Computers in Human Behavior Reports 14 (2024) 100403

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

Investigating the behavioral differences in the acceptance of MOOCs and E-learning technology

Bernardinus Harnadi [*], Albertus Dwiyoga Widiantoro, F.X. Hendra Prasetya

Soegijapranata Catholic University, Information Systems Department, Semarang, 50234, Indonesia

ARTICLE INFO

Keywords:
E-Learning
MOOCs
Behavioral difference
TAM
ECM

ABSTRACT

This study aims to investigate the behavioral differences in the acceptance of MOOCs and E-learning. The study employs combining models TAM and ECM to reveal user's behavior in using MOOCs and E-learning. In accessing these learning systems, e-learning users are more mandatory in accessing the learning contents than MOOCs. The eight latent variables derived from reviewing previous related literatures including information quality, self-efficacy, perceived ease of use, perceived usefulness, attitude, confirmation, satisfaction, and behavioral intention are employed to reveal the behavioral differences in using these systems. This study also employs type of learning systems (MOOCs and E-learning) as difference variable. The respondents of this study are MOOCs and e-learning users in Indonesia. The online questionnaires are delivered to e-learning and MOOCs users in high school and university and the supplemental questionnaires are delivered to employers and entrepreneurs as MOOC users. There are 706 questionnaire data collected and examined in statistically manner using smart-PLS to prove the hypotheses in proposed model. Several analyses including the structural model and hypotheses, MGA, and IPMA are employed in this study. This study has findings on the accepted of all hypotheses on the model in adoption of MOOCs technology. For the adoption of e-learning technology all hypotheses on the model are accepted excluding the hypothesis of information quality which has positive direct effect on the perceived usefulness. The difference values on the MGA result reveals that there is difference on the correlation of between information quality and perceived usefulness, perceived usefulness and attitude, confirmation and satisfaction, and attitude and behavioral intention. IPMA analysis reveals the difference on importance and performance among indicators of construct of the model and serves interesting insights into the role of indicators of construct and their relevance for managerial implications.

1. Introduction

Education has undergone substantial transformation in recent decades, especially since the emergence of revolutionary information and communications technologies. Online learning is a form of transformation on learning including Massive Open Online Courses (MOOCs) and e-learning. These two types of learning provide wider access to knowledge and education to the people.

MOOCs are a type of online course that is open to the peoples and can be accessed by anyone without geographic restrictions or significant access costs (N et al., 2023). The online survey was conducted in the United States in November 2023 of 1241 respondents (©Global Market Insights (2023) stated that the level of use of MOOC services from various online education platforms shows significant growth. Based on this survey, 1241 respondents with an age range of 18–64 years, Rosetta Stone as a MOOC service provider shared 61% of respondents, followed by Babbel with 51%, and LinkedIn Learning with 45%. Other providers such as Duolingo, Khan Academy, and Coursera are also recorded as having a significant percentage of users, at 43%, 39%, and 34% respectively.

Meanwhile, e-learning encompasses various forms of learning that utilize technology, including online university/school courses, corporate training, and customized self-education (Allen & Seaman, 2017). E-learning technology has become a very significant economic sector with a variety of technologies that support online learning. The growth of mobile e-learning represents a shift in how people choose to learn for flexibility of access. Based on the world market report of e-learning usage (@Statista (2023)), LMS (Learning Management System) has a market of $38,700.7 million, mobile e-learning is worth $46,005.7 million, Rapid e-learning is worth $4885.1 million, and virtual

* Corresponding author. Soegijapranata Catholic University, Information Systems Department, Pawiyatan Luhur IV/1, Semarang, 50234, Indonesia.
E-mail addresses: bharnadi@unika.ac.id (B. Harnadi), yoga@unika.ac.id (A.D. Widiantoro), hendra@unika.ac.id (F.X.H. Prasetya).

https://doi.org/10.1016/j.chbr.2024.100403
Received 2 December 2023; Received in revised form 16 February 2024; Accepted 7 March 2024
Available online 13 March 2024

classroom is worth $34,325.1 million. Meanwhile, the world e-learning market based on region, Asian including Indonesia has a market of $77, 147.4 million.

1.1. Problem statement

The two types of learning systems MOOCs and E-learning have the potential to change the way people learn. The fundamental differences in accessibility, structure, and participation in these systems may influence the behavior and acceptance in using the systems by users.

The related previous studies (Hsu, Chen, & Ting, 2018; Janelli, 2018) employed various theoretical frameworks to investigated the distinct nature of these learning environments. Hsu et al. (2018) used TAM and Social Support Theory to reveal factors which affect user behavior in using MOOCs and e-learning differently. Other study by Janelli (2018) used several theoretical frameworks naming behaviorism, cognitivism, constructivism, digital media theory, active learning theory to understand the unique aspects of MOOCs and e-learning. The applicability of different theoretical frameworks for investigating MOOCs and e-learning can reveal the complexity and diversity of these online learning environments. Every theory serves unique insights to reveal different behaviors, motivations, and engagements of learners in using these learning environments.

This study investigates behavioral differences in the acceptance of MOOCs and e-learning employing a combination of TAM and ECM to reveal user behavior and its differences in using MOOCs and e-learning. TAM is a robust theoretical framework to understand user behavior towards information technology (Al-Adwan, 2020; Davis, 1989; Valverde-Berrocoso, Garrido-Arroyo, Burgos-Videla, & Morales-Cevallos, 2020). ECM is a framework to understand the satisfaction and continued intention of the user when using a service or product (Lee, Song, & Kim, 2023; Oliver, 1980; Rekha, Shetty, & Basri, 2023). Integrating TAM and ECM in this study will reveal not only the initial acceptance of MOOCs and e-learning but also factors influencing continued use of these learning environments.

1.2. Purpose of the study

This study aims to understand behavioral differences in the acceptance of MOOCs and e-learning. These differences can serve as theoretical contributions to learning systems. Two theories, TAM and ECM are employed simultaneously to predict the acceptance of MOOCs and e-learning either as unified learning system or as separate entities including MOOCs or e-learning. The effect of each factor on the theory is investigated to explore their contributions to the acceptance of the learning system. The differences can also serve valuable insights for online learning developers, students, teachers and mentors, education division on government, and others who have concern in gaining education of people. Students and Teacher have difference perceptions about the effectiveness of leaning systems (N. et al., 2023). On the students' perception, N. et al. (2023) stated that the issues of leaning efficiency come from the standardization of learning subjects and the assessments. Besides that, on the teachers' perception, the issues of learning efficiency come from the lack of teacher' technical skill and their expertise on the subjects. Finally, the difficulty in managing all course-related activities by learning administrators is also an issue of effectiveness.

The research question that arises is: "How is the acceptance of online learning environments (MOOCs and e-learning), and how do behavioral differences in acceptance of MOOCs and e-learning provide insight into managerial implications?" The respondents of this study come from MOOCs and e-learning users (student, employee, and entrepreneur) in Indonesia.

1.3. Research gap

The newness of this study come from the analysis of behavioral difference of MOOCs and e-learning users in one integrated data using structural model, MGA, and IPMA analyses. The difference values on the MGA result reveals the difference on the correlation values of variables in the model and IPMA analysis reveals the difference on importance and performance among indicators of construct of the model.

This study is delivered in five sections. The first section, introduction introduces the background, purpose, research questions, and contribution of this study. The second section introduces review of literatures to propose the research model and hypotheses. The third section introduces the methodology of the research. The fourth section present finding the research and their discussion. The fifth section summarizes the findings and serve theoretical and practical implication of the study.

2. Proposed model and hypotheses

The related previous researches on e-learning and MOOCs are shown on Tables 1 and 2. Tables 1 and 2 summarize previous research employing extended TAM or ECM to predict e-learning and MOOCs acceptance. From Table 1 it is seen that the variable Seff-efficacy was employed on extended TAM or ECM by Prasetya, Harnadi, Widiantoro, and Nugroho (2021), Alharthi, Awaji, and Levy (2017), Alassafi. (2022), and Widiantoro, Murniati, and Hartono (2022) and the variables Information Quality was also employed on extended TAM or ECM by Prasetya et al. (2021), Alassafi. (2022), and Widiantoro et al. (2022).

Table 2 summarizes previous research on MOOCs acceptance with TAM and ECM. It seen on Table 2, The variable self-efficacy was employed on extended TAM or ECM by Al-Adwan (2020), Harnadi et al., (2022b), Hsu et al. (2018), and Rekha et al. (2023). Lee et al. (2023) and Dai, Teo, and Rappa (2020) employed Information Quality on extended ECM.

From Tables 1 and 2 it is seen that the TAM and ECM are important models on E-learning and MOOCs. From Table 2 it is that Hsu et al. (2018) conducted study on competing platforms of E-learning and MOOCs using TAM.

2.1. Information quality, perceived ease of use, perceived usefulness, attitude, and behavioral intention

The relation of perceived usefulness, perceived ease of use, and attitude are the essence of TAM (Hu et al., 2022; Raza et al., 2021; Widiantoro & Harnadi, 2019; Prasetya & Harnadi, 2019; Wu & Chen, 2017; Alraimi et al., 2015). Wu and Chen (2017) define perceived usefulness as the extent to which and individual perceives that MOOCs and e-learning can be a driving force towards attaining learning objectives. They also define perceived ease of use as the extent to which an individual perceives that using learning systems are free of effort. Attitude also defines by Wu and Chen (2017) as the degree to which an individual perceives a positive or negative feeling related to learning systems. Adapt to the study conducted by Harnadi (2017), behavioral intention can be defined as the extent to which a person intends to continue to use learning systems in the future.

On the studies conducted by Widiantoro and Harnadi (2019), Hsu et al., 2018, and Wu and Chen (2017), perceived ease of use has positive direct effect on perceived usefulness. Perceived ease of use also has positive direct effect on attitude (Hsu et al., 2018; Hu et al., 2022; Raza, Qazi, Khan, & Salam, 2021; Widiantoro & Harnadi, 2019). Other studies conducted by Hu et al. (2022), Raza et al. (2021), Hsu et al. (2018), Wu and Chen (2017), and Alraimi et al., (2015) stated that perceived usefulness has positive direct effect on attitude.

Furthermore, perceived usefulness, perceived ease of use, and attitude have positive direct effect on behavioral intention to use learning systems (Raza et al., 2021; Dai et al., 2020; Widiantoro & Harnadi, 2019; Wu & Chen, 2017; Alraimi et al., 2015). Perceived usefulness has direct

Table 1
Previous Research on e-learning technology acceptance.

Model/Theory	Causal effect on BI	Significant variables	Data Collection	Reference
Voluntariness difference in acceptance based on TAM	Attitude	Perceived Ease of Use, Perceive Usefulness, Attitude, BI	Quantitative online survey	Widiantoro and Harnadi (2019)
Smartphone acceptance for learning	Perceive Usefulness	Perceive Usefulness, BI	Quantitative online survey	Prasetya and Harnadi (2019)
Extending ECM	Satisfaction	Information Quality, Self-efficacy, Confirmation, Perceive Usefulness, Satisfaction, BI	Quantitative online survey	Prasetya et al. (2021)
Satisfaction and continued intention based on ECM	Satisfaction	Confirmation, Perceive Usefulness, Satisfaction, System Quality, Service Quality, BI	Quantitative online survey	Prasetya, Harnadi, Widiantoro, and Pamudji (2022)
E-learning intention of students with anxiety	Attitude	Perceive Usefulness, Perceived Ease of Use, Attitude, BI	Quantitative online survey	Hu et al. (2022)
Empirical assessment of the factors that influence instructors to use E-learning	Satisfaction, Self-efficacy	Satisfaction, Self-efficacy, Resistance to Use, BI	Quantitative online survey	Alharthi et al. (2017)
E-learning intention material using TAM	Perceive Usefulness, Academic Motivation	Self-efficacy, Knowledge Quality, Perceive Usefulness, Perceived Ease of Use, Technology Fit, Academic Motivation, BI.	Quantitative online survey	Alassafi, (2022)
E-learning intention material using ECM	Self-efficacy Satisfaction	Self-efficacy, Information Quality, Confirmation, Perceived Usefulness, Satisfaction, System Quality, BI	Quantitative online survey	Widiantoro, et al. (2022)

effect on behavioral intention to use learning systems (Lee et al., 2023; Rekha et al., 2023; Raza et al., 2021; Al-Adwan, 2020; Alraimi et al., 2015). Perceived ease of use has direct effect on behavioral intention to use learning systems (Raza et al., 2021; Alraimi et al., 2015). Furthermore, attitude is prominent variable on TAM and it is a significant determinant on behavioral intention in using learning systems (Dai et al., 2020; Widiantoro & Harnadi, 2019; Hsu et al., 2018; Wu & Chen, 2017).

Information Quality is significant factor on study of e-learning systems. Information and system quality are a prominent variables of information system quality (Lee et al., 2023). Mulhem (2020) and Alharthi et al. (2017) conducted research on e-learning quality and stated that Information Quality has positive direct effect on Perceived ease of use. Information Quality has also positive direct effect on Perceived usefulness (Mulhem, 2020).

According to these reviews, authors propose the hypotheses.

H1. Information Quality has positive direct effect on Perceived ease of use

H2. Information Quality has positive direct effect on Perceived usefulness

H3. Perceived ease of use has positive direct effect on Perceived usefulness

H4. Perceived ease of use has positive direct effect on Attitude

H5. Perceived usefulness has positive direct effect on Attitude

H6. Attitude has positive direct effect on Behavioral Intention

H7. Perceived usefulness has positive direct effect on Behavioral Intention

2.2. *Perceived usefulness, confirmation, satisfaction, and behavioral intention*

ECM is interesting model on user adoption of learning system. Several researchers conducted study in this context using ECM model (Harnadi et al., 2022b; Prasetya et al., 2021, 2022; Hadji & Degoulet, 2016; Kumar & Natarajan, 2020; Alam et al., 2022; Shiau, Yuan, Pu, Ray, & Chen, 2020). The studies on the user acceptance to use learning systems (Alam et al., 2022; Hadji & Degoulet, 2016; Kumar & Natarajan, 2020; Lee et al., 2023; Prasetya and Harnadi, 2019; Prasetya et al., 2021; Prasetya et al., 2022; Rekha et al., 2023; Harnadi, Widiantoro, & Prasetya, 2022a; Shiau et al., 2020) state that confirmation has positive direct effect on satisfaction. Confirmation also has positive direct effect on perceived usefulness (Harnadi et al., 2022b; Rekha et al., 2023; Shiau et al., 2020). Furthermore, perceived usefulness has positive direct effect on Satisfaction (Alam et al., 2022; Hadji & Degoulet, 2016; Kumar & Natarajan, 2020; Lee et al., 2023; Prasetya et al., 2021; Rekha et al., 2023; Shiau et al., 2020) and satisfaction has positive direct effect on behavioral intention (Alam et al., 2022; Hadji & Degoulet, 2016; Kumar & Natarajan, 2020; Lee et al., 2023; Prasetya and Harnadi, 2019; Prasetya et al., 2021; Prasetya et al., 2022; Rekha et al., 2023; Harnadi et al., 2022b).

According to these reviews, authors propose the hypotheses.

H8. Confirmation has positive direct effect on Perceived usefulness

H9. Perceived usefulness has positive direct effect on Satisfaction

H10. Confirmation has positive direct effect on Satisfaction

H11. Satisfaction has positive direct effect on Behavioral Intention

2.3. *Self-efficacy, perceived ease of use, confirmation, and satisfaction*

Harnadi, Widiantoro, and Prasetya (2022) and Prasetya et al. (2021) define self-efficacy as the individual's believe in their ability to access academic content of learning systems. Self-efficacy is the prominent variable on the study of user intention to use learning systems. Self-efficacy has positive direct effect on perceived ease of use (Al-Adwan, 2020; Alassafi, 2022). According to Harnadi, Widiantoro, and Prasetya (2022) and Prasetya et al. (2021), self-efficacy also has positive direct effect on satisfaction. Other researchers (Shiau et al., 2020); Shiau et al. (2020); Harnadi et al. (2020b) also stated that self-efficacy also has positive direct effect on confirmation.

According to these reviews, authors propose the hypotheses.

H12. Self-efficacy has positive direct effect on Perceived Ease of use

H13. Self-efficacy has positive direct effect on Confirmation

H14. Self-efficacy has positive direct effect on Satisfaction

Table 2
Previous Research on MOOC technology acceptance.

Model/Theory	Causal effect on BI	Significant variables	Data Collection	Reference
ECM to predict students' intention to continue online business courses	Satisfaction, Psychological Safety	Task Skill, Perceived Enjoyment, Task Challenge, Satisfaction, Confirmation, Perceived Usefulness, BI	Quantitative online survey	Alam, Mahmud, Hoque, Akter, and Rana (2022)
The drivers and barriers to MOOCs acceptance on TAM based	Perceived Usefulness, Perceived Ease of Use	Self-efficacy, Perceived Usefulness, Perceived Ease of Use, BI	Quantitative online survey	Al-Adwan (2020)
The role of habit on continuance intention among MOOC participants	Attitude, Habit	Habit, Confirmation, Satisfaction, Attitude, Knowledge Quality, Interaction Quality, BI	Quantitative online survey	Dai et al. (2020)
User Acceptance of MOOCs based on ECM	Satisfaction, Perceived Usefulness	Self-efficacy, Satisfaction, Confirmation, Perceived Usefulness, BI	Quantitative online survey	Harnadi et al., (2022b)
Social support theory and TAM on competing platforms MOOCs and E-learning	Attitude	Self-efficacy, Perceived Usefulness, Perceived Ease of Use, Attitide, BI	Quantitative online survey	Hsu et al. (2018)
MOOCs continuance intention with ECM	Satisfaction, Perceived Usefulness, Perceived Enjoyment	Satisfaction, Confirmation, Perceived Usefulness, Perceived Enjoyment, BI	Quantitative online survey	Alraimi et al., (2015)
Quality Factors that influence the continuance intention to use MOOCs	Satisfaction, Perceived Usefulness	Information Quality, Satisfaction, Confirmation, Perceived Usefulness, BI	Quantitative online survey	Lee et al. (2023)
Students' continuance intention to use MOOCs	Self-efficacy, Satisfaction	Self-efficacy, Perceived Usefulness, Satisfaction, Confirmation, Enjoyment, BI	Quantitative online survey	Rekha et al. (2023)
Integrating TAM and task technology fit (TTF) to predict continuance intention to use MOOCs	Perceived Usefulness, Attitude	Perceived Usefulness, Perceived Ease of Use, TTF, Attitude, BI	Quantitative online survey	Wu and Chen (2017)

This study proposes theoretical model on Fig. 1 based on the review of several related literatures.

3. Methodology

This study employs TAM and ECM to reveal the behavioral differences of users in using MOOCs and E-learning. Previous related studies in the technology acceptance especially on MOOCs and E-Learning are reviewed to obtain salient variables and propose hypotheses and model to investigate the behavioral differences towards in using these two learning technologies. The online questionnaires were distributed to MOOCs and e-learning users in Indonesia. The questionnaires were tested first to nine students to get some improvement suggestion. Respondents from high school and university students, employers, and entrepreneurs participated in the study. There are 749 questionnaires collected and 43 of them are dropped for reason of incomplete answers and outliers. Finally, the 706 questionnaires are used as sample data to examine the proposed hypotheses and models. The response rate of collecting data was 94.26% and highly acceptable (Amin, 2022). Firstly, the sample data must pass the internal consistency, reliability, and convergent validity tests on all constructs and items in the model. This process is conducted to ensure the properness of the sample data to be used in the structural model and hypotheses testing. The testing of the model and hypotheses has resulted in the accepting or not the hypotheses. Furthermore, multi-group analysis for MOOCs and E-learning is conducted to examine the difference of acceptance of these two learning technologies. This analysis can reveal the behavioral differences of users in using the technologies and serve the theoretical and practical implication. In addition, the practical implication can be detailed for every significant indicator in the model with IPMA analysis to serve useful insights for learning managers, teachers, and government who have concern in improvement of learning and education in their institutions.

4. Findings and discussion

The finding on respondent's characteristic is presented on Table 3. There are age, gender, education, status, technology used, and user experience in using learning technology. The respondents on Table 3 represent the characteristic of: most of them are student (92.8%) and university student (83.4%); half of them (54.1%) are female, almost half of them (43.1%) are MOOCs users, and half of them (51.8%) have experienced in using learning system for at least one year.

4.1. Measurement model test

The internal consistency of reliability and convergent validity is shown on Table 4 presenting loading factor, ρA, CR, and AVE.

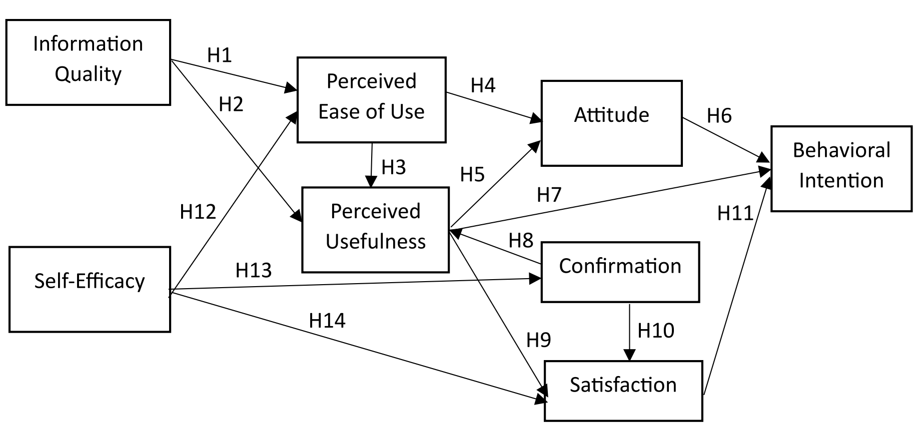

Fig. 1. Proposed theoretical model.

Table 3
Profile of respondents.

Age			Gender			Education		
Age	Frequency	%	Gender	Frequency	%	Education	Frequency	%
16	178	25.2	Male	324	45.9	High School	96	13.6
17	36	5.1	Female	382	54.1	Undergraduate	589	83.4
43	1	0.1				Graduate	21	3.0
47	4	0.6						
48	2	0.3						
52	2	0.3						
53	6	0.8						
54	1	0.1						
56	1	0.1						
Total	706	100.0	Total	706	100.0	Total	706	100.0
Status			Technology used			Experience		
Status	Freq	%	Tech Used	Freq	%	Experience	Freq	%
Student	655	92.8	MOOCs	304	43.1	1 year	366	51.8
Employee	29	4.1	E-learning	402	56.9	2 years	202	28.6
Entrepreneur	22	3.1				3 years	92	13.0
						4 years	9	1.3
						5 years	23	3.3
						6 years	14	2.0
Total	706	100.0	Total	706	100.0	Total	706	100.0

Table 4
Internal consistency reliability and convergent validity.

Construct and Items	Loading	ρA	CR	AVE
Information Quality		0,809	0,884	0,718
InfQty1	0,869			
InfQty2	0,866			
InfQty3	0,805			
Self-efficacy		0,808	0,886	0,722
SE1	0,858			
SE2	0,847			
SE3	0,844			
Perceived Ease of Use		0,840	0,903	0,756
PEOU1	0,869			
PEOU2	0,874			
PEOU3	0,864			
Perceived Useful		0,808	0,885	0,719
PU1	0,858			
PU2	0,878			
PU3	0,805			
Attitude		0,844	0,906	0,762
Att1	0,881			
Att2	0,848			
Att3	0,890			
Confirmation		0,861	0,915	0,781
Conf1	0,870			
Conf2	0,885			
Conf3	0,896			
Satisfaction		0,881	0,927	0,808
Sat1	0,893			
Sat	0,895			
Sat	0,908			
Behavioral Intention		0,879	0,924	0,802
BI1	0,895			
BI2	0,875			
BI3	0,916			

4.2. Structural model and hypotheses testing

The result of structural model and hypotheses testing is presented on Table 6. The structural model and hypotheses are reviewed using several indicators including *β, T value, VIF,* R^2*,* R^2 *Adjusted,* Q^2*, and* f^2 values.

According to Sarstedt, Ringle, and Hair (2021), VIF values are above 3 indicate of collinearity among variables. Table 6 shows most of VIF values are below 3, except for the regression of attitude and behavioral intention (3,219) and satisfaction and behavioral intention (3,504). However, the two VIF values are very close to 3, it is concluded that the collinearity among these variables is not critical issue in the structural model. This is in accordance with Sarstedt et al. (2021).

The f2 is the effect size value of each path model. The value has the criteria of: low for 0.02 and above, medium for 0.15 and above, and large for 0.35 and above. (Hair et al., 2019; Cohen, 1988). Meanwhile, According to Hair, Risher, Sarstedt, and Ringle (2019), Q2 the value at 0, 0.25, and 0.50 express the small, medium, and huge predictive relevance of the path model. Q2 values on Table 4 stated that the path model has a huge predictive relevance.

Furthermore, based on Table 6, the final model for this study is presented on Fig. 1. All of hypotheses on the model are accepted. Information quality has positive direct effect on perceived ease of use ($\beta = 0.394$, $p < 0.001$) and perceived usefulness ($\beta = 0,292$, $p < 0.001$). These results indicate that H1 and H2 are accepted. Perceived ease of use has positive direct effect on perceived usefulness ($\beta = 0.476$, $p < 0.001$) and attitude ($\beta = 0.488$, $p < 0.001$). Therefore, H3 and H4 are accepted. Perceived usefulness has positive direct effect on attitude ($\beta = 0.384$, $p < 0.001$), behavioral intention ($\beta = 0.139$, $p < 0.05$), confirmation ($\beta = 0.478$, $p < 0.001$), and satisfaction ($\beta = 0.188$, $p < 0.001$) indicating H5, H7, H8, and H9 are accepted. Attitude has direct effect on behavioral intention ($\beta = 0.432$, $p < 0.001$), therefore H6 is accepted. Furthermore, confirmation has positive direct effect on satisfaction ($\beta = 0.515$, $p < 0.001$) and satisfaction also has direct effect on behavioral intention ($\beta = 0.285$, $p < 0.001$). This result indicates that H10 and H11 are accepted. Finally, self-efficacy has direct effect on perceived ease of use ($\beta = 0.459$, $p < 0.001$), confirmation ($\beta = 0.351$, $p < 0.001$), and satisfaction ($\beta = 0.276$, $p < 0.001$). These results indicate that H12, H13, and H14 are accepted. Fig. 2 presents the final model.

4.3. Multi group analysis

According to Cheah, Thurasamy, Memon, Chuah, and Ting (2020), multi-group analysis (MGA) is conducted to reveal the heterogeneity on user behavior. Multi-group analysis in this study is employed to analyze the difference of MOOCs and e-learning users in any correlation on the model and the result presents on Table 7. There are the discernible differences (mean values of MOOCs > e-learning) in the correlation between information quality and perceived usefulness, perceived usefulness and attitude, and attitude and behavioral intention. Other result, the correlation of confirmation and satisfaction has also discernible differences with the mean values of e-learning > MOOCs).

Table 5
Discriminant validity
The discriminant validity of latent variable is presented on Table 5 using Fornell-Lacker criterion.

Fornell-Larcker Criterion								
	InfQty	SE	PEOU	PU	ATT	Conf	Sat	BI
Information Quality	0,847							
Self-efficacy	0,659	0,850						
Perceived Ease of Use	0,697	0,719	0,869					
Perceived Useful	0,623	0,673	0,679	0,848				
Attitude	0,735	0,701	0,748	0,715	0,873			
Confirmation	0,695	0,673	0,733	0,714	0,782	0,884		
Satisfaction	0,719	0,749	0,748	0,742	0,814	0,835	0,899	
Behavioral Intention	0,671	0,688	0,677	0,659	0,763	0,693	0,739	0,895

Table 6
Structural model and hypotheses testing.

Relationship	*β*	*T* value	VIF	R^2	R^2 Adjusted	Q^2	f^2
InfQty - > PEOU	0.394	10.400**	1.766	0.605	0.604	0.453	0.223
InfQty - > PU	0.144	3.030**	2.268	0.571	0.570	0.406	0.021
SE - > PEOU	0.459	11.265**	1.766				0.302
SE - > Conf	0.673	27.094**	1.000	0.453	0.452	0.350	0.827
SE - > Sat	0.276	6.880**	2.121	0.777	0.776	0.623	0.161
PEOU - > PU	0.278	5.595**	2.531				0.071
PEOU - > Att	0.487	12.285**	1.855	0.639	0.638	0.483	0.355
PU - > Att	0.384	9.642**	1.855				0.220
PU - > Sat	0.188	5.129**	2.369				0.067
PU - > BI	0.140	3.436**	2.421	0.632	0.630	0.502	0.022
Conf - > PU	0.410	7.980**	2.521				
Conf - > Sat	0.515	14.179**	2.366				0.502
Att - > BI	0.432	8.941**	3.219				0.157
Sat - > BI	0.284	6.100**	3.504				0.063

Note(s): n = 1000 subsample; **p value < 0.01, *p value < 0.05 (one-tailed test).

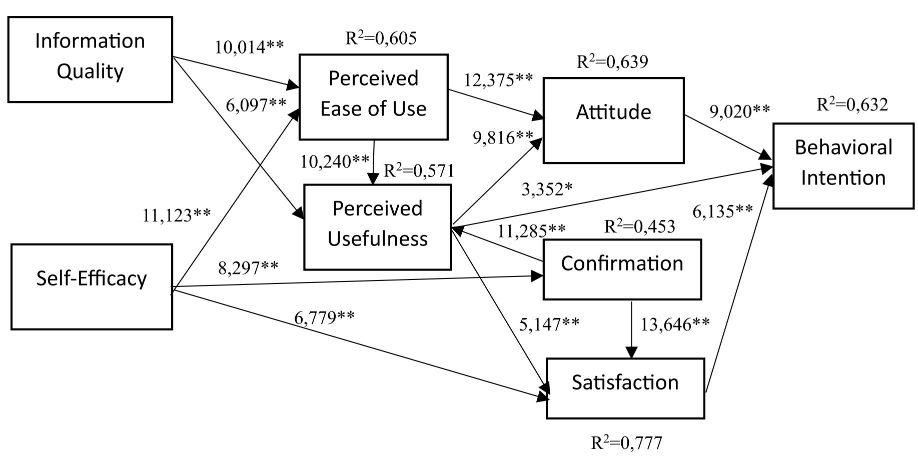

Fig. 2. Final model.

4.4. Structural model and hypotheses testing for MOOCs and E-learning

This study separates the sample data into two user categories, MOOCs and e-learning users and each of them are analyzed using the structural model and hypotheses testing (Table 8). All hypotheses on the MOOCs model are accepted. All hypotheses on the e-learning model are accepted excluding hypothesis H2, self-efficacy has no significant direct effect on perceived usefulness.

The final model of MOOCs model is presented on Fig. 3.

The final model of E-learning model is presented on Fig. 4.

4.5. Importance-performance analysis

According to Ringle and Sarstedt (2016), importance-performance matrix analysis (IPMA) of the model can suggest interesting insights into the role of indicators of construct and their relevance for managerial implications (Ringle & Sarstedt, 2016). The result of importance-performance analysis presents on Table 9. The construct Att2 is more important and has higher performance than Att1 and Att3. The construct Conf3 is more important and has higher performance than conf1 and conf2. The construct PEOU3 is more important than PEOU1 and PEOU2 and PEOU2 have higher performance than PEOU1 and PEOU3. Furthermore, the construct InfQuality1 is more important than InfQuality2 and InfQuality3 and InfQuality2 has higher performance than InfQuality1 and InfQuality3. The construct PU2 is more important than PU1 and PU3 and PU3 has higher performance than PU1 and PU2. The construct SE3 is more important and has higher performance than SE1 and SE2. The last, the construct Sat1 and Sat2 are more important

Table 7
Multi-group analysis for MOOCs and E-learning.

Relationship	*ρ*-value	*Difference value (*MOOCs – E-learning)
InfQty - > PEOU	1.000	
InfQty - > PU	0.002	0.265
SE - > PEOU	*null*	
SE - > Conf	0,145	
SE - > Sat	0,089	
PEOU - > PU	0,919	
PEOU - > Att	0,843	
PU - > Att	0.015	0.178
PU - > Sat	0,249	
PU - > BI	0,435	
Conf - > PU	0,262	
Conf - > Sat	0.986	−0.165
Att - > BI	0.025	0.189
Sat - > BI	0,942	

Table 8
Structural model and hypotheses testing for MOOCs and E-learning.

Relationship	MOOCs			E-learning		
	β	*T* value	R^2	β	*T* value	R^2
InfQty - > PEOU	0.394	10.598*	0.605	0.553	14.350**	0.565
InfQty - > PU	0.144	3.043**	0.571	0.103	3.074**	0.375
SE - > PEOU	0.459	11.529**		0.284	11.128**	
SE - > Conf	0.473	25.725**	0.453	0.396	6.960**	0.490
SE - > Sat	0.276	7.118**	0.777	0.217	4.663**	0.743
PEOU - > PU	0.278	5.263**		0.535	8.797**	
PEOU - > Att	0.487	12.507**	0.639	0.536	10.691**	0.527
PU - > Att	0.384	9.895**		0.262	10.691**	
PU - > Sat	0,188	5.187**		0.154	3.998**	
PU - > BI	0.140	3.485**	0.632	0.129	2.488**	0.516
Conf - > PU	0.410	7.671**		0.410	7.975**	
Conf - > Sat	0.515	13.792**		0.603	13.966**	
Att - > BI	0.432	8.925**		0.306	4.617**	
Sat - > BI	0.284	6.167**		0.362	6.158**	

than Sat3 and Sat2 has higher performance than Sat1 and Sat3.

5. Conclusions

This study reveals the behavioral differences in the acceptance of MOOCs and e-learning. The questionnaires from MOOCs and e-learning users are used to test the proposed model. The proposed model employs fourteen hypotheses and the results on the final model reveal all hypotheses all accepted. The separate analyses on MOOCs and e-learning acceptances and multi-group analysis on the correlation between constructs reveal the difference and no behavioral differences in using MOOCs and e-learning technology. The other interesting results come from the importance performance matrix analysis (IPMA) of the indicators on the model and their relevance for managerial implications.

The theoretical implication of this study is derived from the final model on accepted and no accepted the hypotheses. Firstly, from the findings and discussion section, this study concludes that TAM and ECM can be employed together to predict the acceptance of MOOCs and e-learning in one proposed model. On the TAM stage, perceived usefulness, perceived ease of use, attitude, and behavioral intention is proven the prominent variables on the learning technology, MOOCs, and e-learning acceptances. ECM stage on the final model also has same results, perceived useful, confirmation, satisfaction, and behavioral intention is proven the prominent variables. The effect of self-efficacy on TAM and ECM is presented on the significantly effect of self-efficacy on perceived ease of use, confirmation, and satisfaction. Meanwhile the effect of information quality on perceived ease of use and perceived usefulness is significant for learning technology acceptance (the mix of MOOCs and e-learning), but it has different results on the analyses of MOOCs and e-learning acceptances. The difference of effect is on the significant effect of information quality on perceived usefulness in the MOOCs model and no significant effect on e-learning model. MGA also reveal that the correlation of between information quality and perceived usefulness, perceived usefulness and attitude, confirmation and satisfaction, and attitude and behavioral intention have significant difference results. The correlations of information quality and perceived usefulness, perceived usefulness and attitude, and attitude and behavioral intention have differences in the mean values of MOOCs and they are greater than e-learning. For the correlation of confirmation and satisfaction, the mean value of MOOCs is lower than e-learning.

The practical implications of this study are insights for education institutions as which provide the system to students or users, MOOCs and e-learning developers, teachers and mentors, and others who have concern in gaining MOOCs and e-learning acceptance. Firstly, the result of IPMA on the indicators construct of the model stated that the relevancy to user's needs of the information available on the online learning systems is more important than their easy access and their relevancy with current trends. In the context of performance, the easy access of information is higher than their relevancy to user's need and current trends. The result indicates that teachers and mentors must serve students with the information that relevant to their need and ascertain the information that are ease to access. Secondly, it is more important to make users feel confident in accessing academic content of learning systems than other belief. Thirdly, the feeling of users in clear and easy use of their interaction with the online system is more important than their experience in easily use or become proficient in using online system. On the other hand, becoming proficient in using online system has higher performance than having clear and easy interaction or just feel easy. It indicates that learning system developers must serve users with

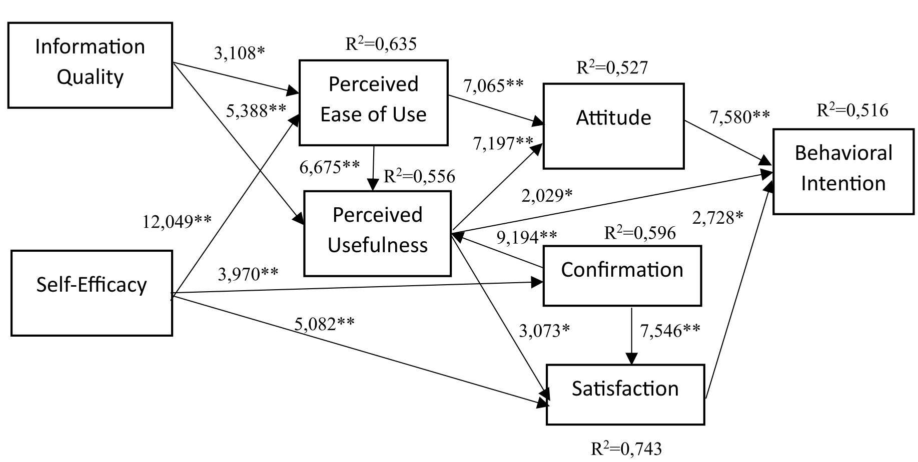

Fig. 3. Final model (MOOCs).

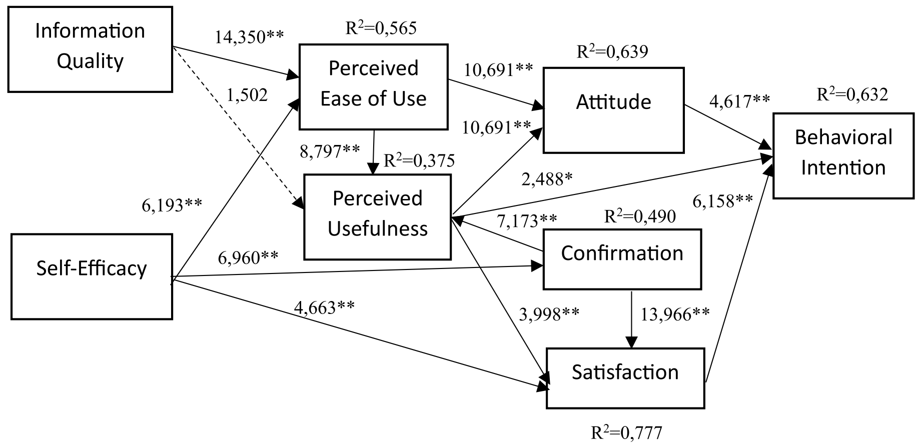

Fig. 4. Final model (E-learning).

Table 9
Importance-performance analysis of behavioral Intention.

Construct - Indicators	Importance	Performance
Attitude	0,436	68,929
Att1	0,143	68,378
Att2	0,148	71,105
Att3	0,145	67,245
Confirmation	0,148	63,859
Conf1	0,049	58,026
Conf2	0,047	65,687
Conf3	0,052	67,741
PEOU	0,395	69,239
PEOU1	0,129	68,520
PEOU2	0,128	69,865
PEOU3	0,138	69,334
InfQuality	0,306	68,750
InfQty1	0,110	61,284
InfQty2	0,104	73,194
InfQty3	0,092	72,627
PU	0,392	67,267
PU1	0,132	65,085
PU2	0,135	68,095
PU3	0,125	68,661
SE	0,324	69,447
SE1	0,100	68,307
SE2	0,109	69,901
SE3	0,115	70,007
Satisfaction	0,292	70,745
Sat1	0,098	69,936
Sat2	0,096	71,494
Sat3	0,098	70,822

clear and easy interaction with the system and teachers and mentors must train users to make them proficient with the system. Fourthly, increasing user's work/study effectiveness as a result of using online learning system is more important than improving their work/study performance or helping them in turning the academic material into knowledge. Furthermore, user's feeling in no difficulty of understanding the academic material and turning it into knowledge has higher performance than increasing user's work/study effectiveness or improving their work/study performance. This result indicates that learning system developers must enhance the system to gain user's work/study effectiveness as outcome in using the system. Teachers and mentors also can serve the users with the good learning material to help them in turning the learning material into knowledge. Fifthly, how to transfer beliefs that using online learning system is a good idea for user's study/work is important This result indicates that online learning developers and teachers and mentors must serve users with many things to evoke positive attitude regarding their experience in using online learning system. Sixthly, the final confirmation of users in their experience in using online learning systems is interesting. The confirmation about their most expectation in using online learning service has been confirmed that it is more important than just their expectations or more. This result indicates that online learning developers and teachers and mentors must know the most expectation and it is confirmed by users or not. Seventhly, it is important to satisfy the users in using online learning system. The feeling on their decision to use the online learning system is the right thing, and it is more important and has higher performance than just they satisfy. This result indicates that online learning developers and teachers and mentors must keep user's decision to use the system by setting the system menu and service better.

CRediT authorship contribution statement

Bernardinus Harnadi: Methodology, Investigation, Formal analysis. **Albertus Dwiyoga Widiantoro:** Validation, Project administration. **F.X. Hendra Prasetya:** Visualization, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: FX. Hendra Prasetya reports article publishing charges was provided by Ministry of Research and Technology National Research and Innovation Agency of Indonesia. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2024.100403.

References

@Statista. (2023). Leading online education services ranked by brand awareness in the United States in 2023. available at: https://www.statista.com/statistics/1343406/most-well-known-online-education-services-in-the-united-states/.

Al-Adwan, A. S. (2020). Investigating the drivers and barriers to MOOCs adoption: The perspective of TAM. *Education and Information Technologies, 25*, 5771–5795. https://doi.org/10.1007/s10639-020-10250-z

Alam, S., Mahmud, I., Hoque, S. M. S., Akter, R., & Rana, S. M. S. (2022). Predicting students' intention to continue business courses on online platforms during the Covid-19: An extended expectation confirmation theory. *International Journal of*

Management in Education, 20(3), Article 100706. https://doi.org/10.1016/j.ijme.2022.100706. ISSN 1472-8117.

Alassafi, M. O. (2022). E-Learning intention material using TAM: A case study. *Materials Today: Proceedings, 61*(Part 3), 873–877. https://doi.org/10.1016/j.matpr.2021.09.457. ISSN 2214-7853.

Alharthi, S. H., Awaji, M. H., & Levy, Y. (2017). Empirical assessment of the factors that influence instructors' usage of E-learning systems in Saudi arabia. In *AMCIS 2017 proceedings* (Vol. 30). https://aisel.aisnet.org/amcis2017/StrategicIT/Presentations/30.

Allen, I. E., & Seaman, J. (2017). *Digital compass learning: Distance education enrollment report 2017*. Babson Survey Research Group. https://files.eric.ed.gov/fulltext/ED580868.pdf.

Alraimi, K. M., Zo, H., Andrew, P., & Ciganek. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education, 80*, 28–38. https://doi.org/10.1016/j.compedu.2014.08.006

Amin, H. (2022). An analysis of online sadaqah acceptance among university graduates in Malaysia. *International Journal of Islamic and Middle Eastern Finance and Management, 15*(6), 1019–1034. https://doi.org/10.1108/IMEFM-01-2019-0020

Cheah, J. H., Thurasamy, R., Memon, M. A., Chuah, F., & Ting, H. (2020). Multigroup analysis using smartpls: Step-by-step guidelines for business research. *Asian Journal of Business Research, 10*(3), I–XIX. https://doi.org/10.14707/ajbr.200087

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). New York: Routledge.

Dai, H. M., Teo, T., & Rappa, N. A. (2020). Understanding continuance intention among MOOC participants: The role of habit and MOOC performance. *Computers in Human Behavior, 112*, Article 106455. https://doi.org/10.1016/j.chb.2020.106455

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Hadji, B., & Degoulet, P. (2016). Information system end-user satisfaction and continuance intention: A unified modeling approach. *Journal of Biomedical Informatics, 61*, 185–193. https://doi.org/10.1016/j.jbi.2016.03.021. ISSN 1532-0464.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Harnadi, B. (2017). An investigation of the adoption of online game technologies in Indonesia. *International Journal of Gaming and Computer-Mediated Simulations, 9*(1), 1–27. https://doi.org/10.4018/IJGCMS.2017010101

Harnadi, B., Widiantoro, A., & Prasetya, F. (2022a). Investigating fintech service adoption using extended-ECM. *SISFORMA, 9*(1), 18–25. https://doi.org/10.24167/sisforma.v9i1.4143

Harnadi, B., Prasetya, F. H., & Widiantoro, A. D. (2022b). Examining user acceptance of MOOCs: The role of openness, task technology fit, and self-efficacy. In *Seventh international conference on informatics and computing (ICIC), denpasar, bali, Indonesia* (pp. 1–6). https://doi.org/10.1109/ICIC56845.2022.10006981

Hsu, J., Chen, C., & Ting, P. (2018). Understanding MOOC continuance: An empirical examination of social support theory. *Interactive Learning Environments, 0*(0), 1–19. https://doi.org/10.1080/10494820.2018.1446990

Hu, X., Zhang, J., He, S., Zhu, R., Shen, S., & Liu, B. (2022). E-learning intention of students with anxiety: Evidence from the first wave of COVID-19 pandemic in China. *Journal of Affective Disorders, 309*, 115–122. https://doi.org/10.1016/j.jad.2022.04.121. ISSN 0165-0327.

Janelli, M. (2018). *E-learning in theory, practice, and research* (Vol. 4). https://doi.org/10.17323/1814-9545-2018-4-81-98

Kumar, K. A., & Natarajan, S. (2020). An extension of the Expectation Confirmation Model (ECM) to study continuance behavior in using e-Health services. *Innovative Marketing, 16*(2), 15–28. https://doi.org/10.21511/im.16(2).2020.02

Lee, J., Song, H.-D., & Kim, Y. (2023). Quality factors that influence the continuance intention to use MOOCs. *European Journal of Psychology Open, 82*(3), 109–119.

Mulhem, A. A. (2020). Investigating the effects of quality factors and organizational factors on university students' satisfaction of e-learning system quality. *Information & Communications Technology in Education, 7*(1). https://doi.org/10.1080/2331186X.2020.1787004

N, A., Kulal, A., M.S, D., & Dinesh, S. (2023). Effectiveness of MOOCs on learning efficiency of students: A perception study. *Journal of Research in Innovative Teaching & Learning*. https://doi.org/10.1108/JRIT-12-2022-0091. ahead-of-print No. ahead-of-print.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460–469. https://doi.org/10.2307/3150499

Prasetya, F. H., & Harnadi, B. (2019). Investigation of adoption of smartphone technology for learning. *ICSEC 2019 - 23rd Int. Comput. Sci. Eng. Conf.*, 251–254. https://doi.org/10.1109/ICSEC47112.2019.8974802

Prasetya, F. H., Harnadi, B., Widiantoro, A. D., & Nugroho, A. C. (2021). Extending ECM with quality factors to investigate continuance intention to use E-learning. In *2021 sixth international conference on informatics and computing (ICIC), jakarta, Indonesia* (pp. 1–7). https://doi.org/10.1109/ICIC54025.2021.9632995

Prasetya, F. H., Harnadi, B., Widiantoro, A. D., & Pamudji, A. K. (2022). Expectation-confirmation model (ECM) to see satisfaction and continued intention of e-learning ("Cyber"). In *2022 6th international conference on information technology (InCIT), nonthaburi, Thailand* (pp. 303–308). https://doi.org/10.1109/InCIT56086.2022.10067619

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021). Social isolation and acceptance of the learning management system (LMS) in the time of COVID-19 pandemic: An expansion of the UTAUT model. *Journal of Educational Computing Research, 59*(2), 183–208. https://doi.org/10.1177/0735633120960421

Rekha, I. S., Shetty, J., & Basri, S. (2023). Students' continuance intention to use MOOCs: Empirical evidence from India. *Education and Information Technologies, 28*, 4265–4286. https://doi.org/10.1007/s10639-022-11308-w

Ringle, C., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems, 116*. https://doi.org/10.1108/IMDS-10-2015-0449

Sarstedt, M., Ringle, C., & Hair, J. (2021). *Partial least squares structural equation modeling.* https://doi.org/10.1007/978-3-319-05542-8_15-2

Shiau, W.-L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding fintech continuance: Perspectives from self-efficacy and ECT-IS theories. *Industrial Management & Data Systems, 120*(9), 1659–1689. https://doi.org/10.1108/IMDS-02-2020-0069

Valverde-Berrocoso, J., Garrido-Arroyo, M.d. C., Burgos-Videla, C., & Morales-Cevallos, M. B. (2020). Trends in educational research about e-learning: A systematic literature review (2009–2018). *Sustainability, 12*, 5153. https://doi.org/10.3390/su12125153

Widiantoro, A. D., & Harnadi, B. (2019). Voluntariness difference in adoption of E-learning technology among university students. In *Icsec 2019 - 23rd international computer science and engineering conference* (pp. 402–408). https://doi.org/10.1109/ICSEC47112.2019.8974819

Widiantoro, A. D., Murniati, C. T., & Hartono, H. (2022). Examining user acceptance and satisfaction of HE's E-learning platform. *World Journal on Educational Technology: Current Issues, 14*(5), 1234–1245. https://doi.org/10.18844/wjet.v14i5.7200

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior, 67*, 221–232. https://doi.org/10.1016/j.chb.2016.10.028. ISSN 0747-5632.

©Global Market Insights. (2023). E-learning market report 2023-2032. available at: https://portals.gminsights.com/gmidrive/sales/Secure/access/SPtlqQ==?leadid=331867.