-technology fit on Continuance intention.	
H <sub>012</sub>	There is no mediation effect of satisfaction in the influence of Learning engagement on Continuance intention.	Cheng (2022)
Ha12	There is a mediation effect of satisfaction in the influence of Learning engagement on Continuance intention.	





## Methodology

This study employs a quantitative survey approach to examine vocational students' perceptions of MOOCs used for Ideological and Political Education (IPE). The methodology is designed to capture comprehensive data on key constructs—including perceived usefulness, confirmation, task-technology fit, learning engagement, satisfaction, continuance intention, and continuance behavior—by surveying students with direct experience in MOOC-based IPE courses.

### Research Design

A cross-sectional quantitative survey design was adopted to yield measurable and statistically analyzable data from a substantial number of respondents. This design facilitates the exploration of relationships between variables and allows for hypothesis testing using advanced statistical techniques. Structural Equation Modeling (SEM) was chosen over other analytical methods because it permits the simultaneous examination of multiple relationships, including both direct and indirect effects, and effectively tests the integrated theoretical framework comprising the Expectation Confirmation Model (ECM) and Task-Technology Fit (TTF) model (Hu & Bentler, 1999). This approach is particularly suited to understanding the complex interplay of factors influencing satisfaction and continuance intention in an online learning context.

### Research Treatment and Procedure

The research treatment spanned a 10-week period during which students participated in a structured MOOC-based IPE course. This treatment was divided into three phases:

**Orientation and Pre-Survey (Week 1):** Students were introduced to the MOOC platform, familiarizing themselves with the course content and navigation. A pre-survey was administered to capture baseline attitudes toward online courses.

**Instructional Phase (Weeks 2–9):** During these weeks, students received weekly content through videos, readings, and assignments. Interactive elements, such as discussion forums and quizzes, were integrated to foster engagement. Mid-treatment check-ins via brief surveys were conducted to monitor evolving perceptions.

**Post-Course Data Collection (Week 10):** At the end of the course, a comprehensive post-survey was distributed to gather detailed data on students' experiences, satisfaction, and their intentions to continue using MOOCs.

This phased approach ensures that the data reflect both the initial expectations and the ongoing experience of students throughout the course (Creswell, 2014).

### Population and Sample

The study was conducted at a vocational university in China, a context chosen for its unique focus on practical skill development. Vocational colleges in China emphasize applied knowledge and technical skills, making them an ideal setting to explore how students, who are typically oriented toward hands-on learning, adapt to and perceive theoretical content delivered through MOOCs (Li, 2017; Zheng, Han, & Rosson, 2018). From a target population of 1,200 students enrolled in IPE courses, 248 students were purposively selected. Purposive sampling was used because it ensured that only those students with direct experience in the MOOC-based IPE course were included. This targeted approach enhances the relevance and quality of the data, as respondents are well-positioned to provide informed feedback regarding the course design, engagement levels, and overall satisfaction. Additionally, the sample size of 248 was determined using a Structural Equation Modeling (SEM) Sample Size Calculator, which recommended a minimum of 247 participants to reliably test complex variable relationships (Rai & Thapa, 2015). This sample size not only meets the statistical requirements for SEM but also enhances the reliability and generalizability of the findings within the context of vocational education in China.

### Research Instruments

The primary research instrument was a structured questionnaire designed to measure seven key variables:





Perceived Usefulness: Evaluates the benefits that students perceive from using MOOCs (adapted from Davis, 1989; Bhattacharjee, 2001).

Confirmation: Assesses whether the MOOC platform meets the initial expectations of the students (Bhattacharjee, 2008).

Task-Technology Fit: Measures the extent to which the MOOC’s features align with the learning tasks (Goodhue & Thompson, 1995; Lee & Lehto, 2013).

Learning Engagement: Captures the level of students’ active involvement in the course (Newmann, Wehlage, & Lamborn, 1992; Fredricks et al., 2004).

Satisfaction: Reflects overall contentment with the MOOC experience (Bhattacharjee, 2001; Albelbisi & Yusop, 2019).

Continuance Intention: Indicates the students’ intent to continue using MOOCs in the future (Roca et al., 2006; Chiu et al., 2005).

Continuance Behavior: Records actual continued usage behavior (Liu et al., 2019; Wang et al., 2022).

Each construct was measured using multiple items on a 5-point Likert scale (ranging from 1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire underwent rigorous validation, including a pilot test with 30 students and subsequent reliability analysis using Cronbach’s Alpha, which yielded high internal consistency across all variables (Cronbach, 1951; Haertel, 2006).

**Data Collection and Analysis**

Data collection was facilitated using an online survey platform (Questionnaire Star), which ensured efficiency and broad accessibility for the target population. The survey was administered anonymously, and no incentives were provided, thereby minimizing potential response biases. Detailed instructions and informed consent were provided, clearly outlining the study’s purpose, procedures, risks, and benefits. Participants were assured of the confidentiality and anonymity of their responses, and all data were securely stored in compliance with ethical standards (Polit & Beck, 2006).

Data analysis was performed using JAMOVI version 2.4.11. Descriptive statistics were used to summarize central tendencies and variability within the dataset. Structural Equation Modeling (SEM) was employed for hypothesis testing due to its capability to assess complex relationships, including mediating effects, simultaneously. This method was chosen over simpler techniques, such as multiple regression, because SEM provides a more comprehensive understanding of the interrelationships among multiple latent constructs, making it ideal for testing the integrated theoretical framework of ECM and TTF (Hu & Bentler, 1999).

**Results**

This section presents the findings of the study, organized into subsections on demographic information, descriptive statistics, normality testing, confirmatory factor analysis (CFA), and structural equation modeling (SEM), including mediation analysis.

**Demographic Information**

As shown in Table 2, the sample consisted of 248 participants, with 64.5% male (n = 160) and 35.5% female (n = 88). In terms of academic level, the majority of respondents were in Grade 2 (63.3%, n = 157), followed by Grade 1 (19.4%, n = 48) and Grade 3 (17.3%, n = 43). This distribution reflects a robust representation of intermediate-grade students, providing a sound basis for analyzing their perceptions of MOOCs.

**Table 2** Demographic Information of Samples

Variable	Category	Frequency	Percentage
Gender	Male	160	64.5 %
	Female	88	35.5 %
	Total	248	100.0 %





Variable	Category	Frequency	Percentage
Grade	1	48	19.4 %
	2	157	63.3 %
	3	43	17.3 %
	Total	43	100.0 %

### Descriptive Statistics of Key Variables

Descriptive statistics were calculated using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Table 3 shows the descriptive statistics of variables interpreted by the arbitrary interpretation level of Norman, G. (2010).

**Table 3** Descriptive Statistics of Variables

Item	Item Statement	Mean	SD	Interpretation
PU1	Using MOOCs improves my learning performance.	3.69	0.861	Agree
PU2	Using MOOCs increases my learning effectiveness.	4.12	0.799	Agree
PU3	I find MOOCs are useful for me.	3.96	0.781	Agree
PU4	I find it useful to use MOOCs on my assignments.	4.09	0.785	Agree
PU5	MOOCs are useful because they help me to improve my own work.	4.10	0.793	Agree
PU6	MOOCs are useful because they help me to reflect on my work.	4.02	0.82	Agree
Perceived Usefulness		4.00	0.658	Agree
C1	My experience with using MOOCs was better than I expected.	3.83	0.853	Agree
C2	The service level provided by MOOCs was better than I expected.	4.09	0.817	Agree
C3	Overall, most of my expectations from using MOOCs were confirmed.	3.91	0.846	Agree
C4	The MOOC platform is evaluated over a longer period of time with respect to confirmation (fulfillment of intent or fulfillment of expectations)	3.89	0.879	Agree
Confirmation		3.93	0.716	Agree
TTF1	I think that using MOOCs would be well-suited for the way I like to study tasks.	4.08	0.788	Agree
TTF2	MOOCs would be a good tool to provide the way I like to study tasks.	4.00	0.764	Agree
TTF3	Using MOOCs fits well with the way I like to study tasks.	4.01	0.83	Agree
TTF4	MOOCs are fit for the requirements of my learning	3.75	0.834	Agree
TTF5	Using MOOCs fits with my educational practice.	4.01	0.832	Agree
TTF6	MOOCs are suitable for helping me complete online courses.	4.11	0.748	Agree
Task-Technology Fit		3.99	0.628	Agree
LE1	I often put more effort into my work than is required when participating in MOOCs.	4.15	0.827	Agree
LE2	I am inspired to expand my knowledge in MOOCs.	3.88	0.848	Agree
LE3	If I have trouble understanding a concept or an example when I am learning in MOOCs, I go over it again until I figure it out.	4.17	0.825	Agree





Item	Item Statement	Mean	SD	Interpretation
LE4	I am active in interacting with instructors and other learners in the MOOCs learning process.	3.96	0.934	Agree
Learning Engagement		4.04	0.741	Agree
S1	I enjoy using MOOC for my studies.	3.98	0.839	Agree
S2	I believe that MOOC allows me to acquire new knowledge.	3.96	0.831	Agree
S3	I believe that MOOC enhances my learning experience.	3.85	0.809	Agree
S4	I believe that MOOC increases the quality of learning because they integrate all forms of media.	4.15	0.75	Agree
S5	I believe that studying courses that use MOOC is interesting.	3.83	0.845	Agree
S6	In my MOOC learning experiences, the content of the course is up to date.	4.02	0.839	Agree
Satisfaction		3.96	0.649	Agree
CI1	I will continue using MOOCs in the future.	3.83	0.825	Agree
CI2	I will strongly recommend MOOCs to others to use them.	3.96	0.888	Agree
CI3	I will keep using MOOCs as regularly as I do now.	3.92	0.809	Agree
CI4	If I were to take this subject again, I would like the teacher to use MOOCs as part of the content.	4.03	0.819	Agree
CI5	I recommend that other course subjects use MOOCs as part of their content.	3.82	0.87	Agree
CI6	I think I made the right choice when I enrolled in an institution that uses MOOCs in its subjects.	3.86	0.854	Agree
Continuance Intention		3.91	0.696	Agree
CB1	If I heard about a new information technology, I would look for ways to experiment with it.	3.84	0.865	Agree
CB2	Among my peers, I am usually the first to explore new information technologies.	3.94	0.859	Agree
CB3	I like to experiment with new information technologies	4.09	0.766	Agree
CB4	In the future, I will use MOOCs as an additional study course.	3.91	0.832	Agree
CB5	In the future, I will recommend MOOCs to my friends.	3.93	0.791	Agree
CB6	In the future, I will share my own MOOCs learning experience with my friends.	4.15	0.767	Agree
Continuance Behavior		3.98	0.648	Agree

The descriptive statistics in Table 3 provide an overall positive evaluation of the MOOC platform across all measured constructs.

#### Perceived Usefulness (PU)

The six items measuring perceived usefulness exhibit mean scores ranging from 3.69 to 4.12, with an overall mean of 4.00 (SD = 0.658). Notably, PU2 (“Using MOOCs increases my learning effectiveness”)





achieved the highest mean (4.12), while PU1 (“Using MOOCs improves my learning performance”) recorded the lowest mean (3.69). These results indicate that students generally agree that MOOCs are beneficial in enhancing various aspects of their learning, including effectiveness and practical improvements in their work. The relatively low standard deviation suggests moderate response consistency among participants (Davis, 1989; Bhattacharjee, 2001).

#### Confirmation (C)

The four items assessing confirmation yield mean scores between 3.83 and 4.09, with a total mean of 3.93 (SD = 0.716). The highest agreement is observed for the item “The service level provided by MOOCs was better than I expected” (mean = 4.09), while “My experience with using MOOCs was better than I expected” is at 3.83. Overall, these scores indicate that respondents generally agree that MOOCs meet or exceed their initial expectations, suggesting a favorable evaluation of the platform’s performance and service quality.

#### Task-Technology Fit (TTF)

For the TTF construct, the mean scores for the six items range from 3.75 to 4.11, with an overall mean of 3.99 (SD = 0.628). The highest score is associated with TTF6 (“MOOCs are suitable for helping me complete online courses”), indicating strong agreement that the platform effectively supports their learning tasks. The item TTF4 (“MOOCs are fit for the requirements of my learning”) received the lowest mean of 3.75, although it still falls within the “Agree” range. The results suggest that students perceive the technological features of MOOCs as well-aligned with their educational needs.

#### Learning Engagement (LE)

The four items under learning engagement yield means ranging from 3.88 to 4.17, with a total mean of 4.04 (SD = 0.741). The item LE3 (“If I have trouble understanding a concept or an example when I am learning in MOOCs, I go over it again until I figure it out”) achieved the highest mean (4.17), highlighting a strong commitment to overcoming learning difficulties. These findings suggest that students are actively engaged in their learning processes when using MOOCs, which is critical for enhancing educational outcomes (Newmann, Wehlage, & Lamborn, 1992).

#### Satisfaction (S)

The satisfaction construct is measured by six items, with mean scores ranging from 3.83 to 4.15 and an overall mean of 3.96 (SD = 0.649). The highest level of agreement is found in S4 (“I believe that MOOC increases the quality of learning because it integrates all forms of media”), while S5 (“I believe that studying courses that use MOOC is interesting”) receives the lowest mean. These statistics suggest that students are generally satisfied with the MOOC experience, particularly appreciating the multimedia integration and the up-to-date course content.

#### Continuance Intention (CI)

The six items addressing continuance intention produce mean scores from 3.82 to 4.03, with an overall mean of 3.91 (SD = 0.696). For instance, CI4 (“If I were to take this subject again, I would like the teacher to use MOOCs as part of the content”) has the highest mean (4.03), indicating a strong intention among students to continue engaging with MOOCs. These results demonstrate that students are positively inclined toward the future use of MOOCs, which is a crucial indicator of the platform's sustained acceptance.

#### Continuance Behavior (CB)

Finally, the six items measuring continuance behavior show means between 3.84 and 4.15, with an overall mean of 3.98 (SD = 0.648). The highest score is recorded for CB6 (“In the future, I will share my own MOOCs learning experience with my friends”), suggesting that students are not only likely to continue using MOOCs but also to advocate for them among their peers. This behavior reinforces the overall positive perception of MOOCs as a valuable learning tool.

Overall, the descriptive analysis demonstrates that respondents consistently agree with all constructs, with all total mean scores falling within the “Agree” range. This uniformity in positive responses supports the study’s premise that MOOCs are perceived as beneficial in enhancing learning outcomes and fostering engagement among students in IPE. The consistency in standard deviations further indicates reliable and stable responses across the sample (Norman, 2010).

## Hypotheses Testing

### Normality of Data

In order to test the distribution of data, the skewness and kurtosis statistics are applied to measure the normality of the data on the items used. According to Hair et.al. (2010), the skewness ranges between





2 and +2, and the Kurtosis range of -7 to +7. The results in Table 4 show that all the skewness values in this study fall within the range of -0.71 to -0.119, and the kurtosis values range between -0.93 and 0.3299, both well within the acceptable thresholds. This indicates that the data for all items, including perceived usefulness, task-technology fit, confirmation, learning engagement, satisfaction, continuance intention, and continuance behavior, exhibit no significant deviations from normality.

**Table 4** Normality of Data

	N	Mean	SD	Skewness		Kurtosis	
				Skewness	SE	Kurtosis	SE
PU1	248	3.69	0.861	-0.122	0.155	-0.4764	0.308
PU2	248	4.12	0.799	-0.454	0.155	-0.6473	0.308
PU3	248	3.96	0.781	-0.296	0.155	-0.4864	0.308
PU4	248	4.09	0.785	-0.36	0.155	-0.7387	0.308
PU5	248	4.1	0.793	-0.337	0.155	-0.9272	0.308
PU6	248	4.02	0.82	-0.386	0.155	-0.6002	0.308
TTF1	248	4.08	0.788	-0.586	0.155	0.2175	0.308
TTF2	248	4	0.764	-0.275	0.155	-0.5471	0.308
TTF3	248	4.01	0.83	-0.444	0.155	-0.4798	0.308
TTF4	248	3.75	0.834	-0.143	0.155	-0.6107	0.308
TTF5	248	4.01	0.832	-0.576	0.155	0.035	0.308
TTF6	248	4.11	0.748	-0.356	0.155	-0.607	0.308
C1	248	3.83	0.853	-0.213	0.155	-0.6818	0.308
C2	248	4.09	0.817	-0.532	0.155	-0.422	0.308
C3	248	3.91	0.846	-0.388	0.155	-0.2822	0.308
C4	248	3.89	0.879	-0.391	0.155	-0.5768	0.308
LE1	248	4.15	0.827	-0.71	0.155	0.1048	0.308
LE2	248	3.88	0.848	-0.297	0.155	-0.6167	0.308
LE3	248	4.17	0.825	-0.621	0.155	-0.463	0.308
LE4	248	3.96	0.934	-0.64	0.155	-0.1552	0.308
S1	248	3.98	0.839	-0.493	0.155	-0.1357	0.308
S2	248	3.96	0.831	-0.486	0.155	0.1232	0.308
S3	248	3.85	0.809	-0.37	0.155	-0.0405	0.308
S4	248	4.15	0.75	-0.419	0.155	-0.5738	0.308
S5	248	3.83	0.845	-0.328	0.155	-0.2834	0.308
S6	248	4.02	0.839	-0.569	0.155	-0.0333	0.308
CI1	248	3.83	0.825	-0.119	0.155	-0.7442	0.308
CI2	248	3.96	0.888	-0.524	0.155	-0.1491	0.308
CI3	248	3.92	0.809	-0.322	0.155	-0.239	0.308
CI4	248	4.03	0.819	-0.461	0.155	-0.4483	0.308
CI5	248	3.82	0.87	-0.16	0.155	-0.8104	0.308
CI6	248	3.86	0.854	-0.512	0.155	0.3299	0.308
CB1	248	3.84	0.865	-0.295	0.155	-0.623	0.308
CB2	248	3.94	0.859	-0.386	0.155	-0.5905	0.308
CB3	248	4.09	0.766	-0.486	0.155	-0.2469	0.308
CB4	248	3.91	0.832	-0.293	0.155	-0.6023	0.308
CB5	248	3.93	0.791	-0.265	0.155	-0.5225	0.308
CB6	248	4.15	0.767	-0.586	0.155	0.1463	0.308



### Confirmatory Factor Analysis

CFA was performed to assess the measurement model. Table 5 summarizes the CFA results, including estimates, standard errors, Z-values, p-values, standardized loadings, Composite Reliability (CR), Average Variance Extracted (AVE), and the square root of AVE. All factor loadings ranged from 0.657 to 0.900 ( $p < 0.001$ ), and AVE values for all constructs exceeded the 0.50 threshold, indicating convergent validity (Hair et al., 2006). Discriminant validity was confirmed as the square roots of the AVE for each construct were higher than the inter-construct correlations (Fornell & Larcker, 1981), as shown in Table 6. **Table 5** Confirmatory factor analysis result, Composite Reliability (CR), and Average Variance Extracted (AVE)

Factor	Indicator	Estimate	SE	Z	P	Stand. Estimate	AVE >. 5	CR >. 7	SQRT AVE
PU	PU1	0.647	0.048	13.500	<.001	0.753	0.600	0.900	0.775
	PU2	0.618	0.044	14.000	<.001	0.776			
	PU3	0.554	0.045	12.400	<.001	0.711			
	PU4	0.650	0.042	15.500	<.001	0.830			
	PU5	0.645	0.043	15.100	<.001	0.815			
	PU6	0.620	0.046	13.600	<.001	0.758			
TTF	TTF1	0.576	0.045	12.800	<.001	0.732	0.544	0.877	0.738
	TTF2	0.568	0.043	13.100	<.001	0.745			
	TTF3	0.544	0.049	11.000	<.001	0.657			
	TTF4	0.630	0.047	13.400	<.001	0.757			
	TTF5	0.618	0.047	13.100	<.001	0.745			
	TTF6	0.584	0.042	14.100	<.001	0.783			
C	C1	0.606	0.050	12.200	<.001	0.712	0.617	0.865	0.785
	C2	0.637	0.046	13.900	<.001	0.781			
	C3	0.672	0.047	14.200	<.001	0.796			
	C4	0.742	0.048	15.500	<.001	0.846			
LE	LE1	0.611	0.047	13.100	<.001	0.741	0.662	0.886	0.814
	LE2	0.694	0.046	15.200	<.001	0.820			
	LE3	0.647	0.045	14.300	<.001	0.786			
	LE4	0.839	0.048	17.500	<.001	0.900			
S	S1	0.606	0.048	12.600	<.001	0.724	0.556	0.882	0.746
	S2	0.604	0.047	12.800	<.001	0.728			
	S3	0.561	0.047	12.000	<.001	0.696			
	S4	0.564	0.042	13.400	<.001	0.753			
	S5	0.662	0.047	14.200	<.001	0.785			
	S6	0.658	0.046	14.200	<.001	0.785			
CI	CI1	0.683	0.044	15.600	<.001	0.829	0.617	0.906	0.786
	CI2	0.688	0.049	14.100	<.001	0.776			
	CI3	0.600	0.045	13.300	<.001	0.744			
	CI4	0.657	0.044	14.900	<.001	0.803			
	CI5	0.663	0.048	13.800	<.001	0.764			
	CI6	0.677	0.046	14.600	<.001	0.795			
CB	CB1	0.665	0.048	13.800	<.001	0.770	0.563	0.885	0.751
	CB2	0.629	0.049	12.900	<.001	0.735			
	CB3	0.544	0.044	12.300	<.001	0.711			
	CB4	0.643	0.046	13.900	<.001	0.775			



Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate	AVE >. 5	CR >. 7	SQRT AVE
	CB5	0.564	0.046	12.400	<.001	0.714			
	CB6	0.608	0.042	14.400	<.001	0.794			

Remark: CR = Composite Reliability, AVE = Average Variance Extracted

**Table 6** Discriminant Validity

	M_PU	M_TTF	M_C	M_LE	M_S	M_CI	M_CB
M_PU	0.775						
M_TTF	0.112	0.738					
M_C	0.269	0.236	0.785				
M_LE	0.156	0.257	0.230	0.814			
M_S	0.340	0.373	0.391	0.362	0.746		
M_CI	0.288	0.420	0.318	0.395	0.436	0.786	
M_CB	0.230	0.193	0.301	0.284	0.366	0.431	0.751

The CFA model fit was also evaluated. As seen in Table 7, the model achieved a good fit with RMSEA = 0.037, CFI = 0.957, and TLI = 0.954 (Navarro & Foxcroft, 2019).

**Table 7** Confirmatory Factor Analysis Fit Indices

Fit Index	Acceptable Criteria	Source	Statistical Values
RMSEA	≤ 0.08	Navarro and Foxcroft (2019)	0.037
CFI	≥ 0.90	Navarro and Foxcroft (2019)	0.957
TLI	≥ 0.90	Navarro and Foxcroft (2019)	0.954
Model Summary			In harmony with empirical data

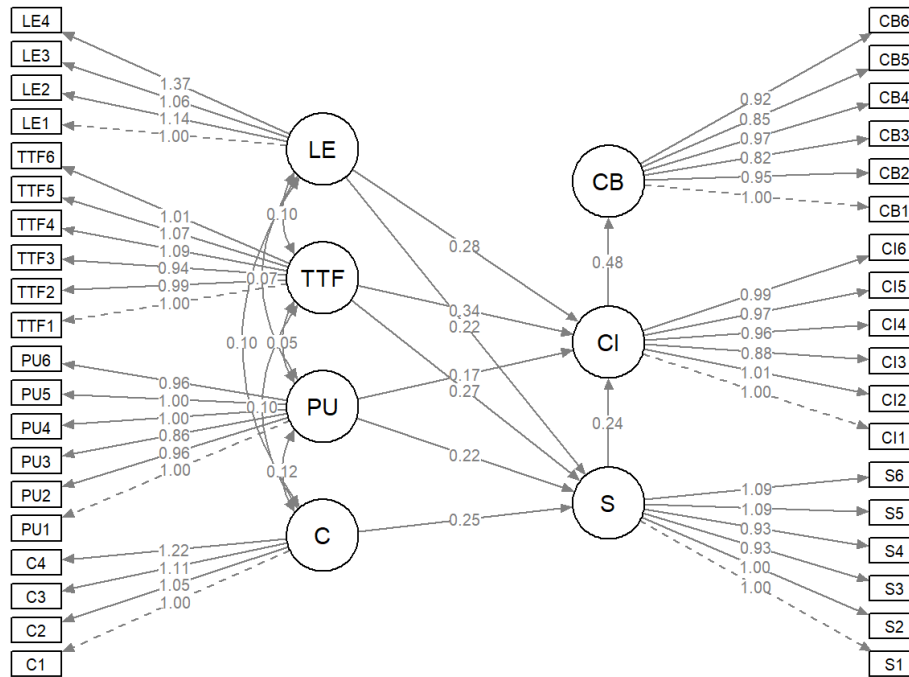
### Structural Equation Model

The structural model was evaluated using SEM. Table 8 presents the fit indices for the SEM, indicating excellent model fit: GFI = 0.976, SRMR = 0.057, RMSEA = 0.037, CFI = 0.957, and TLI = 0.954 (Cho et al., 2020; Hooper et al., 2008; Sharma et al., 2005). Figure 2 displays the SEM path diagram.

**Table 8** Fit Indices Results of the Structural Equation Model

Fit Index	Acceptable Criteria	Source	Statistical Values
GFI	≥ 0.80	Cho et.al. 2020	0.976
SRMR	≤ 0.08	Cho et.al. 2020	0.057
RMSEA	≤ 0.10	Hooper et al. 2008	0.037
CFI	≥ 0.80	Hooper et al. 2008	0.957
TLI	≥ 0.80	Sharma et al., 2005	0.954
Model Summary			In harmony with empirical data





**Figure 2** The Structural Equation Model (SEM) Path Diagram of the Study

The parameter estimates (Table 9) for the structural model indicate that all hypothesized paths are statistically significant ( $p < 0.05$ ):

Satisfaction (S)

Influenced by Confirmation ( $\beta = 0.254, z = 3.61, p < 0.001$ ), Perceived Usefulness ( $\beta = 0.232, z = 3.56, p < 0.001$ ), Task-Technology Fit ( $\beta = 0.260, z = 3.85, p < 0.001$ ), and Learning Engagement ( $\beta = 0.221, z = 3.37, p < 0.001$ ).

Continuance Intention (CI)

Predicted by Satisfaction ( $\beta = 0.214, z = 2.81, p = 0.005$ ), Perceived Usefulness ( $\beta = 0.164, z = 2.59, p = 0.01$ ), Task-Technology Fit ( $\beta = 0.286, z = 4.17, p < 0.001$ ), and Learning Engagement ( $\beta = 0.253, z = 3.82, p < 0.001$ ).

Continuance Behavior (CB)

Significantly influenced by Continuance Intention ( $\beta = 0.495, z = 6.93, p < 0.001$ ).

**Table 9** SEM Parameter Estimates

Dep	Pred	Estimate	SE	95% Confidence Intervals		$\beta$	z	p
				Lower	Upper			
S	C	0.253	0.07	0.1155	0.39	0.254	3.61	<.001
S	PU	0.217	0.0607	0.0975	0.336	0.232	3.56	<.001
S	TTF	0.272	0.0706	0.1337	0.41	0.26	3.85	<.001
S	LE	0.219	0.065	0.0914	0.346	0.221	3.37	<.001
CI	S	0.241	0.0858	0.0726	0.409	0.214	2.81	0.005
CI	PU	0.173	0.0669	0.042	0.304	0.164	2.59	0.01
CI	TTF	0.339	0.0812	0.1795	0.498	0.286	4.17	<.001

95% Confidence Intervals								
Dep	Pred	Estimate	SE	Lower	Upper	$\beta$	z	p
CI	LE	0.282	0.0739	0.1376	0.427	0.253	3.82	<.001
CB	CI	0.481	0.0694	0.3446	0.616	0.495	6.93	<.001

The mediating role of Satisfaction in the relationships between the predictor variables (Perceived Usefulness, Task-Technology Fit, and Learning Engagement) and Continuance Intention was tested using an indirect effects approach. Table 5.16 shows that the indirect effects are statistically significant:

PU  $\rightarrow$  S  $\rightarrow$  CI:  $\beta = 0.047$ ,  $z = 2.183$ ,  $p = 0.029$ ; 95% CI = [0.005, 0.095]  
 TTF  $\rightarrow$  S  $\rightarrow$  CI:  $\beta = 0.053$ ,  $z = 2.266$ ,  $p = 0.023$ ; 95% CI = [0.008, 0.117]  
 LE  $\rightarrow$  S  $\rightarrow$  CI:  $\beta = 0.045$ ,  $z = 2.14$ ,  $p = 0.032$ ; 95% CI = [0.004, 0.096]

These results confirm that Satisfaction significantly mediates the effects of Perceived Usefulness, Task-Technology Fit, and Learning Engagement on Continuance Intention.

**Table 10** Mediating Effect Testing

95% Confidence Intervals									
Label	Description	Parameter	Estimate	SE	Lower	Upper	$\beta$	z	p
IE2	PU $\Rightarrow$ S $\Rightarrow$ CI	p34*p37	0.05	0.023	0.005	0.095	0.047	2.183	0.029
IE3	TTF $\Rightarrow$ S $\Rightarrow$ CI	p35*p37	0.063	0.028	0.008	0.117	0.053	2.266	0.023
IE4	LE $\Rightarrow$ S $\Rightarrow$ CI	p36*p37	0.05	0.024	0.004	0.096	0.045	2.14	0.032

Table 11 summarizes the outcomes of the hypothesis testing. All null hypotheses were rejected, supporting the theoretical model that Perceived Usefulness, Confirmation, Task-Technology Fit, and Learning Engagement positively influence Satisfaction, which in turn affects Continuance Intention and ultimately predicts Continuance Behavior.

**Table 11** Summary of Hypothesis Testing and Results

Hypotheses	Statement	Result after Analysis
H <sub>01</sub>	Perceived usefulness does not influence Satisfaction.	Rejected
H <sub>02</sub>	Confirmation does not influence Satisfaction.	Rejected
H <sub>03</sub>	Task-technology fit does not influence Satisfaction.	Rejected
H <sub>04</sub>	Learning engagement does not influence Satisfaction.	Rejected
H <sub>05</sub>	Satisfaction does not influence Continuance intention.	Rejected
H <sub>06</sub>	Perceived usefulness does not influence Continuance intention.	Rejected
H <sub>07</sub>	Task-technology fit does not influence Continuance intention.	Rejected
H <sub>08</sub>	Learning engagement does not influence Continuance intention.	Rejected
H <sub>09</sub>	Continuance intention does not influence Continuance Behavior.	Rejected
H <sub>010</sub>	There is no mediation effect of satisfaction in the influence of perceived usefulness on Continuance intention.	Rejected
H <sub>011</sub>	There is no mediation effect of satisfaction in the influence of Task-technology fit on Continuance intention.	Rejected
H <sub>012</sub>	There is no mediation effect of satisfaction in the influence of Learning engagement on Continuance intention.	Rejected



## Discussion

The present study examined factors influencing students' satisfaction and continuance intention in using MOOCs for Ideological and Political Education (IPE) by integrating the Expectation Confirmation Model (ECM) and Task-Technology Fit (TTF) model with Learning Engagement Theory. Our findings indicate that perceived usefulness, confirmation, task-technology fit, and learning engagement each exert a significant positive influence on students' satisfaction with MOOCs. These results are consistent with earlier research, such as Bhattacharjee (2001), which highlighted the role of perceived usefulness in driving satisfaction, and Goodhue and Thompson (1995), who underscored the importance of aligning technology with specific tasks. In our study, when students perceive that MOOCs effectively enhance their learning performance and meet or exceed their initial expectations, their overall satisfaction increases. This reinforces prior work by Davis (1989) and Lin, Wu, and Tsai (2005) while extending these insights specifically to the IPE context.

Moreover, the study reveals that satisfaction, alongside perceived usefulness, task-technology fit, and learning engagement, significantly influences continuance intention. These findings echo those of Lin, Wu, and Tsai (2005) and Chiu et al. (2005), suggesting that a positive learning experience fosters a strong intention to continue using the platform. Notably, mediation analysis confirmed that satisfaction partially mediates the effects of perceived usefulness, task-technology fit, and learning engagement on continuance intention. This mediation highlights satisfaction as a crucial mechanism linking positive user experiences to future behavioral intentions, supporting the theoretical assertions of ECM and further corroborating findings by Chiu et al. (2005) and Liu et al. (2019).

A particularly strong impact of task-technology fit was observed on both satisfaction and continuance intention, reinforcing prior studies by McGill and Klobas (2009) and Lee and Lehto (2013), which indicate that the alignment of technological features with learning tasks is essential for effective MOOC adoption. However, while our findings align with these studies, they also reveal that in the context of IPE, integrating theoretical content with practical application presents unique challenges that require enhanced instructional design and support mechanisms.

### Limitations

Despite the valuable insights, the study has several limitations. First, the sample was drawn from a single vocational university in China, which may limit the generalizability of the findings to other educational contexts or regions. Future research should include multiple institutions and diverse educational settings to validate and extend these findings. Second, purposive sampling was used to ensure that respondents had direct experience with MOOC-based IPE; however, this method may introduce sampling bias that could affect the representativeness of the results (Rai & Thapa, 2015). Third, the cross-sectional design captures a snapshot of student perceptions and does not account for changes over time. Longitudinal studies would help examine the evolution of satisfaction and continuance intention with extended MOOC exposure. Finally, reliance on self-reported data may be subject to response biases; incorporating objective measures of engagement and performance in future research would provide additional robustness.

### Future Research and Implications

Our findings underscore the need for MOOC designers and educators to focus on enhancing task-technology fit, managing expectations, and fostering active learning engagement. Institutions should invest in robust technological infrastructure and provide continuous support to address potential digital literacy gaps and technical challenges (Zhao et al., 2020). Future research should explore additional factors such as digital literacy, self-regulated learning, and social support networks to develop a more comprehensive understanding of MOOC adoption in IPE. Moreover, employing qualitative methods alongside quantitative approaches could yield deeper insights into the nuanced experiences of learners, further informing effective pedagogical strategies.

## Conclusion

In summary, this study provides compelling evidence that students' satisfaction with MOOCs for IPE is driven by multiple interrelated factors, including perceived usefulness, confirmation, task-technology fit, and learning engagement. Satisfied students are more likely to develop a strong continuance intention, which, in turn, predicts their future use of MOOCs. The mediation analysis further emphasizes that satisfaction serves as a key mechanism through which the positive effects of the aforementioned factors are transmitted to continuance intention.





The results align with established theoretical frameworks such as the Expectation Confirmation Model and Task-Technology Fit theory, confirming that both the perceived efficacy of the MOOC platform and its alignment with learners' tasks are critical for sustained engagement. The study contributes to the broader body of research on online education by offering nuanced insights into the dynamics of MOOC adoption in the context of Ideological and Political Education. These findings have significant implications for educators, course designers, and policymakers aiming to improve online learning environments and promote sustained engagement in digital education platforms.

## Recommendation

Based on the study's findings, several actionable recommendations emerge for both institutional practice and future research. First, to improve the task-technology fit—which our results showed as a key predictor of both satisfaction and continuance intention—MOOC designers and instructors should enhance the platform's alignment with the specific learning tasks of Ideological and Political Education (IPE). Institutions can achieve this by incorporating adaptive learning pathways, integrating interactive multimedia content, and designing problem-based tasks that directly address the unique requirements of IPE courses. These measures are likely to increase students' perception that the platform meets their learning needs, thereby boosting both satisfaction and the likelihood of continued usage (Goodhue & Thompson, 1995; McGill & Klobas, 2009).

Second, fostering deeper learning engagement is critical, as our findings indicate that higher learning engagement significantly improves satisfaction and continuance intention. Educators should implement strategies such as collaborative projects, structured discussion forums, and peer feedback mechanisms. Additionally, incorporating gamification elements can serve to maintain student interest and mitigate the isolation often experienced in online environments. By promoting cognitive, emotional, and behavioral engagement, institutions can ensure that students remain actively involved throughout the course, ultimately leading to better learning outcomes (Hew & Cheung, 2016; Sun & Rueda, 2012).

Third, managing student expectations effectively is essential. The study revealed that confirmation—where students' initial expectations are met or exceeded—has a strong influence on satisfaction. Institutions should therefore provide comprehensive pre-course orientation sessions and detailed syllabi that clearly outline course objectives, delivery methods, and technical requirements. This approach can help set realistic expectations, reduce potential frustration, and enhance overall satisfaction with the MOOC experience (Oliver, 1980; Bhattacharjee, 2001).

Fourth, continuous institutional and technical support is imperative for sustained MOOC success. Our findings underscore the need for robust technical assistance and advanced learning management systems to address digital literacy gaps and potential technological disruptions. Institutions should also invest in professional development programs for instructors, enabling them to effectively deliver and manage online courses while preserving the pedagogical integrity of IPE (Zhao et al., 2020).

Finally, future research should build on these findings by adopting longitudinal designs to track changes in student satisfaction and continuance intention over time. Expanding the research to include multiple institutions and diverse educational contexts will help to enhance the generalizability of the results. Additionally, incorporating qualitative methods—such as interviews or focus groups—could provide deeper insights into the subjective experiences of students. Further investigation into additional variables, such as digital literacy, self-regulated learning strategies, and social support networks, would also contribute to a more comprehensive understanding of the factors that influence MOOC adoption in IPE (Selwyn, 2011; Arbaugh, 2014).

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