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RESEARCH PAPER

Comparative Analysis of the Essential Factors for the Adoption of Massive Open Online Courses in Higher Education of a Developing Country

Pre and Post COVID-19

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ABSTRACT

Although massive open online courses (MOOCs) offer numerous benefits to students, developing countries are still in the early stages of promoting their implementation. This study aims to investigate how the factors influencing MOOC adoption have evolved in response to the increased usage of online courses during the pandemic. The proposed model is based on the Technology Acceptance Model, and research hypotheses are presented based on six different factors: Perceived Usefulness, Perceived Ease of Use, Openness, Self-Efficacy, Quality of Service, and Reputation of the MOOC Provider. To test these hypotheses two surveys were conducted, one before and one after the COVID-19 period. Analyzing the data from these two time periods provides insight into the level of influence each of these factors has had on increased MOOC usage. Survey data was tested using the novel Partial Least Squares-Artificial Neural Network approach, which can effectively analyze complex human decisions. The findings indicate that Perceived Usefulness was the most influential factor

in the adoption of MOOCs both before and after the COVID-19 pandemic. Interestingly, changes have been observed in the impact of Openness between the pre-pandemic and post-pandemic periods.

1 Introduction

Massive Open Online Courses (MOOCs) are considered a contemporary evolution of online education that leverages virtual technology to enhance learning environments (Wu & Zhang, 2014). According to Ahmed et al. (2023), MOOCs are a disruptive technology that was created during the Information Revolution with the goal of providing extensive education for students. They are purposefully structured to surpass the limitations of traditional courses by granting access to a wide array of resources globally (Ferguson & Sharples, 2014). Siemens (2013) identifies several characteristics of MOOCs: they involve hundreds and thousands of students; they are highly and publicly accessible, allowing broad access to participants; they are delivered virtually, with most learning activities, content, and interactions occurring exclusively over the internet; they feature a definitive structure, with a pre-determined start and end time, and even if the course's archives may be accessible after completion, social interactions typically take place within the designated timeframe of the offering.

Although MOOCs have appeared in many countries in recent decades, their significance has been better understood since the outbreak of the COVID-19 pandemic. COVID-19 affected many aspects of our lives and changed our lifestyles, and education is no exception. The pandemic demanded a global reimagining of education, prompting schools, universities, and other higher educational institutions to temporarily cease in-person learning (Prasetyo et al., 2021). This meant conducting educational activities via online learning methods. This has substantially increased demand for and utilization of MOOC platforms (Nur & Safri, 2020). In 2020, MOOCs experienced an exceptional year. Major MOOC providers across the globe witnessed increases in user traffic of more than 50% (Shah et al., 2023). In certain instances, enrollments surpassed three to four times the numbers seen in corresponding periods of the previous year (Papadakis, 2023). The expansion of MOOCs worldwide, especially in developing countries, where access to educational resources is limited, has significantly impacted higher education (Ahmed et al., 2023).

Given the substantial potential and breadth of MOOCs in developing countries, a deeper understanding of the factors that impact their adoption becomes crucial for MOOC designers and regulators (Gupta, 2019). Many previous studies have extensively explored MOOC adoption. That research can be divided into three categories: studies examining factors influencing MOOC adoption prior to COVID-19 (e.g., Ma & Lee, 2019; Yadav et al., 2020; Al-Adwan, 2020); studies investigating MOOC adoption during COVID-19 (e.g., Ahmed et al., 2023; Alamri, 2022); and studies exploring MOOC adoption post-COVID-19 (e.g., Ucha, 2023; K. Wang, 2023; Meet et al., 2022). However, few studies have considered student intentions to use MOOCs both pre- and post-COVID-19.

Taking these points into consideration, and considering and recognizing that the adoption of MOOCs in a developing country faces numerous challenges that have not been thoroughly studied, investigating the factors influencing MOOC acceptance is crucial for improving higher education. To address these issues, this study adopts Iran as a case study, exploring the factors influencing the adoption of MOOCs in the country both before and after the COVID-19 pandemic. This study represents the first study to investigate MOOC adoption in Iran. The study seeks to answer the following research questions:

> **RQ1:** What factors influence MOOC adoption in a developing country?
>
> **RQ2:** How do student attitudes toward MOOCs differ between the periods before and after the COVID-19 pandemic?
>
> **RQ3:** Which factor has most substantial impacted MOOC adoption in the pre- and post-COVID-19 eras?

2 Related Work

2.1 MOOCs

The term MOOC was initially coined to describe “Connectivism and Connective Knowledge,” a course created in 2008 by George Siemens and Stephen Downes (Baturay, 2015). The popularity of MOOCs surged in 2011 when Stanford University offered the free online course “Introduction to Artificial Intelligence,” taught by Sebastian Thrun and Peter Norvig, attracting nearly 160,000 registrants. This marked a significant milestone, and several other renowned universities – including Harvard, the University of California, MIT, and Berkeley – subsequently launched MOOCs (Morgan, 2023). Subsequently, with an increasing number of colleges offering MOOCs, their popularity has continued to grow. There are currently over 16,500 MOOCs offered by more than 950 institutions globally, encompassing a total of 20,000 courses (M. Mutawa, 2023).

2.2 MOOC Adoption

Understanding the motivations behind MOOC usage and the factors influencing MOOC adoption is crucial for improving participation and completion rates among participants (Mohan et al., 2020). Additionally, examining factors related to MOOC adoption provides MOOC providers with valuable insights, enabling them to enhance their services (Fu et al., 2021). Students are motivated to enroll in MOOCs for reasons such as acquiring knowledge, seeking certifications, pursuing career aspirations, and achieving professional development (Wei et al., 2023). Research on MOOC adoption typically employs one or both of two perspectives: MOOC drivers and MOOC barriers (Abdel-Maksoud, 2019).

As indicated by Albelbisi et al. (2023), some of the challenges associated with MOOC adoption include a lack of instructor support, inadequate technology infrastructure, low self-regulated learning skills, the absence of openness features, and a requirement for specific knowledge and skills. Regarding drivers, Maphosa and Maphosa (2023) have identified several factors associated with MOOC adoption in previous studies, including Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Zero Costs, Self-Directed Learning Ability, Perceived Enjoyment, and Collaborative Knowledge Creation.

Numerous studies have been undertaken to elucidate students' acceptance behavior towards MOOCs. These investigations have identified several factors that could impact students' behavioral intention (BI) to adopt MOOCs. Ucha (2023) examined factors that are likely to influence students' intention to use MOOCs using the Technology Acceptance Model (TAM). Elsewhere, Zaremohzzabieh et al. (2022) explored the impact of eight factors on BI to adopt MOOCs and found that Performance Expectancy and Effort Expectancy have a significant effect. However, their hypotheses regarding Social Influence and Facilitating Conditions were rejected, with these factors having no effect on user intentions to adopt MOOCs. Ahmed et al. (2023) conducted a study to investigate the intention to participate in MOOCs during the COVID-19 pandemic in Northwestern Nigeria. The results of their study indicate that all constructs considered positively affect BI, with the impact of PU being particularly significant. Table 1 summarizes the factors analyzed in the studies mentioned.

Table 1: Factors Considered by Previous Studies

Period	Source	Model	Model Factors
Pre COVID-19	Ma & Lee (2019)	TUE[1]	Perceived Usefulness (PU), performance to cost, interactivity, accessibility, self-regulation, experience, gender, learning tradition, peer's impact, instruction, and publicity.
	Khan et al. (2018)	TTF[2]	Task technology fit, social recognition, social influence, perceived relatedness, perceived autonomy, perceived competence, and reputation.
	Yadav & Gupta (2020)	TAM[3]	PU, Perceived Ease of Use (PEOU), computer self-efficacy, and Gender.
	Al-Adwan (2020)	TAM	Computer self-efficacy, perceived convenience, learning tradition, PEOU, PU, and self-regulated learning.
During COVID-19	Ahmed et al. (2023)	TAM	PU, PEOU, subjective norms, perceived reputation, and technology awareness.
	Suriyapaiboonwattan & Hone (2023)	UTAUT2[4]	Performance expectancy, hedonistic motivation, habit, and local language support.
	Alamri (2022)	IDT[5] and TAM	Observability, complexity, trialability, PEOU, PU, academic self-efficacy, learning engagement, and learning persistence.
Post Covid-19	Zaremohzzabieh et al. (2022)	TPB[6], TTF, and UTAUT	Performance expectancy, effort expectancy, social influence, facilitating conditions, user's attitude, technology characteristics, task characteristics, and task-technology fit.
	K. Wang (2023)	TAM and TPB	PU, PEOU, attitude, subjective norms, perceived behavioral control, and behavioral control.

1 Technology, User and Environment

2 Task-Technology Fit

3 Technology Acceptance Model

4 Unified Theory of Acceptance and Use of Technology

5 Innovation Diffusion Theory

6 Theory of Planned Behavior

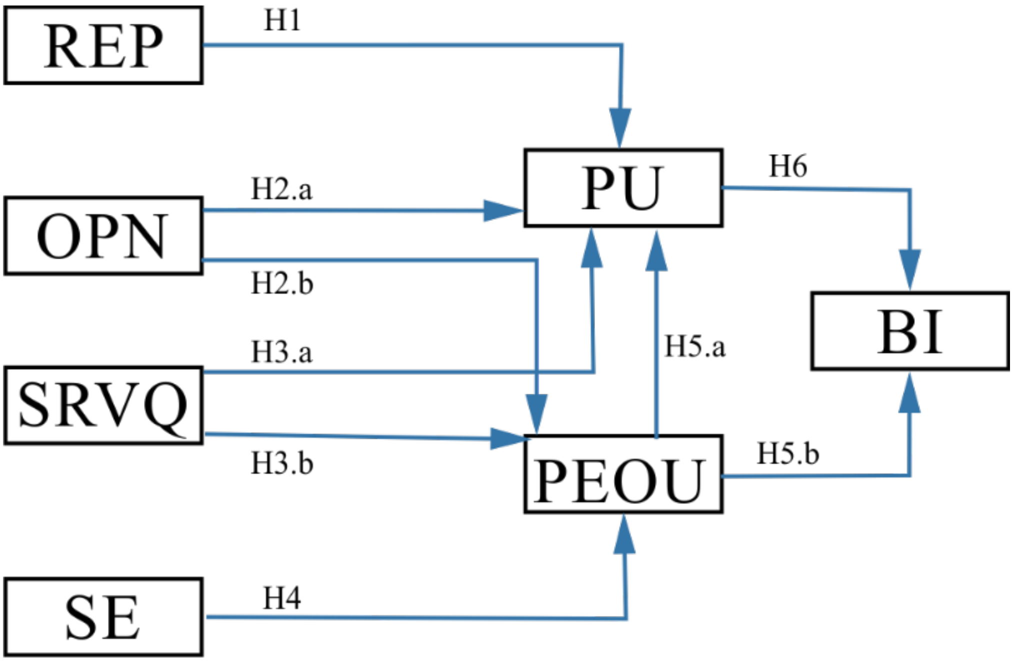
Ucha (2023)	TAM	Course content quality, course relevance, course instructor quality, course design quality, learner-instructor interaction, PU, PEOU, and learner interaction.
Chaveesuk et al. (2022)	UTAUT2	Performance expectancy, effort expectancy, absorptive capacity, social influence, facilitating conditions, hedonic motivation, price value, habit, social distancing, and culture.
Meet et al. (2022)	UTAUT2	Price value, hedonic motivation, facilitating conditions, performance expectancy, effort expectancy, social influence, habit, language competency, and teacher influence.

3 Research Model

The outbreak of the COVID-19 pandemic brought uncertainties to higher education institutions. The lack of information regarding the duration of the pandemic's consequences and the nature of the recovery phase made it necessary to increase the intention to use MOOCs during this period (Lavidas et al., 2022). Before the COVID-19 era, MOOCs were not extensively adopted in developing countries. Hence, adopting Iran as a case study, this study investigates student intentions to participate in MOOCs in a developing country.

This research uses the TAM as the foundation for the proposed model. TAM has been widely employed as a fundamental framework in various studies modeling BI around technology, including in studies concerned with MOOC utilization (Ahmed et al., 2023; Al-Adwan, 2020; Singh, 2022; Ucha, 2023; Yadav et al., 2020). This study explores the influence of initial TAM factors – PU and PEOU (Davis, 1989) – and additionally investigates factors specific to the context and conditions of MOOCs, which previous research has demonstrated to positively impact BI directly or indirectly. These factors include Perceived Reputation (REP) (Ahmed et al., 2023; Jyothi & Savitha, 2023), Perceived Openness (OPN) (Alraimi et al., 2015; Chen et al., 2018; Harnadi et al., 2022), Service Quality (SRVQ) (Alturki & Aldraiweesh, 2023; M. Yang et al., 2017), and Self-Efficacy (SE) (Al-Adwan, 2020; Hsu et al., 2018; Jiang et al., 2021; Sayaf et al., 2021). Figure 1 visualizes the proposed model for this study.

Figure 1: Proposed Model



1. Perceived Reputation
2. Perceived Openness
3. Service Quality
4. Self-Efficacy
5. Perceived Usefulness
6. Perceived Ease of Use
7. Behavioral Intention

3.1 Perceived Reputation

REP plays a significant role in the early stages of establishing trust and influencing decisions to choose an organization, such as a university (Alraimi et al., 2015). In the MOOC context, reputation depends on renowned educators offering courses (Khan et al., 2018). Previous studies have investigated the effect of REP in MOOC adoption (Ahmed et al., 2023; Jyothi & Savitha, 2023), with Huanhuan and Xu (2015) and Wu and Chen (2017) emphasizing that REP influences PU. Hypothesis 1 is formulated based on these findings:

> **H1:** REP has a positive effect on the PU of MOOCs.

3.2 3.2 Perceived Openness

According to Alraimi et al. (2015), OPN refers to the degree of freedom of access to and use of course materials (including videos and slides), as well as easy access to these resources, with no registration fees and no restrictions, free download of course materials, and participation in discussions to improve learning (Chen et al., 2018). According to Ma and Lee (2019), OPN occurs before the acceptance stage, and providing certificates is essential for familiarizing users with this innovation. This is especially important in developing countries and areas where students are not familiar with such learning opportunities. As Wu and Chen (2017) have recognized, the openness of MOOCs gives users more freedom to choose their learning method, which leads to flexibility in learning. Accordingly, this feature increases PU and PEOU among users. Previous studies have shown that OPN has been effective at enhancing PU and PEOU (Alraimi et al., 2015; Chen et al., 2018; Harnadi et al., 2022; Wu & Chen, 2017). Based on this foundation, the following hypotheses have been formulated:

H2.a: OPN has a positive effect on the PU of MOOCs.

H2.b: OPN has a positive effect on the PEOU of MOOCs.

3.3 Service Quality

Nong et al. (2022) define SRVQ in the context of MOOCs as the comprehensive assessment and judgment made by users regarding the excellence and quality of the offerings on MOOC platforms. People make their decision to use a system based on information quality, response time, access to system services, and their goals. MOOC SRVQ encompasses good system performance, availability, and usability (Aparicio et al., 2019). Chavoshi and Hamidi (2019) have described various key metrics for a system's technical quality, including accessibility, maintainability, system speed, reliability, personalization, usability, maintainability, security, and flexibility. Althunibat (2015) emphasized that if the SRVQ does not meet the service provider's promises in terms of integrating information technology into higher education, it can severely impact BI.

Aparicio et al. (2019) defined SRVQ as having strong support staff available when problems arise and responding appropriately. This fact, often referred to as "facilitating conditions," has been investigated in studies by Chavoshi and Hamidi (2019), Singh (2022), and Songkram et al. (2023). It has been shown to have a positive impact on PU, PEOU, or both. M. Yang et al. (2017) have demonstrated that service quality is significantly associated with PU. Additionally, research findings by Alturki and Aldraiweesh (2023) indicate that PU is directly and significantly impacted by the SRVQ. Hypotheses are formulated as follows:

H3.a: SRVQ has a positive effect on the PU of MOOCs.

H3.b: SRVQ has a positive effect on the PEOU of MOOCs.

3.4 Self-Efficacy

SE entails the belief that a task is attainable and that the environment supports its accomplishment (Bandura, 1978). According to Alqurashi (2016), students possessing high SE do not view challenging tasks as hurdles to evade; instead, they see them as opportunities to enhance their skills by overcoming them. Additionally, individuals with high SE tend to invest more time and effort into their work compared to those with lower levels of SE (Chung et al., 2015). As demonstrated by Cheon et al. (2012), who measured SE levels, higher levels of convenience in the system increase user confidence (i.e., SE). Furthermore, studies on MOOCs have consistently found that SE has a positive influence on PEOU (Al-Adwan, 2020; Hsu et al., 2018; Jiang et al., 2021; Sayaf et al., 2021; Songkram et al., 2023). Therefore, we have formulated the following hypothesis:

H4: SE has a positive effect on the PEOU of MOOCs.

3.5 Perceived Ease of Use

PEOU is included by Davis (1989) in the TAM, where it is defined as "the degree to which a person believes that using a particular system would be free of effort" (p. 320). Simplicity of use is especially important during the initial phases of a new technology's adoption (Y. S. Wang et al., 2009), and because MOOCs are not widely used in Iran yet, PEOU in this study is predicted to be an important factor. Furthermore, users find technology that is simpler to use more advantageous when other factors are equal (Chavoshi & Hamidi, 2019). For international MOOCs, PEOU is an important factor, because learners who encounter MOOCs from countries other than English-speaking countries may be unfamiliar with the novel platform (Zhang et al., 2017).

According to Songkram et al. (2023) when students perceive digital learning platforms as easy to use, they are more inclined to adopt them. Therefore, PEOU influences BI. Moreover, the more MOOCs are recognized as being easy to use, the more learners are likely to view them as effective resources for reaching their educational objectives (Wu & Chen, 2017).

Furthermore, PEOU has been identified as a pivotal determinant of PU. Most prior studies have emphasized the positive effect of PEOU on PU, BI, or both. (Ahmed et al., 2023; Al-Adwan, 2020; Alamri, 2022; Hsu et al., 2018; Priyadarshini et al., 2023; Singh, 2022; Teo & Dai, 2022; Thi et al., 2023; Ucha, 2023; Yadav & Gupta, 2020). Consequently, the following hypotheses have been developed:

H5.a: PEOU has a positive effect on the PU of MOOCs.

H5.b: PEOU has a positive effect on the BI to adopt MOOCs.

3.6 Perceived Usefulness

PU is one of the most important factors in the adoption of a technology. It has been introduced as a key component in the TAM and is utilized in many similar models. PU is defined as "the degree of belief that using a particular system leads to improved performance" (Davis, 1989, p. 320). Meanwhile, elaborating the role of PU in the TAM, Venkatesh et al. (2003) define performance expectancy as "the degree of one's belief that using the system will help them achieve their goals." According to Songkram et al. (2023), individuals frequently decide whether to use or avoid an application based on their perception of how it will enhance their work performance.

MOOCs offer especially valuable opportunities to learners in developing countries with restricted access to high-quality educational resources (Ma & Lee, 2019). According to Ma and Lee (2017), PU represents the strongest predictor of MOOC adoption. Numerous studies have shown that PU has a positive effect on BI to adopt or continue using MOOCs (Ahmed et al., 2023; Al-Adwan, 2020; Alraimi et al., 2015; Hamidi & Chavoshi, 2018; Hsu et al., 2018; Ma & Lee, 2017; Singh, 2022; Teo & Dai, 2022; Ucha, 2023; Wu & Chen, 2017; Yadav & Gupta, 2020; Zhang et al., 2017). Therefore, we have formulated the following hypothesis:

H6: PU has a positive effect on BI.

4 Research Method

This study's research method is based on a quantitative approach that involves employing a questionnaire tool to test the hypotheses and evaluate the proposed model.

4.1 Questionnaire Development

The questionnaire employed to evaluate the theoretical model featured a structured format. The questionnaire was divided into two sections. The initial section was dedicated to collecting demographic information from the participants, and the second section was designed to gather data on the key study variables, encompassing a total of 32 questions. To measure the construct items, a 5-point Likert scale was employed. Participants were asked to indicate their level of agreement or disagreement with each statement on a scale that ranged from (1), representing "strongly disagree," to (5), indicating "strongly agree.

4.2 Data Collection

To conduct this research, two rounds of online questionnaires were conducted. The first round of questionnaires was administered before the onset of the COVID-19 pandemic in 2019, and the second round took place in the post-COVID-19 era in 2023. In both cases, the distribution was entirely randomized between student groups, associations, and social networks.

The questionnaire included questions in both Farsi and English to eliminate potential ambiguities and misunderstandings when translating from English to Farsi. Additionally, a pilot study was conducted involving 30 postgraduate students majoring in e-commerce engineering to identify and rectify potential flaws in the questionnaire, with their feedback and suggestions guiding subsequent revisions. Participation in the questionnaire was voluntary, and each round of the research included a total of 100 participants. Respondents indicating no experience with MOOCs implied that they had not participated in any such courses. Table 2 provides an overview of the demographic characteristics of the study participants.

Table 2: Demographic Factors of Pre- and Post-COVID-19 Respondents

Variable	**Type**	**Pre-COVID Frequency**	**Post-COVID Frequency**
Gender	Male	58	51
	Female	42	49
Age	18–26	53	45
	27–34	26	36
	34<	21	19
Marriage status	Single	63	58
	Married	37	42
Education level	Bachelor	29	24
	Master	69	71
	Ph. D.	2	5
Experience with MOOCs	Yes	21	62
	No	79	38

5 Data Analysis

The data analysis method employed in this study is based on that used by Chavoshi and Hamidi (2019), integrating Partial Least Squares (PLS) and an Artificial Neural Network (ANN). PLS has been extensively employed in studies examining the BI to use MOOCs, such as those by Mohan et al. (2020), K. Wang et al. (2022), and Wu and Chen (2017). PLS is accurate for small populations and predictive purposes. Given the low number of participants in this study and the lack of use of MOOCs in Iranian universities, PLS is the most appropriate option for the data analysis. However, PLS and other conventional linear statistical techniques are often insufficient for modeling complex human decisions, such as the decision to adopt a given technology. Artificial intelligence techniques, such as the ANN method, can address this issue. However, the black-box nature of ANN makes it unsuitable for testing hypotheses. To leverage the strengths of both methods and overcome their limitations, this study utilizes the PLS-ANN method.

5.1 Reliability and Validity

Following Songkram et al. (2023), reliability is calculated using Cronbach's alpha. For this purpose, Cronbach's alpha should be greater than 0.7 (Fornell & Larcker, 1981). According to Chavoshi and Hamidi (2019), convergent and discriminant validity must be measured to assess validity. Convergent validity signifies the degree of correlation between items in a questionnaire, as calculated using the average variance extracted (AVE) and composite reliability. To establish convergent validity, the AVE should be greater than 0.5, and composite reliability should surpass the AVE. The outcomes of the analysis are summarized in Table 3, confirming the reliability and validity of this study.

Table 3: Reliability and Convergent Validity

Factor	Cronbach's alpha	Composite Reliability	AVE
REP	0.709	0.838	0.634
OPN	0.731	0.832	0.554
SRVQ	0.892	0.912	0.537
SE	0.878	0.911	0.672
PEOU	0.719	0.842	0.640
PU	0.724	0.829	0.547
BI	0.783	0.860	0.607

Discriminant validity refers to the extent to which a construct stands apart from other constructs according to empirical criteria. Therefore, confirming discriminant validity indicates that a construct possesses its own distinct qualities and represents phenomena that are not accounted for by other constructs in the model (Hair et al., 2021). Discriminant validity is evaluated by comparing the square root of AVE with factor correlations. Accordingly, if the square root of AVE is higher than the correlation coefficient of other factors, the discriminant validity of the questionnaire will be confirmed. Table 4 shows these comparisons. Bold numbers represent the square root of the AVE, which should exceed all corresponding row and column numbers. In summary, the discriminant validity of this questionnaire is also confirmed, making the findings acceptable.

Table 4: Discriminant Validity

	BI	OPN	PEOU	PU	REP	SE	SRVQ
BI	**0.779**						
OPN	0.475	**0.774**					
PEOU	0.560	0.590	**0.800**				
PU	0.630	0.719	0.648	**0.740**			
REP	0.444	0.401	0.392	0.544	**0.796**		
SE	0.251	0.354	0.550	0.384	0.353	**0.820**	
SRVQ	0.585	0.509	0.515	0.636	0.398	0.388	**0.733**

5.2 Hypotheses Testing

The nine hypotheses presented in Section 3 of this paper have been tested using the PLS method, and Tables 5 and 6 present the test results. The findings of the pre-COVID study (Table 5) show that all nine hypotheses were supported.

The findings of the post-COVID study (Table 6) demonstrate that several hypotheses (3.a, 3.b, 4, 5.a, 5.b, and 6) were supported, with t-values exceeding ±1.96 at the 5% significance level (Hair et al., 2010). However, hypotheses 1, 2.a, and 2.b, with t-values below ±1.96, were not supported. The study revealed several positive relationships, such as SRVQ and PEOU being positively related to PU, SRVQ, and SE being positively related to PEOU, and PEOU and PU demonstrating a positive relationship with BI to adopt MOOCs.

Table 5: Hypotheses Testing Pre-COVID-19 Period

No.	Hypothesis	Path correlation	Standard Deviation	t-statistics	Supported?
1	REP → PU	0.208	0.085	2.446	Yes
2.a	OPN → PU	0.385	0.123	3.116	Yes
2.b	OPN → PEOU	0.370	0.104	3.577	Yes
3.a	SRVQ → PU	0.248	0.118	2.107	Yes
3.b	SRVQ → PEOU	0.194	0.096	2.021	Yes
4	SE → PEOU	0.343	0.107	3.202	Yes
5.a	PEOU → PU	0.212	0.097	2.180	Yes
5.b	PEOU → BI	0.262	0.126	2.086	Yes
6	PU → BI	0.460	0.125	3.674	Yes

Table 6: Hypotheses Testing Post-COVID-19 Period

No.	Hypothesis	Path correlation	Standard Deviation	t-statistics	Supported?
1	REP → PU	0.139	0.089	1.552	No
2.a	OPN → PU	0.145	0.089	1.622	No
2.b	OPN → PEOU	0.108	0.071	1.525	No
3.a	SRVQ → PU	0.326	0.092	3.560	Yes
3.b	SRVQ → PEOU	0.406	0.080	5.056	Yes
4	SE → PEOU	0.407	0.072	5.629	Yes
5.a	PEOU → PU	0.197	0.099	1.995	Yes
5.b	PEOU → BI	0.317	0.087	3.643	yes
6	PU → BI	0.553	0.087	6.359	Yes

The predictive relevance of the structural model was investigated using the blindfolding procedure (Ucha, 2023). This criterion is calculated using Q^2. If it is above zero, it indicates predictive relevance. Values of 0.02, 0.15, and 0.35 correspond to low, medium, and high predictive relevance. As Table 7 shows, this study's proposed model demonstrates moderate predictive relevance.

Table 7: Predictive Relevance

Dependent factor	Q^2
REP → PU	0.139
REP → PU	0.139
REP → PU	0.139

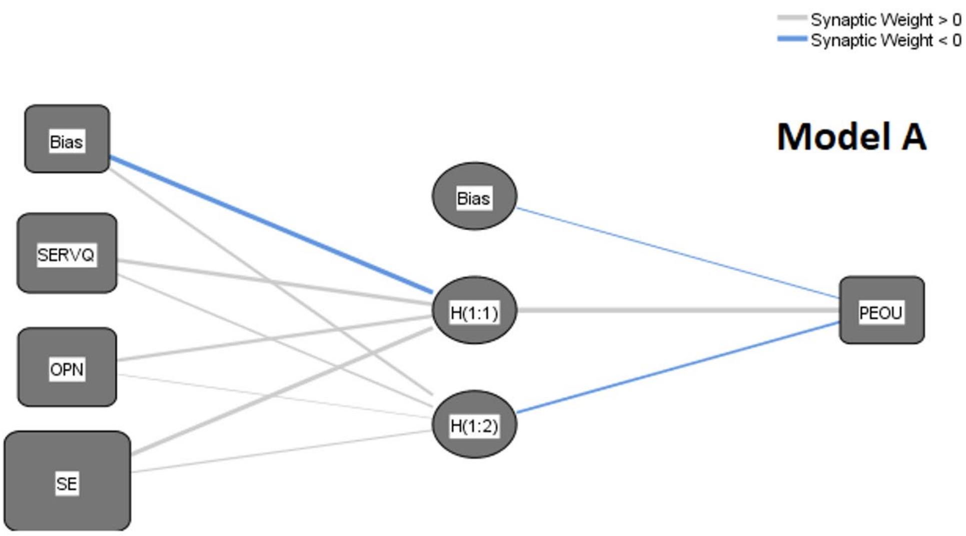
5.3 ANN

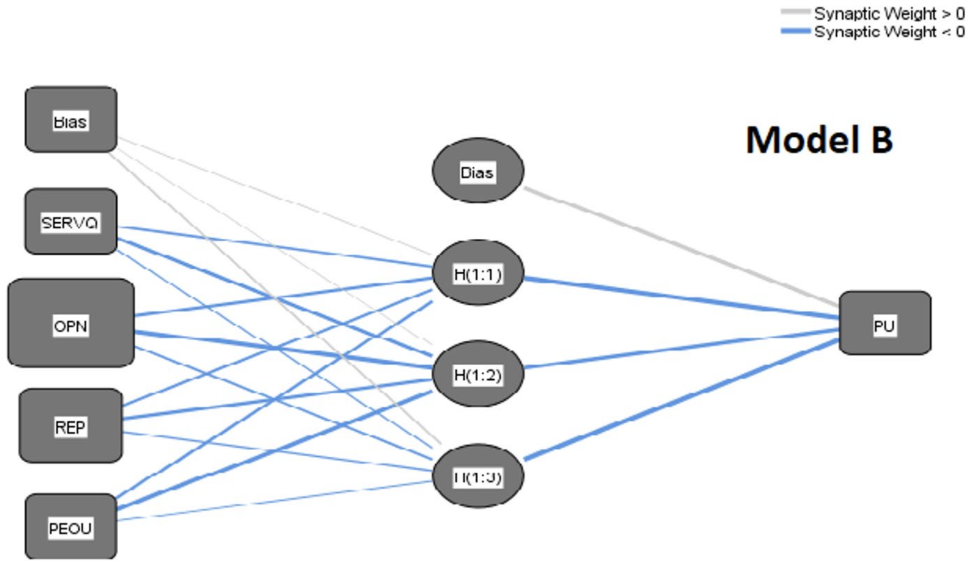
ANNs have been described as "parallel distributed processor[s] consisting of simple processing units, called neurons, used to store knowledge and make it available for use." (Haykin, 1999) An ANN model emulates human brain functions, including memory, learning, production, and generalization, to mathematically model the brain's learning style (Al-Shihi et al., 2018; Özbey & Kayri, 2023).

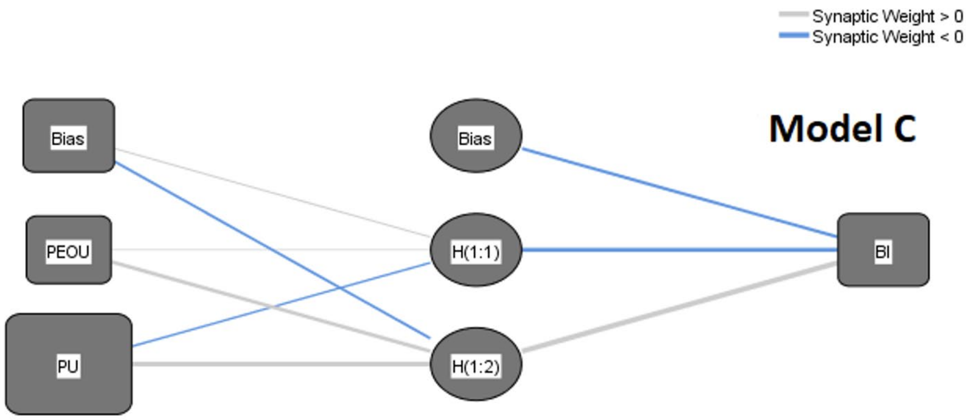
An ANN typically comprises three layers: input, output, and hidden layers. As indicated by Chavoshi & Hamidi (2019), the ANN model selected for this study is a multilayer perceptron, with the number of hidden layers, input, and output neurons automatically calculated by SPSS V.25 software. The activation function used is the sigmoid.

As depicted in Figures 2 and 3, the proposed model is divided into three sub-models based on the number of dependent variables and pathways. In Model A, the variables SRVQ, OPN, and SE are considered as inputs for PEOU, while in Model B, the variables SRVQ, OPN, REP, and PEOU serve as inputs for PU. In Model C, PU and PEOU are also inputs for BI.

Figure 2: ANN Models Pre-COVID-19



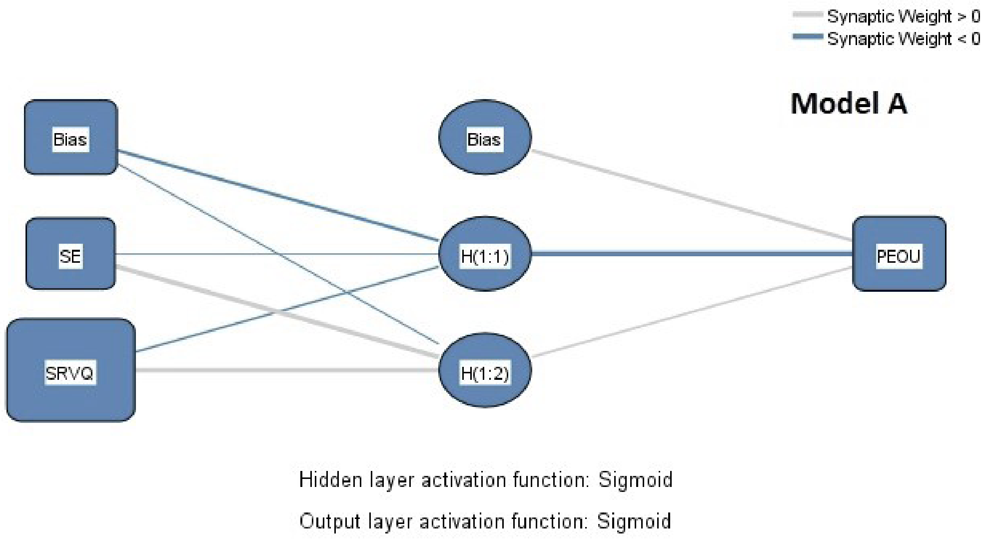


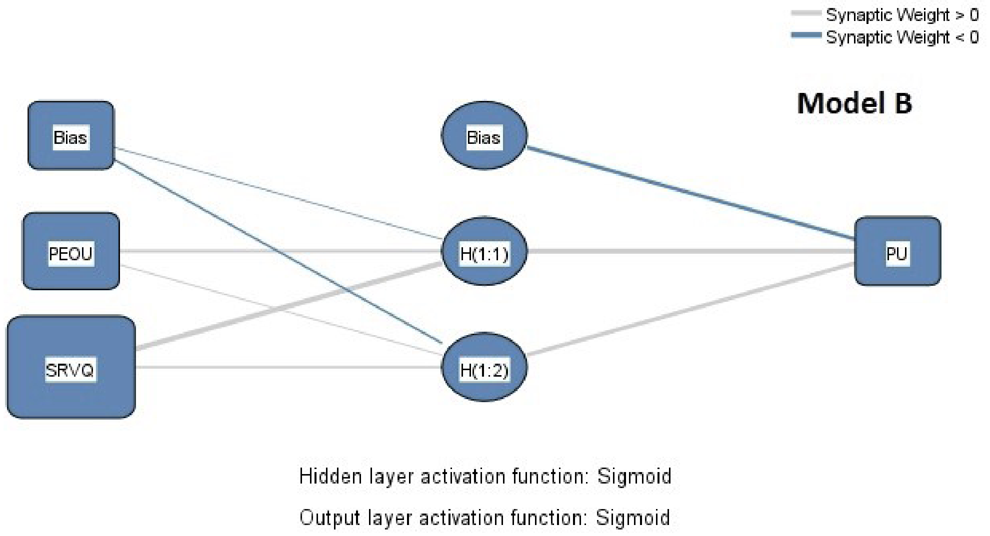


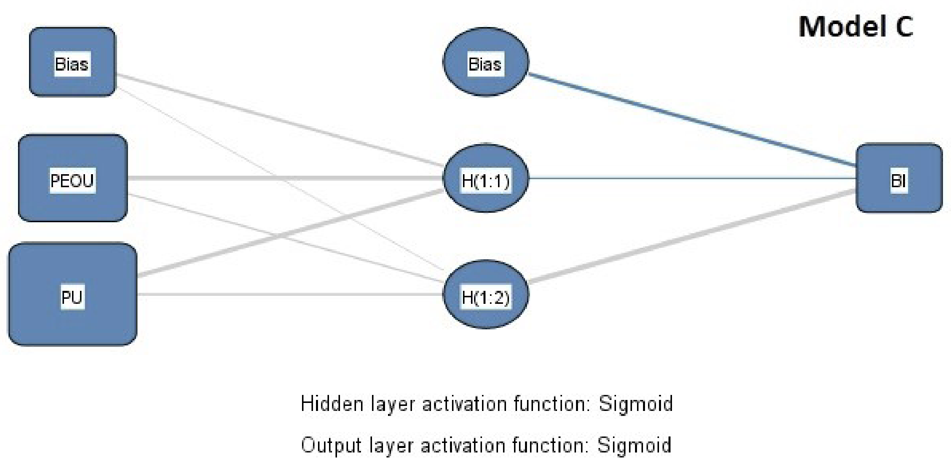
Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

Figure 3: ANN Models Post-COVID-19







Following Chavoshi and Hamidi (2019), to avoid the risk of over-fitting, a 10-fold cross-validation procedure was employed. In this procedure, 90% of the data was used for training and the remaining 10% for testing. Model predictions were assessed using Root Mean Square Error (RMSE), and the resulting values for both the training and test datasets, across all three models and all 10 networks, as well as their mean values and standard deviation, are presented in Tables 8 and 9. All three ANN models demonstrate highly accurate predictions, as evidenced by the very small RMSE mean values for both the training and test datasets.

Table 8: RMSE Values Pre-COVID-19

Network	**Model A Inputs: SRVQ, OPN, and SE Output: PEOU**		**Model B Inputs: REP, OPN, SRVQ, and PEOU Output: PU**		**Model C Inputs: PEOU, and PU Output: BI**	
	Training	*Test*	*Training*	*Test*	*Training*	*Test*
1	0.113	0.070	0.125	0.129	0.174	0.189
2	0.110	0.073	0.134	0.064	0.202	0.201
3	0.109	0.096	0.129	0.111	0.183	0.183
4	0.106	0.116	0.130	0.050	0.176	0.175
5	0.111	0.070	0.129	0.100	0.181	0.147
6	0.119	0.070	0.120	0.151	0.182	0.191
7	0.108	0.096	0.126	0.115	0.177	0.097
8	0.113	0.101	0.124	0.138	0.169	0.219
9	0.109	0.112	0.131	0.070	0.177	0.152
10	0.109	0.108	0.131	0.072	0.177	0.175
Mean	0.111	0.091	0.128	0.100	0.180	0.173
Standard Deviation	0.003	0.017	0.003	0.032	0.008	0.032

Table 9: RMSE Values Post-COVID-19

Network	**Model A Inputs: SRVQ, and SE Output: PEOU**		**Model B Inputs: SRVQ, and PEOU Output: PU**		**Model C Inputs: PEOU, and PU Output: BI**	
	Training	*Test*	*Training*	*Test*	*Training*	*Test*
1	0.118	0.094	0.172	0.049	0.107	0.110
2	0.105	0.081	0.105	0.119	0.109	0.140
3	0.139	0.108	0.123	0.065	0.128	0.092
4	0.116	0.082	0.108	0.081	0.107	0.183
5	0.105	0.071	0.147	0.074	0.129	0.089
6	0.109	0.151	0.110	0.066	0.121	0.140
7	0.105	0.094	0.106	0.098	0.137	0.106
8	0.104	0.081	0.109	0.084	0.140	0.094
9	0.112	0.090	0.107	0.080	0.111	0.094
10	0.111	0.067	0.110	0.076	0.110	0.085
Mean	0.112	0.092	0.120	0.079	0.120	0.113
Standard Deviation	0.010	0.022	0.021	0.018	0.012	0.029

Finally, sensitivity analysis was conducted to measure the sensitivity of the predictors for each dependent variable. Sensitivity analysis, using relative importance, reveals how much the predicted output value varies with different inputs. To this end, the normalized importance is calculated for each model. Tables 10 and 11 present the results of sensitivity analyses for the studies conducted before and after the COVID-19 pandemic.

Table 10: Sensitivity Analysis Pre-COVID-19

Network	Model A			Model B				Model C	
	SRVQ	*OPN*	*SE*	*SRVQ*	*OPN*	*REP*	*PEOU*	*PEOU*	*PU*
1	0.221	0.374	0.404	0.226	0.279	0.252	0.243	0.342	0.658
2	0.243	0.424	0.333	0.228	0.384	0.216	0.173	0.351	0.649
3	0.249	0.409	0.342	0.165	0.414	0.201	0.220	0.377	0.623
4	0.220	0.450	0.330	0.207	0.364	0.224	0.204	0.416	0.584
5	0.225	0.394	0.382	0.264	0.285	0.254	0.197	0.325	0.675
6	0.238	0.482	0280	0.228	0.262	0.236	0.274	0.335	0.665
7	0.262	0.337	0.401	0.244	0.251	0.261	0.244	0.223	0.777
8	0.158	0.573	0.269	0.285	0.232	0.225	0.258	0.333	0.667
9	0.163	0.478	0.359	0.202	0.357	0.229	0.212	0.351	0.649
10	0.289	0.285	0.426	0.191	0.374	0.249	0.186	0.290	0.710
Average importance	0.227	0.421	0.353	0.224	0.320	0.234	0.222	0.334	0.666
Normalized importance	54%	100%	84%	70%	100%	73%	69%	50%	100%

Table 11: Sensitivity Analysis Post-COVID-19

Network	Model A			Model B				Model C	
	SRVQ	*SE*	*SRVQ*	*PEOU*	*PEOU*	*PU*	*PEOU*	*PEOU*	*PU*
1	0.511	0.489	0.613	0.387	0.436	0.564	0.243	0.342	0.658
2	0.690	0.310	0.469	0.531	0.483	0.517	0.173	0.351	0.649
3	0.555	0.445	0.760	0.240	0.433	0.567	0.220	0.377	0.623
4	0.508	0.492	0.629	0.371	0.442	0.558	0.204	0.416	0.584
5	0.596	0.404	0.651	0.349	0.306	0.694	0.197	0.325	0.675
6	0.558	0.442	0.633	0.367	0.421	0.579	0.274	0.335	0.665
7	0.627	0.373	0.538	0.462	0.489	0.511	0.244	0.223	0.777
8	0.662	0.338	0.544	0.456	0.643	0.357	0.258	0.333	0.667
9	0.596	0.404	0.612	0.388	0.446	0.554	0.212	0.351	0.649
10	0.547	0.453	0.552	0.448	0.377	0.623	0.186	0.290	0.710
Average importance	0.585	0.415	0.600	0.400	0.448	0.552	0.222	0.334	0.666
Normalized importance	100%	70%	100%	66%	81%	100%	69%	50%	100%

As Table 10 shows, OPN is the most important determinant of PEOU, followed by SE and SRVQ. However, the post-COVID-19 analysis reveals a shift in the importance of these factors. Table 11 demonstrates that SRVQ is now the primary determinant of PEOU, followed by SE, and OPN no longer impacts PEOU. This change is also evident in the findings concerning Model B. In the pre-COVID-19 period, OPN is the most significant factor for PU, with REP in the second position, and SRVQ and PEOU holding lower levels of importance for PU. However, in the post-pandemic era, SRVQ becomes the most important factor for PU, followed by PEOU, with OPN and REP not affecting PU. For BI, PU remains the most significant determinant, both before and after COVID-19.

6 Discussion

With the onset of the COVID-19 pandemic and the closure of universities and educational institutions, MOOCs experienced a substantial increase in user numbers. The uncertainty of the COVID-19 conditions and concerns about the reopening of educational institutions led students to align themselves with MOOCs to prevent the interruption of their education. This resulted in widespread MOOC adoption among students. Given all the benefits of MOOCs and the equal opportunities they provide for students, it is crucial to investigate the adoption of MOOCs and the impact of COVID-19 on student attitudes toward their use, particularly in a developing country with limited educational resources.

This study's findings suggest that, during the pre- and post-COVID-19 periods, SRVQ positively influenced both PU and PEOU. This positive influence aligns with previous research (Alturki & Aldraiweesh, 2023; Chavoshi & Hamidi, 2019; Singh, 2022; Songkram et al., 2023; M. Yang et al., 2017). Notably, in the pre-COVID-19 study, SRVQ was the least important factor for PEOU, and it was also the least important factor for PU after PEOU. However, in the post-COVID-19 study, SRVQ was most important for both PU and PEOU.

Furthermore, the findings for both pre- and post-COVID-19 showed that SE had a positive effect on PEOU, a result consistent with previous studies (Al-Adwan, 2020; Hsu et al., 2018; Songkram et al., 2023; Zhang et al., 2017). In the pre-COVID-19 study, SE was identified as the most significant determinant for PEOU after OPN; in the post-COVID-19 study, it was the most important factor for PEOU after SRVQ. Additionally, the results show that PEOU positively affected user PU during both the pre- and post-COVID-19 periods. This finding aligns with prior research (Al-Adwan, 2020; Alamri, 2022; Hsu et al., 2018; Joo et al., 2018; Thi et al., 2023; Ucha, 2023; Wu & Chen, 2017). PEOU also positively influenced BI both pre- and post-COVID-19, a finding consistent with the results from Al-Adwan (2020), Joo et al. (2018), Ucha (2023), Yadav and Gupta (2020), Yang and Su (2017), and Zhang et al. (2017).

Regarding PU, this study's findings are consistent with studies conducted by Ahmed et al. (2023), Al-Adwan (2020), Alraimi et al. (2015), Chen et al. (2018), Ma and Lee (2019), Singh (2022), Ucha (2023), and Yadav and Gupta (2020), all of which confirm that PU positive impacts BI. Notably, PU was the most important factor for BI during both the pre- and post-COVID-19 periods.

This study's findings suggest that REP and OPN had an indirect impact on BI pre-COVID-19 but did not have any substantial impact according to the research conducted after the pandemic. In the pre-COVID-19 study, REP had a positive effect on PU and was the most significant determinant for PU after OPN, a result consistent with the findings of Huanhuan and Xu (2015) and Wu and Chen (2017). However, post-COVID-19, the findings reveal no impact of REP on PU.

Regarding OPN, the study's pre-COVID-19 results conform with prior research (Alraimi et al., 2015; Chen et al., 2018; Harnadi et al., 2022; Wu & Chen, 2017) to affirm the positive impact of OPN on both PU and PEOU, with OPN identified as the most critical determinant for both PU and PEOU. Meanwhile, in the post-COVID-19 study, OPN demonstrated no positive effect on either PU or PEOU.

The decrease in the importance of OPN in MOOC adoption in the post-COVID-19 era can be explained in several ways. During the COVID-19 pandemic, universities and educational institutions worldwide offered their courses online, often for free or at a significantly reduced cost to facilitate continued learning for students during quarantine conditions. Furthermore, governments enhanced internet access for students, providing better and often free internet connectivity. Improved access to online resources made it less challenging for students to engage with MOOCs compared to before the pandemic.

Also, due to the absence of a physical instructor in MOOCs and the pandemic circumstances, responsive support staff capable of promptly addressing students' academic or technical challenges, along with effective design, functionality, and clear navigation, became essential for the many students who were using a MOOC platform for the first time. Therefore, it should come as no surprise that the post-COVID-19 study identified SRVQ as the most important factor for PU and PEOU. MOOC developers are advised to pay particular attention to this critical factor, which directly impacts the user experience.

To enhance SRVQ, MOOCs should provide well-structured, engaging, and up-to-date content that aligns with learning objectives (Almaiah et al., 2016). This should involve collaborating with subject matter experts to develop comprehensive course materials, including videos, readings, quizzes, and interactive elements (Puzziferro & Shelton, n.d.). Regular updates and improvements to content based on learner feedback and emerging trends are essential to maintaining relevance and quality (Harris, 2015). Furthermore, learner support services play a vital role in enhancing SRVQ in MOOCs (Nong et al., 2022).

Providing comprehensive support mechanisms—such as online forums, FAQs, and dedicated help desks—can help learners navigate challenges and technical issues effectively.

SE, PU, and PEOU are other factors that MOOC providers should prioritize. SE, which relates directly to users' self-confidence and their past experiences, allows them to use technology without any concerns. To enhance SE, providing comprehensive and user-friendly guides tailored to different skill levels can empower learners to navigate the complexities of MOOC platforms confidently (Hodges, 2016). By offering clear, step-by-step instructions, learners, regardless of their prior experience, can feel equipped to engage with MOOCs independently. Moreover, providing readily accessible support channels, such as live chat assistance or responsive email support, can reassure users that help is available whenever needed.

Regarding PEOU, simplifying system interfaces is crucial (Briz-Ponce et al., 2016). Inexperienced users may discontinue MOOC usage when faced with complexity. One approach involves implementing intuitive navigation structures to ensure that users can effortlessly locate desired content and features without feeling overwhelmed (Milošević et al., 2015). Furthermore, providing contextual guidance and support within the platform, such as tooltips or contextual help menus, assists users in understanding functionalities and completing tasks efficiently. Finally, ongoing user feedback mechanisms play a vital role in iteratively refining the platform's usability, ensuring that it evolves to meet users' evolving needs and expectations.

Furthermore, to address PU, considering the limited access to appropriate educational content in developing regions, offering relevant courses that meet users' diverse needs can encourage the utilization of MOOC platforms (Mohammadi, 2015). Moreover, integrating practical and applicable knowledge into course content, such as real-world case studies and hands-on projects, can enhance PU (Boling et al., 2012).Additionally, providing access to supplementary resources and learning materials, such as e-books, articles, and interactive tools, enriches the learning experience and reinforces the platform's utility for users.

7 Conclusion

This study contributes to our understanding of MOOC adoption by examining the impact of the COVID-19 pandemic on student BI to adopt and use MOOCs. The insights gained from this research provide suggestions and guidelines for promoting the diffusion of MOOCs among potential learners. Specifically, for learners from developing countries (Liyanagunawardena et al., 2013).

This study assessed the fundamental factors mentioned in previous research during both the pre- and post-COVID-19 periods. In the pre-COVID-19 era, all the factors considered were determinants of MOOC adoption: REP, OPN, SRVQ, SE, PU, and PEOU. Meanwhile, in the post-COVID period, the factors influencing MOOC adoption were SRVQ, SE, PU, and PEOU, with REP and OPN no longer impacting MOOC adoption.

Based on the results of this study, it can be concluded that, prior to the COVID-19 pandemic, accessibility and the reputation of MOOC providers held significance for MOOC adoption. However, in the post-COVID-19 era, SRVQ and PEOU have gained more importance. This suggests that, in general, students were initially resistant to adopting new technology and had doubts about the usefulness of MOOCs. During this period, factors such as OPN and REP played a significant role in addressing their concerns and influencing their decision-making when it came to using MOOCs. However, the widespread adoption of MOOCs during the COVID-19 period changed users' perspectives and led them to understand the importance and usefulness of MOOCs in their educational journey, leading to other factors, such as SRVQ and PEOU, becoming more influential in terms of MOOC adoption. In fact, it can generally be said that the COVID-19 era has influenced students' concerns regarding the use of MOOCs.

8 Future Research and Limitations

Future research can separately examine the effect of the quality of each MOOC service on PU, PEOU, and BI. However, due to the importance of customization in learning, the acceptance of users in various fields of engineering, humanities, behavioral sciences, and other sciences needs to be explored to understand the role of customizing MOOCs. Meanwhile, because other key contributors to MOOCs include providers and teachers, and there are many technology-resistant educators, future research should address needs around improving MOOC implementation. Additionally, given the geographical context of this research, examining the impact of cultural variables on MOOC adoption should be a subject of future investigations.

In terms of research limitations, university-based studies, such as this one, may not cover all aspects of MOOCs and the factors influencing user acceptance due to sample size limitations. Moreover, treating responses from individuals with no prior MOOC experience as equal to those who have MOOC experience may have produced inaccuracies.

Ultimately, the absence of prior experience with MOOC implementation in Iran and the limited sample size of this study restrict the generalizability of its findings. Additionally, differences in the personal characteristics of individuals who participated in the first and second questionnaires may have impacted the results of each section of the research and the final research outcome.

Appendix

Construct	Item	Measurements	References
Service Quality	SRVQ1	MOOCs can provide comprehensive and sufficient content for me.	(Almaiah et al., 2016; Pham et al., 2019)
	SRVQ2	MOOCs can offer engaging educational content.	
	SRVQ3	MOOCs can provide up-to-date content for me.	
	SRVQ4	MOOCs can provide reliable and credible educational content.	
	SRVQ5	MOOCs can provide textual, audio, and video content for me.	
	SRVQ6	In MOOCs, it is easy to find the necessary materials.	
	SRVQ7	MOOCs support can assist users in resolving any issues that arise and enhance the user experience.	
	SRVQ8	I have access to the necessary resources to use MOOCs.	
	SRVQ9	The necessary infrastructure exists for using MOOC systems.	
Openness	OPN1	I have the freedom to participate in any course in MOOCs without any prerequisites.	(Alraimi et al., 2015; Harnadi et al., 2022)
	OPN2	I am free to access course materials in MOOCs without any cost.	
	OPN3	I can revisit course resources in MOOCs whenever I want.	
	OPN4	I can download resources in MOOCs.	

Perceived Reputation	REP1	MOOCs courses are offered by reputable universities.	(Jarvenpaa et al., 2000; Kim et al., 2008; Munisamy et al., 2014)
	REP2	MOOC providers (such as Coursera, edX, etc.) are renowned universities.	
	REP3	Professors from prestigious universities offer MOOC courses.	
Self-Efficacy	SE1	I have the necessary skills to use MOOCs.	(Briz-Ponce et al., 2016; Mohammadi, 2015; Pituch & Lee, 2006)
	SE2	If there are only online guides for using MOOCs, I'm confident using them.	
	SE3	I'm confident using MOOCs, if I have support.	
	SE4	Even without someone teaching me, I'm confident using MOOCs.	
	SE5	Even if I'm new to MOOCs, I'm confident using them.	
Perceived Ease of Use	PEOU1	Using MOOCs is probably easy for me.	(Hsin Chang, 2010; Wu & Zhang, 2014)
	PEOU2	The interaction with MOOCs is clear and understandable.	
	PEOU3	Learning to use MOOCs probably doesn't require much effort for me.	
Perceived Usefulness	PU1	Using MOOCs is beneficial for my learning.	(Bhattacherjee, 2001; Wu & Zhang, 2014)
	PU2	MOOCs help me accomplish my tasks faster.	
	PU3	Using MOOCs reduce my expenses.	
	PU4	Using MOOCs improve my academic performance.	
Behavioral Intention to Use	BI1	I am inclined to use MOOCs.	(Almaiah et al., 2016; Milošević et al., 2015; Sabah, 2016)
	BI2	I plan to use MOOCs in the future.	
	BI3	I recommend using MOOCs to others.	
	BI4	I believe using MOOCs will be enjoyable for me.	

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