Pertanika J. Soc. Sci. & Hum. 30 (4): 1781 - 1807 (2022)

SOCIAL SCIENCES & HUMANITIES

Journal homepage: http://www.pertanika.upm.edu.my/

Predictors of Massive Open Online Courses (MOOC) Learning Satisfaction: A Recipe for Success

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ABSTRACT

Massive Open Online Courses (MOOCs) have recently gained great attention. However, the biggest challenge to the success of MOOCs is their low completion rate. During the lockdown of the COVID-19 pandemic, MOOCs were in high demand by many higher education institutions to replace their face-to-face lessons. MOOCs have great potential to grow and reinvent the way of learning in the 21st century. This study uses the Virtual Learning Environment (VLE) effectiveness model to understand how the five key factors (learner, instructor, course, technology system, and interactivity) influence student learning satisfaction from a holistic approach and determine the best predictor of student learning satisfaction in the MOOC learning environment. A set of online data based on a 5-point Likert scale was collected from 333 undergraduate students from the top five public universities in Malaysia whose students are actively using MOOCs in their learning. The Partial Least Squares Structural Equation Modelling (PLS-SEM) technique was used to analyse the data. The empirical results revealed that all factors significantly influence student learning satisfaction positively. Learner and interactivity factors were the strongest predictors in determining student learning satisfaction in MOOCs. These findings provide an empirically justified framework for developing successful online courses such as MOOCs in higher education.

Keywords: Higher education, interactivity, Massive Open Online Courses (MOOC), online learner, online learning, student learning satisfaction, technology system, virtual learning effectiveness

ARTICLE INFO

Article history:
Received: 26 September 2021
Accepted: 28 July 2022
Published: 10 November 2022

DOI: https://doi.org/10.47836/pjssh.30.4.17

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ISSN: 0128-7702
e-ISSN: 2231-8534

INTRODUCTION

Massive Open Online Courses (MOOCs) are a recognised form of learning in today's borderless digital world because they provide more online learning opportunities to people who prefer to learn at their own pace. Teaching and learning in the twenty-first 21st century are no longer limited to a traditional classroom setting but are now more location-independent and individualisation-based. During the COVID-19 lockdown, this type of learning mode (e.g., MOOCs) has become significantly important and highly demanded by many students studying in higher education institutions.

Despite the increasing growth of MOOCs, one of the issues that have hampered their success is the low completion rate. Many participants who join MOOCs abandon the course even before completing it. Previous research has found that the primary cause of this problem is low satisfaction in student learning (Albelbisi et al., 2021; Albelbisi & Yusop, 2020; Albelbisi & Yusop, 2019; Gameel, 2017; Wu & Chen, 2017), which is linked to several critical factors such as pedagogical rigour (Hew et al., 2020), and low learner motivation (Gameel, 2017; Gomez-Zermeno & de La Garza, 2016; Hew et al., 2020).

Although many studies have been conducted on factors that influence students' learning experiences, more research needs to be done holistically to understand MOOCs (Jansen et al., 2016). Most studies on MOOCs have taken a narrow conceptual approach, focusing on either human (e.g. Hew et al., 2020) or non-human factors (e.g. Kuo et al., 2014; Kuo & Belland, 2016; Zhang & Lin, 2020). However, more explorations from a broader perspective are needed, where all factors (learner, instructor, course, technology system, and interactivity) are systematically investigated, including how each of these factors relates to one another. Such research is essential as it may provide a more comprehensive framework for evaluating MOOC effectiveness and determining the best predictor of students' learning satisfaction. At the moment, determining the best predictor to improve students' learning satisfaction is ambiguous and uncertain. However, it is critical, particularly in assisting stakeholders in identifying which factors are the most crucial to focus on and prioritising improving the effectiveness of MOOCs.

As a result, this study investigates a broader range of factors influencing student learning satisfaction in MOOCs and identifies the best factor to predict student learning satisfaction in MOOCs. The following research questions guide the study from this point of view:

1. How do the learner, instructor, course, technology system, and interactivity influence students' satisfaction in the MOOC learning environment?

2. What is the best predictor of students' satisfaction in the MOOC learning environment?

LITERATURE REVIEW

MOOC

Massive Open Online Courses (MOOCs) are a relatively new learning model for delivering online courses to students. It is considered *massive* with its infinite scalability, *open* with no prerequisites, *online* with its web-based delivery, and *courses* with its well-organised curriculum design (Bates, 2014). It was founded in 2008 by Stephen Downes and George Siemens and was popularised by world-renowned universities such as MIT, Harvard, and Stanford, resulting in the emergence of numerous prestigious MOOC platforms such as Coursera, Udacity, Swayam, edX, FutureLearn, and OpenLearning (Albelbisi & Yusop, 2019).

Generally, MOOCs are divided into two categories: cMOOC and xMOOC. cMOOC stands for "connectivist MOOC" (Rodriguez, 2012), facilitating communication and interaction among participants in the learners' network. In contrast, xMOOC, which stands for "extension MOOC," allows students to learn by completing tasks assigned by course instructors (Dubosson & Emad, 2015). xMOOC is a more traditional method of learning in which a pre-recorded video lecture is combined with tests, interactive quizzes, or other computer-graded assessments (Siemen, 2013). However, different types of MOOCs are emerging globally, such as Little Open Online Courses (LOOC), Small Online Private Courses (SPOC), and Blended Massive Open Online Courses (bMOOC), where the definition of MOOC remains ambiguous (Yousef et al., 2014).

Students Learning Satisfaction with MOOC

Students learning satisfaction refers to how positive they feel about their academic experience (Rajabalee & Santally, 2021). The use of students' learning satisfaction as a measurement has a relatively high degree of validity and reliability in evaluating the effectiveness of online learning (Weng et al., 2015; Zhao, 2016), including MOOCs (Albelbisi et al., 2021; Bryant, 2017; Daneji et al., 2019).

Nonetheless, past studies have examined students' learning satisfaction based only on a specific point of view, such as from an attitudinal perspective (e.g. Joksimović et al., 2018; Li et al., 2017), course design (e.g. Gameel, 2017; Goh et al., 2017), technical aspect (e.g. Albelbisi et al., 2021; Alzahrani & Seth, 2021), and interactions (e.g. Kuo & Belland, 2016; Zhang & Lin; 2020) which resulted in a narrow view of what contributes towards learning satisfaction. As a result, it is critical to investigate the relationships between a variety of multidimensional factors at the same time and develop a model that can predict student satisfaction in a MOOC learning environment. In order to close the gap, this study used Piccoli et al.'s (2001) virtual learning environment effectiveness model as the foundation to assess students' learning satisfaction, which was then used as a metric to assess MOOC effectiveness.

Virtual Learning Environment (VLE) Effectiveness Model

The VLE effectiveness model assesses a web-based distance learning course's effectiveness in terms of performance, self-efficacy, and satisfaction. Human dimensional factors include student and instructor factors, while design dimensional factors include learning models, technology quality, content design, learner control, and interaction. All these factors play important roles in maximising learning effectiveness (Piccoli et al., 2001).

The VLE effectiveness model has been widely used in research on the effectiveness of educational technology learning environments such as learning management systems (Ozkan & Koseler, 2009) and e-learning (Asoodar et al., 2016; Eom et al., 2006), thus, was considered a natural fit for this research as it covers nearly all key factors in human and non-human dimensions that influence students' learning experience and performance in distance learning environments like MOOCs. To further extend the application of the VLE model, an in-depth literature review was conducted from 2016 to 2021 to identify relevant factors vital to online learning, e-learning, and distance learning. A summary of the literature is presented in Table 1.

Table 1

Relevant references on the key factors influencing students' learning satisfaction in online learning, e-learning, and distance learning

Author (s)	Factors
Eom and Ashill (2016)	Student motivation, instructor feedback and facilitation, dialogue with students, dialogue with the instructors, course structure, self-regulation
Asoodar et al. (2016)	Learner attitude, learner computer anxiety, instructor presence, instructor ability, course flexibility, course quality, technology quality, internet quality, perceived usefulness, perceived ease of use, diversity in assessment, perceived interaction with others, university support
Kuo and Belland (2016)	Learner-content interaction, learner-instructor interaction, learner-learner interaction
Goh et al. (2017)	Course design, interaction with the instructor, interaction with peer student
Gameel (2017) *	Perceived usefulness, teaching and learning aspects, learner-content interaction
Li et al. (2017)	Students' self-efficacy, students' intrinsic motivation, and students' attitude
Chen et al. (2018) *	Human-message interaction, motivation
Cidral et al. (2018)	Collaboration quality, service quality, information quality, system quality, learner computer anxiety, instructor attitude, diversity assessment, learner perceived interaction with others

Table 1 *(Continue)*

Author (s)	Factors
Joo et al. (2018) *	Self-determination, perceived ease of use, perceived usefulness
Pozón-López et al. (2019) *	Quality of the course, entertainment value, usefulness
Lu et al. (2019) *	Perceived usefulness, perceived interest, flow, experience
Zhang and Lin (2020)	Learner-content interaction
Hew et al. (2020) *	Course instructor, content, assessment, course schedule
Venkatesh et al. (2020)	Student characteristics, cognitive factors, social environment
Almaiah et al. (2020)	Trust, self-efficacy, culture, system, and technology quality
Alkhateeb and Abdalla (2021)	Perceived ease of use, perceived usefulness, information quality, system quality, service quality
Alzahrani and Seth (2021)	Service quality, information quality
Albelbisi et al. (2021) *	System quality, information quality, service quality

Note: * Refer to MOOCs studies

Following a review of the prior literature, five key factors were identified and used to assess student learning satisfaction: learner, instructor, course, technology system, and interactivity. Eleven sub-factors were further identified to measure these key factors. Anxiety and motivation were the sub-factors in the *learner factors*. Instructor feedback and facilitation were identified as sub-factors in the *instructor factors*, while course structure and content were identified as sub-factors in the *course factors*. The usefulness and ease of use were sub-factors of *technology systems*. Finally, learner-instructor, learner-learner, and learner-content interactivities were identified in the *interactivity factors*. Researchers actively discussed these factors from 2016 to 2021 in the online distance learning environment context. However, they have never been combined into a single framework in the context of a MOOC learning environment from a holistic standpoint, subject to validation and relationship examination. As a result, this study proposes a research model by incorporating the key factors (Figure 1).

Research Model and Hypotheses Development. The proposed model (Figure 1) is a three-stage hierarchical reflective measurement model because the construct itself causes the indicators of each construct are, and the items are interchangeable (Hair et al., 2017). We propose that five factors influence student learning satisfaction in the MOOC environment: learner, instructor, course, technology system, and interactivity, which make up the first-order constructs of the model. The second-order constructs consist of eleven factors: anxiety, motivation, feedback, facilitation, structure, content, usefulness, ease of use, learner-instructor interactivity, learner-learner interactivity, and learner-content interactivity.

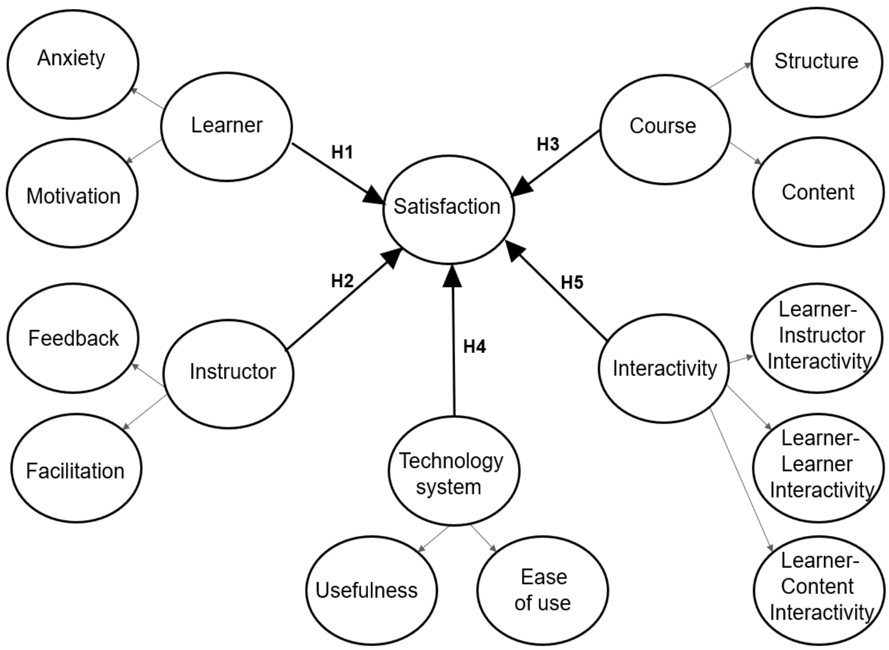

Figure 1. The proposed model

Learner Factors. 'Learner' in this study refers to the students enrolled in MOOC courses. Learners' motivation (Asoodar et al., 2016; Cidral et al., 2018; Eom & Ashill, 2016) and anxiety (Asoodar et al., 2016) strongly correlate to learning satisfaction. For example, Sun et al. (2008) discovered that if a learner is afraid of using technology for e-learning, the barrier to e-learning increases, and the learner's ability to use the e-learning courses suffer. On the other hand, if the students are more motivated (either internally or externally), this encourages them to put more effort into their work and even promotes self-studying awareness (Abdel-Jaber, 2017; Eom & Ashill, 2016; Li et al., 2017). As learner factors are important in determining satisfaction in VLEs and MOOCs, we hypothesise:

H1: Learner factors positively influence student learning satisfaction in MOOCs

Instructor Factors. The MOOCs' facilitator, or teacher, is referred to as the instructor in this study. The learner's perceptions of instructors' attitudes, such as feedback and facilitation skills, strongly influence student learning satisfaction (Asoodar et al., 2016; Eom et al., 2006; Selim, 2007; Sun et al., 2008). Prompt feedback from the instructor can help students improve their cognitive skills and knowledge, activate metacognition, and increase their motivation to learn (Zimmerman, 1989). Furthermore, instructors can provide guidance, effectively demonstrate the use of e-learning communication tools, transfer their knowledge to learners in different locations (Leidner & Jarvenpaa, 1995), and even empower students with freedom and responsibility. As a result, students' interest in learning will be stimulated, positively impacting their learning experience and satisfaction. Therefore, we hypothesise:

H2: Instructor factors positively influence student learning satisfaction in MOOCs

Course Factors. In this study, the course refers to the content knowledge design of MOOCs in achieving what learners expect to learn (Moore & Kearsley, 1996). Learners' perceptions of the course structure (Eom & Ashill, 2016) and perceived value of the course content are two major components that measure the quality of the course content knowledge (Albelbisi et al., 2021; Alzahrani & Seth, 2021; Hew et al., 2020; Sun et al., 2008; Yang et al., 2017). When online learners are pleased and satisfied with the presentation of content knowledge (e.g., well-organised content) and the quality of the content knowledge (e.g., required, relevant, useful, comprehensive, intelligible, up-to-date, and accurate content), then the online learning success rate increases (Naveed et al., 2017). Therefore, we hypothesise that:

H3: Course factors positively influence student learning satisfaction in MOOCs

Technology System Factors. The technology system in this study refers to the desired performance characteristics of MOOCs. Students in MOOCs perform their weekly learning activities using technology features and functions such as video, chat box, audio, and online discussion forums (Almaiah et al., 2020). As a result, high-quality technological attributes are critical for the successful implementation of online learning (Naveed et al., 2017). A good online learning system can be measured by its ease of use (Asoodar et al., 2016; Gameel, 2017; Lu et al., 2019; Sun et al., Pozón-López et al., 2019; 2008; Wu & Chen, 2017) and its usefulness in enhancing learning performance (Alkhateeb & Abdalla, 2021; Asoodar et al., 2016; Joo et al., 2018; Wu & Chen, 2017). When a learning system can assist learners in gaining the desired knowledge, it gives the online course a sense of usefulness (Lu et al., 2019). Furthermore, when a learning system is simple to use, it encourages students to actively participate in the online course, resulting in increased student learning satisfaction (Joo et al., 2018). Therefore, we hypothesise that:

H4: Technology system factors positively influence student learning satisfaction in MOOCs

Interactivity Factors. Interactivity refers to learning engagement in the course. Learner-instructor, learner-learner, and learner-content interactions are all three dimensions of interaction in learning, according to Kuo and Belland (2016). Human interaction (e.g., learner-instructor and learner-learner interactions), which includes guidance, encouragement, and motivational and emotional support, has been shown to positively impact student learning motivation and interest in a subject matter via scaffolding (Murphy & Rodriguez-Manzanares, 2009). Learners can verbalise what they have learned in the course and articulate their current understanding when they actively participate in intellectual exchanges with fellow learners or instructors (Eom et al., 2006). It could speed up the learning process, resulting in better results and satisfaction (Alqurashi, 2018; Eom & Ashill, 2016; Hew et al., 2020).

Non-human interaction (learner-content interaction) is also important in improving student learning outcomes (Kuo & Belland, 2016). It is because e-learners spend most of their time interacting with course learning materials by processing information, digesting content, and learning from a computer screen (Alqurashi, 2018). Moreover, learner-content interaction, as opposed to other forms of interaction, is the strongest predictor of learner satisfaction in the virtual learning environment, according to Kuo et al. (2014) and Zhang and Lin (2020). Therefore, we hypothesise that:

H5: Interactivity factors positively influence student learning satisfaction in MOOCs

METHODS

Population and Sampling Method

Three hundred thirty-three undergraduate students from Malaysia's top five public universities actively using MOOCs in their studies were invited to participate. Table 2 shows the demographics of the participants, with 41.1% from Universiti Malaysia Sarawak (UNIMAS), 21.9% from Universiti Utara Malaysia (UUM), 15% from Universiti Kebangsaan Malaysia (UKM), 12.9% from Universiti Teknologi MARA (UiTM), and 9% from Universiti Teknikal Malaysia Melaka (UTeM). Most participants (64.3%) were female, with 55.6% having no prior learning experience with MOOCs and 44.4% having prior MOOC learning experience. Regarding the voluntariness of using MOOCs for learning, 69.1% of the participants said it was mandatory, while 30.9% said they did it voluntarily. On top of that, only 41.4% of the participants had good internet speed during their learning with MOOCs.

The current study's population is dispersed across many students enrolled in MOOCs. Some MOOCs (e.g., from UNIMAS, UKM, and UUM) have a relatively high number of students due to the uneven student enrolment number of Malaysia's public universities. As a result, cluster sampling is used in this study to ensure that the sample is chosen fairly and representative of the population (Taherdoost, 2018).

Table 2
Summary of the participants' demographics

Variable	Category	Frequency (n = 333)	Valid percent (%)
Gender	Male	119	35.7
	Female	214	64.3
Prior experience with MOOC	Yes	148	44.4
	No	185	55.6
Compulsory to use MOOC	Yes	230	69.1
	No	103	30.9
Internet speed during MOOC	Poor	10	3.0
	Moderate	185	55.6
	Good	138	41.4
University	UKM	48	15.0
	UUM	74	21.9
	UiTM	34	12.9
	UNIMAS	139	41.1
	UTeM	38	9.0

Construct Measurement

Items in the survey were adapted from the relevant online learning, e-learning, and distance learning literature according to the rule of thumb for internal reliability consistency (Hair et al., 2017). In addition, the construct items and sources were adapted from the literature (Table 3).

Table 3
Items of the construct and sources

Constructs	Items	Questions	Source
Anxiety	AX1	I feel comfortable learning with MOOCs	Sun et al. (2008)
	AX2	I feel at ease learning with MOOCs	
	AX3	I feel calm learning with MOOCs	
	AX4	I feel pleasant learning with MOOCs	

Table 3 *(Continue)*

Constructs	Items	Questions	Source
Motivation	MT1	I prefer learning materials that really challenge me so I can learn new things in MOOCs	Eom and Ashill (2016)
	MT2	I choose the assignments that I can learn from even if they do not guarantee a good grade in MOOCs	
	MT3	I do all that I can to make my assignments turn out perfectly in MOOCs	
	MT4	I work hard to get a good grades even if I do not like learning with MOOCs	
	MT5	I want to do well in MOOCs because it is important to show my ability to my family, parents, friends, lecturers, or others	
	MT6 *	I like to be one of the most recognised students in MOOCs	
Feedback	FD1	The instructor of MOOC is responsive to students' concerns	Eom et al. (2006)
	FD2	The instructor of MOOC provides timely feedback to the students	
	FD3 *	The instructor of MOOC provides helpful feedback to the students	
	FD4	The instructor of MOOC cares about my learning	
	FD5	The instructor of MOOC has a genuine interest in students	
Facilitation	FC1	The instructor of MOOC invites students to ask questions and receive answers	Selim (2007)
	FC2	The instructor of MOOC encourages students to participate in the course	
	FC3	The instructor of MOOC has good presentation skills that hold my interest in learning	
	FC4	The instructor of MOOC is actively involved in facilitating the course	
	FC5	The instructor of MOOC is knowledgeable	

Table 3 *(Continue)*

Constructs	Items	Questions	Source
Structure	ST1	The MOOC is well organised in a logical manner	Eom and Ashill (2016)
	ST2	The MOOC's objectives are clearly communicated	
	ST3	The MOOC is structured with an effective range of assessments	
	ST4	The MOOC is structured effectively with text, graphics, or video	
Content	CT1	The content of MOOC is up to date	Yang et al. (2017)
	CT2	The content of MOOC is relevant to the topic	
	CT3	The content of MOOC is covered with an appropriate degree of breadth	
Usefulness	UE1	Learning with MOOCs improves my learning performance	Wu and Chen (2017)
	UE2	Learning with MOOCs helps me accomplish my learning objectives more quickly	
	UE3	Learning with MOOCs increases my productivity in completing assignments	
Ease of use	EU1	Learning with MOOCs is easy for me	Wu and Chen (2017)
	EU2	Learning with MOOCs does not require a lot of mental effort	
	EU3	Learning with MOOCs is simple	
Learner-instructor interactivity	LI1	Positive interaction level between the instructor and students is high in MOOCs	Eom and Ashill (2016)
	LI2	Positive interaction between the instructor and students helps me improve the quality of the learning outcomes in MOOCs	
	LI3	Positive interaction between the instructor and students is an important learning component in MOOCs	
	LI4	Positive interaction with the instructor frequently happens in MOOCs	

Table 3 *(Continue)*

Constructs	Items	Questions	Source
Learner-learner interactivity	LL1	Positive interaction level among students is high in MOOCs	Eom and Ashill (2016)
	LL2	Positive interaction among students helps me improve the quality of the learning outcomes in MOOCs	
	LL3	Positive interaction among students is an important learning component in MOOCs	
	LL4	Positive interaction among students frequently happens in MOOCs	
Learner-content interactivity	LC1	MOOC materials help me to understand the topic easily	Kuo et al. (2014)
	LC2	MOOC materials stimulate my interest in this course	
	LC3	MOOC materials help me to learn new knowledge	
Satisfaction	SA1 *	I would gladly do so if I have an opportunity to take another course via MOOCs	Sun et al. (2008)
	SA2	I am pleased with how MOOCs are conducted	
	SA3	I would recommend MOOCs to others	
	SA4	I feel that MOOCs are useful to me in general	
	SA5	I am satisfied with my overall learning experience of MOOCs	

Note: Items with an asterisk are deleted after data analysis

Data Collection

This cross-sectional study used an online survey questionnaire to collect data from participants. The online survey questionnaire was sent through the chat box in the OpenLearning platform, Malaysia's national MOOC platform, with a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). During the data collection process, tokens of appreciation were distributed to encourage participant responses (Leary, 2014). Although 410 responses were received, 77 were removed due to duplicates and incomplete responses, leaving 333 valid responses that could be further analysed.

Data Analysis

The collected data were analysed using the Partial Least Square Structural Equation Modelling (PLS-SEM) technique (Hair et al., 2017) with Smart PLS version 3 (SmartPLS GmbH, Germany). The analysis involved two main steps: the evaluation of the reflective measurement (outer) model and the evaluation of the structural (inner) model using the Bootstrapping method.

In step one of the PLS-SEM procedure, evaluation of the reflective measurement involved assessment of internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (Average Variance Extracted (AVE) and factor loading), and discriminant validity (Fornell-Larcker criterion, heterotrait-monotrait (HTMT) ratio of correlation criterion) (Fornell & Larcker, 1981; Hair et al., 2017; Schumacker & Lomax, 2004).

Internal consistency reliability was used to measure the reliability of survey items in a construct. Internal consistency reliability is achieved when all items of such measures reflect the same underlying construct (Myrtveit & Stensrud, 2012). Cronbach's alpha (α) and composite reliability are two indicators to measure the internal consistency of reliability. To achieve internal consistency reliability, the recommended level of α should exceed .70, and the composite reliability value should be between .70 and .95 (Hair et al., 2017).

Convergent validity was used to measure the degree of correlation between items in the same construct (Campbell & Fiske, 1959), such as factor loading and Average Variance Extracted (AVE) indicators. It is achieved when items in the same construct are strongly correlated (Bagozzi & Yi, 2012), when each item load of the construct is greater than 0.50, and the value of the Average Variance Extracted (AVE) of each construct exceeds 0.50 (Hair et al., 2017).

Discriminant validity was used to measure the degree of correlation between items in different constructs (Campbell & Fiske, 1959), such as the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of the correlation criterion indicators. It is achieved when items in a particular construct are not highly correlated with any items in other constructs (Hulland, 1999). To achieve this, the square root of the particular construct's AVE should be the highest correlation with any other constructs, and the HTMT value should be lower than .90 (Hair et al., 2017).

In the second step of the PLS-SEM procedure, the evaluation of the structural model used to test the hypothesis was carried out, which involved path coefficients (β), *t*-statistic values, the coefficient of determination (R^2), effect size (f^2), and the predictive relevance (Q^2).

The path coefficients (β) represent the strength of the hypothesised relationships between the constructs. A bootstrapping technique with 5,000 resamples was conducted to estimate the beta (β) and corresponding *t* values as recommended by Chin et al. (2003). The greater the beta coefficient (β), the stronger the effect of an exogenous construct on the endogenous construct. Path coefficients with a value close to 1 represent a strong positive relationship, and conversely, a value closer to -1 represents a strong negative relationship. The overall effect size (f^2) measures the degree of impact of the path relationship. Following Hair et al. (2017), the cut-off of $f^2 = 0.35$ is considered a large effect size, $f^2 = 0.15$ is regarded as a medium, and $f^2 = 0.02$ is considered small. Predictive relevance for the structural model was evaluated using Q^2 (Tenenhaus et al., 2005), so it can be considered an indicator of the quality of the structural model. The interpretation of Q^2 followed that of Hair et al. (2017), with a value of > 0 indicating adequate predictive relevance and a value of < 0 indicating poor predictive relevance. R^2 values of 0.25, 0.50, and 0.75 for target constructs are considered weak, moderate, and substantial based on Henseler et al. (2009).

RESULTS

Modelling the Survey Data

Items of the construct in the (outer) measurement model met all the evaluation criteria of reliability and validity (Table 4). The factor loadings of the measurement items ranged between 0.704 and 0.924, which meets the recommended level of α and confirms the relative importance of each item to the underlying construct factor. The α values for all construct factors were .790-.911, and CR values were .871-.937, indicating the scales had acceptable reliability. AVE values were adequate to accept for motivation, feedback, facilitation, structure, and learner-learner interactivity, which ranged between 0.614 to 0.787, and satisfactory for anxiety, content, usefulness, ease of use, learner-instructor interactivity, learner-content interactivity, and student learning satisfaction, which ranged between .704 and .790, and so convergent validity was established for this studied model.

Table 4

Indicators of internal consistency reliability and convergent validity

Constructs	Items	Loadings	α	CR	AVE
Anxiety	AX1	0.836	.911	.937	0.790
	AX2	0.903			
	AX3	0.924			
	AX4	0.888			

Table 4 *(Continue)*

Constructs	Items	Loadings	α	CR	AVE
Motivation	MT1	0.770	.842	.888	0.614
	MT2	0.776			
	MT3	0.857			
	MT4	0.704			
	MT5	0.804			
Feedback	FD1	0.771	.802	.871	0.628
	FD2	0.763			
	FD4	0.801			
	FD5	0.833			
Facilitation	FC1	0.774	.860	.900	0.643
	FC2	0.801			
	FC3	0.815			
	FC4	0.850			
	FC5	0.765			
Structure	ST1	0.849	0.847	.897	0.687
	ST2	0.751			
	ST3	0.882			
	ST4	0.827			
Content	CT1	0.806	.790	.878	0.706
	CT2	0.895			
	CT3	0.817			
Usefulness	UE1	0.874	.860	.915	0.782
	UE2	0.917			
	UE3	0.861			
Ease of use	EU1	0.850	.790	.877	0.704
	EU2	0.873			
	EU3	0.793			
Learner-instructor interactivity	LI1	0.870	.877	.916	0.732
	LI2	0.884			
	LI3	0.869			
	LI4	0.795			

Table 4 *(Continue)*

Constructs	Items	Loadings	α	CR	AVE
Learner-learner interactivity	LL1	0.800	.811	.875	0.637
	LL2	0.863			
	LL3	0.784			
	LL4	0.742			
Learner-content interactivity	LC1	0.852	.817	.891	0.732
	LC2	0.875			
	LC3	0.840			
Satisfaction	SA2	0.733	.867	.910	0.718
	SA3	0.907			
	SA4	0.903			
	SA5	0.835			

Note: α = Cronbach's alpha, CR = Composite Reliability, AVE = Average Variance Extracted

The studied model also met all the evaluation criteria for discriminant validity. The square root of each construct's AVE was greater than the correlation involving the constructs, confirming the criterion of Fornell and Larcker (1981). From Table 6, the results also passed the HTMT criterion test, in which the values do not exceed 0.90 (Table 5).

Table 5

The Fornell-Larcker criterion test for discriminant validity

	AX	CT	EU	FC	FD	LC	LI	LL	MT	ST	SA	UE
AX	**0.889**											
CT	0.544	**0.840**										
EU	0.513	0.475	**0.839**									
FC	0.430	0.562	0.329	**0.802**								
FD	0.336	0.391	0.289	0.585	**0.792**							
LC	0.541	0.602	0.486	0.514	0.333	**0.856**						
LI	0.581	0.546	0.461	0.521	0.553	0.515	**0.855**					
LL	0.431	0.490	0.403	0.511	0.405	0.568	0.613	**0.798**				
MT	0.703	0.549	0.402	0.453	0.380	0.454	0.689	0.495	**0.784**			
ST	0.450	0.692	0.423	0.590	0.370	0.579	0.422	0.503	0.426	**0.829**		
SA	0.720	0.606	0.546	0.475	0.402	0.690	0.677	0.520	0.675	0.528	**0.848**	
UE	0.475	0.464	0.659	0.401	0.299	0.438	0.387	0.489	0.362	0.459	0.512	**0.884**

Note: Values in bold should be greater than the remaining values in each column

Table 6

The heterotrait-monotrait (HTMT) criterion test for discriminant validity

	AX	CT	EU	FC	FD	LC	LI	LL	MT	ST	SA	UE
AX	**1**											
CT	0.643	**1**										
EU	0.612	0.607	**1**									
FC	0.488	0.687	0.402	**1**								
FD	0.391	0.489	0.367	0.702	**1**							
LC	0.625	0.751	0.610	0.614	0.407	**1**						
LI	0.650	0.656	0.563	0.601	0.656	0.607	**1**					
LL	0.477	0.603	0.503	0.606	0.496	0.684	0.697	**1**				
MT	0.793	0.668	0.495	0.528	0.451	0.539	0.796	0.563	**1**			
ST	0.506	0.842	0.519	0.696	0.449	0.691	0.482	0.606	0.490	**1**		
SA	0.807	0.737	0.668	0.558	0.477	0.833	0.773	0.600	0.775	0.614	**1**	
UE	0.534	0.562	0.795	0.463	0.363	0.521	0.441	0.592	0.419	0.541	0.593	**1**

Note: Values in non-bold should not be lower than 0.90

The next step was to evaluate the (inner) structural model. All factors (i.e., learner, instructor, course, technology system, and interactivity) have significantly and positively influenced student learning satisfaction at a 5% significance level with β = 0.299, 0.097, 0.099, 0.112, and 0.253, respectively (Table 7). Although the path coefficients were significant, the effect sizes may have been too small to attract attention. Therefore, assessing the relevance of the significant relationship is important by considering the f^2. The effect size of the learner factors on students' learning satisfaction was the largest (f^2 = 0.124), while the effect size for the other four paths was small (Table 7). This result indicates that learner factor(s) is the best predictor of student learning satisfaction in MOOCs.

Table 7

Path coefficients, t statistics, and effect size (f^2)

	Hypothesised paths	Std β	Std error	*t* value	*p*-value	f^2
H1	Learner → Satisfaction	0.299	0.048	6.199	0.000**	0.124
H2	Instructor → Satisfaction	0.097	0.058	1.680	0.047*	0.015
H3	Course → Satisfaction	0.099	0.052	1.922	0.027*	0.015
H4	Technology system → Satisfaction	0.112	0.048	2.362	0.009**	0.027
H5	Interactivity → Satisfaction	0.253	0.060	4.208	0.000**	0.067

Note: (*t*-values > 1.65 where $p < 0.05$*), (*t*-values > 2.33 where $p < 0.01$**)

Table 8
The values of R^2 and Q^2

Construct	R^2	Result (R^2)	Q^2	Result (Q^2)
Satisfaction	0.716	Moderate	0.503	Predictive relevance

Note: (if R^2 value is 0.25 = weak, 0.50 = moderate, 0.75 = substantial); (if $Q^2 > 0$, predictive relevance)

On top of that, this study model has sufficient predictive relevance as the Q^2 value exceeded the threshold limit ($Q^2 = 0.503$) (Table 8). Similarly, for R^2, the value for the student learning satisfaction construct is 0.716, meaning that the five exogenous constructs (learner, instructor, course, technology system, and interactivity) explain 71.6% of the variance in this endogenous construct (student learning satisfaction), which is a nearly substantial effect. In sum, the results showed that the five key factors play vital roles in providing high student learning satisfaction in MOOCs.

DISCUSSION

This study uses PLS-SEM analysis to examine the influence of five key factors on students' MOOC learning satisfaction (i.e., learner, instructor, course, technology system, and interactivity). Findings revealed that all five key factors significantly influence students' learning satisfaction. The findings also showed that the learner factor is the best predictor of learning satisfaction and that interactivity has a relatively large impact on increasing student learning satisfaction in MOOCs compared to other key factors (i.e., instructor, course, and system technology). To put it another way, the findings of this study clearly showed that, first, the conceptualisation framework for measuring MOOC success should include all five factors, and second, learner factors, such as learner anxiety and motivation, should always be focused on and prioritised.

The results have drawn attention to explaining and discussing the phenomenon behind them. With less anxiety, students would be more engaged in their learning when they are more confident and comfortable. Abdel-Jaber (2017), Eom and Ashill (2016), and Li et al. (2017) agree that barriers to online learning will increase if students handle e-learning technology with a feeling of nervousness and fear. Moreover, Fawaz and Samaha (2020) and Paul and Glassman (2017) also acknowledge that students feel frustrated and anxious in an online learning environment if internet efficiency is low. In the Malaysian context, poor internet connectivity and limited broadband data were the biggest challenges experienced by online learners (Chung et al., 2020). Thus, learning satisfaction can be increased by reducing learners' anxiety through better internet access. Additionally, online learning anxiety can be reduced by offering an asynchronous mode of online learning (McLoughlin & Lee, 2010), such as MOOCs. Such a situation happens because learners are not bound by the duration of time and internet access as they would experience in synchronous online learning. Thus, online learners can always view instructional materials and perform learning tasks anytime when internet access is available (Guichon, 2010).

Motivation to learn is another important factor that influences learning satisfaction. Students put effort into their self-development of MOOC learning when they are motivated by certain intrinsic (e.g., fun and challenging) and extrinsic (e.g., rewards and recognition) features (Ryan & Deci, 2000). Intrinsic and extrinsic motivation effects were measured in this study. Some 70% of the participants were made compulsory to use MOOCs in their learning during the COVID-19 pandemic. They had to actively participate in the MOOC task activities designed by the lecturers at their respective universities to gain better grades or recognition of the subject (Chen et al., 2020). This form of extrinsic motivation (better grades or recognition) has improved students' satisfaction with learning (Barak et al., 2016).

Similarly, higher intrinsic motivation will create a better online learning experience. According to Hartnett (2016), online learners are more intrinsically motivated than their on-campus counterparts at undergraduate and postgraduate levels. Motivation is related to the view that learning with technology enables several aspects recognised as important in fostering intrinsic motivation, such as challenge, curiosity, fun, novelty, and fantasy (Eom & Ashill, 2016; Lepper & Malone, 1987). Moreover, intrinsic motivation can increase the frequency of learner-content interaction as it elicits attention to learn the content in the sense of curiosity, enjoyment, and others, but no assumption can be made about the level of content knowledge (Renninger, 2000). Although learner motivation to learn online is always complex, designing MOOC courses that sustain student motivation is considered the critical presage variable influencing MOOC success (Albelbisi et al., 2018).

On the other hand, interactivity factors are also significant factors in student learning satisfaction. It includes learner-learner, learner-instructor, and learner-content interactions. This finding was reinforced by Kuo and Belland (2016). They found that human interaction is an essential element of a supportive community in the online learning environment, especially during the COVID-19 crisis, as students must learn under the conditions of the movement control order (Das & Das, 2020).

MOOCs in the current study belong to cMOOCs based on the philosophy of social constructivism, where learners take increasing responsibility for their learning, and instructors are enablers and activators of learning. Therefore, learner interaction, such as dialogue, discussion, and group work, is important in fostering student understanding and improving satisfaction towards MOOCs. When students are actively participating in an intellectual exchange with fellow students in MOOCs, they will be able to verbalise what they have learned in a course and articulate their current understanding based on the posted learning materials (Alqurashi, 2018; Eom & Ashill, 2016; Hew et al., 2020). In addition, comprehension and confirmation checks of the content knowledge can be done by interacting with each other such as through peer assessment, instructors' comments, or self-assessment through learner-content interaction (Pica et al., 1987).

The learning approach of cMOOC is more learner-centred than instructor-centred, where learners construct knowledge through language (Knox, 2018). However, this does not mean that the instructor's role is unnecessary in this learning approach. The findings indicated that learner-instructor interaction had played a significant role in improving the student learning experience during the COVID-19 crisis, in which a learner-centred instructor enables learners to build knowledge through reading, writing, watching videos, navigating the course, and participating in the class discussion forums (Rapanta et al., 2020). Learner-instructor interaction can also be done through non-verbal communication, such as replying to students' comments, sending a private message through a chat box, expressing emotion with an "emoji" or "like," and recording videos for general announcements and reminders (Dehghani et al., 2020; Hew, 2018). Additionally, the embedment of such interactive learning environments between learner-to-learner and learner-to-instructor will further promote the enhancement of MOOC learners' self-regulated learning attitude (Albelbisi & Yusop, 2019).

IMPLICATIONS

This study is important as it provides an empirically justified framework in e-learning for developing distance learning courses such as MOOCs in higher education. Furthermore, it provides a clear understanding from a holistic view to different MOOC stakeholders, such as university administrators, instructors, instructional designers, and policymakers, so that MOOC implementation can be improved and the question of the low completion rate can be resolved.

Since the learner factor has been proven to be the most significant factor in improving students' learning satisfaction, instructors should focus more on increasing students' motivation, reducing students' anxiety, and fostering self-regulated and independent learning during the learning process with MOOCs. Therefore, before starting a MOOC, it is essential to strengthen education and training to give students a better understanding of the abilities, skills, strategies, and attitudes required of an online learner. Furthermore, equipping students with the appropriate knowledge and skills could help them boost their motivation to learn and reduce anxiety when facing difficulties (e.g., slow internet access) in MOOCs (Albelbisi & Yusop, 2019). Moving forward, the government, telecommunication companies, and universities should cooperate to invest in developing better internet infrastructure across the country, as online learning will be the new norm in the foreseeable future (Chung et al., 2020).

The results also suggest that course instructors should always focus on creating more meaningful interactions and communication with the students. For example, they could use a chat box or create a discussion forum in the café for the students to ask questions or seek help. In addition, putting students into small groups is a useful approach to promote frequent interaction among them, and producing interactive learning activities (e.g., matching quizzes and crosswords) helps increase learners' intrinsic motivation (Yusop et al., 2020).

Finally, the course needs to follow the best instructional design practices in developing the course learning objectives, delivery of learning materials, assessments, and discussion forums. At the same time, the technology system must be easy for students to navigate and find relevant resources. Universities should provide training for the instructors on the essential skills needed to facilitate and conduct MOOCs effectively, as teaching in MOOCs is very different from face-to-face teaching.

CONCLUSION AND RECOMMENDATIONS

The rapid growth of MOOCs has profoundly impacted the teaching and learning field. It has changed how people view learning in the 21st century. To better evaluate and anticipate the profound impact of MOOCs on learners, further refining learners' understanding of MOOC adoption is essential. Therefore, this research investigates the roles of the learner, instructor, course, technology system, and interactivity on students' satisfaction in a MOOC learning environment. The findings of this study have indicated that all these factors have been proven to be very significant. Additionally, it has been found that the learner (i.e., motivation and anxiety) and interactivity factors (i.e., learner-instructor, learner-learner, and learner-content interactions) should be emphasised in promoting student learning satisfaction in the MOOC environment.

The adoption of qualitative studies could be used to support and strengthen the validity of the present research to gain a more robust understanding of the relationship between the key factors and student learning satisfaction in MOOCs. Subsequently, further research to investigate the arising view from the current research could be conducted, including a comparison between mandatory and voluntary MOOCs, cMOOCs, and xMOOCs, or low and high self-regulated learners, which has yet to be explored in depth. Finally, longitudinal studies could be conducted in future studies to confirm the obtained results and provide a better insight into the development of MOOCs to improve student learning satisfaction.

ACKNOWLEDGEMENT

This study is partially supported by Universiti Malaya's grant (No. UMG0080-2021).

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