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MOOCs: The Factors Impacting Learners' Continuance Intention, the Intention to Complete or Cancel a Course

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Abstract. *The growing popularity of massive open online courses (MOOCs), especially during the COVID-19 pandemic, has attracted significant attention from researchers and businesses. Though many studies have investigated what motivates learners' continuance intention, it is no less important to reveal the factors that lead to course completion or cancellation. The aim of this study is to reveal the factors impacting three different e-learning behaviour intentions– continuance intention, the intention to complete, and the intention to cancel MOOCs – by applying the theory of planned behaviour (TPB) and the technology acceptance model (TAM). Based on a survey of 299 respondents, it was revealed that the TAM only explains continuance intention but cannot be fully employed to predict two other e-learning behavior intentions. Also, participants' support and self-efficacy, being a part of the TPB model, had an influence on the intention to complete the course, while they did not affect continuance intention. Only participants' support had a moderate positive impact on the intention to cancel it. Moreover, it was revealed that continuance intention positively impacted the intention to complete and negatively impacted the intention to cancel the course. This expands the body of knowledge about lear-*

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ners' motivations for three different e-learning behaviour intentions and has managerial implications for their development in emerging economies.

Keywords: *massive open online courses, perceived usefulness, perceived enjoyment, perceived ease of use, participants' support, self-efficacy, e-learning behaviour intentions*

1. Introduction

The increasing demand for online professional learning and constantly improving communication technologies created a solid basis for the growth of massive open online courses (MOOCs), which offer opportunities for people to gain, develop or change their professional knowledge and skills (Roller-Wirnsberger et al., 2019; Zhu et al., 2020). MOOCs have become very popular not only among developed countries but also among developing countries, where only Asia-Pacific alone accounts for about 40% market share for MOOC courses (Fact. M. R. Market research report, n. d.). The COVID-19 pandemic further encouraged the growth of these types of courses, as it forced participants in the learning process to rethink the risks associated with contact learning and provided individuals with more time that could be used for learning (Qiu et al., 2020; Chakraborty et al., 2021). Therefore, it is not surprising that contemporary education researchers and practitioners are keen on finding factors that trigger different e-learning behaviour intentions in MOOCs.

Most of the studies in this field have focused on the factors that impact learners' MOOCs continuance intention by employing different modifications of the theory of planned behaviour (TPB), the technology acceptance model (TAM) and the unified theory of acceptance of use of technology (UTAUT) (Lin et al., 2014; Song et al., 2017). Some of the studies have used one theory as a theoretical background – specifically the TAM or TPB (e.g., Bazelais et al., 2018; Samed Al-Adwan, 2020) – while others have employed both (Song et al., 2017; Wang et al., 2020). Based on this, previous research has revealed that specific TAM factors such as perceived enjoyment, perceived usefulness and ease of use are clear predictors of students' continuance intention of MOOCs (Wu & Chen, 2017; Shao, 2018; Tao et al., 2019). Furthermore, some studies have noted that the influence of other course participants in this article measured as participants' support (as an aspect of social norms) and self-efficacy (describing individuals' behavioural control) can predict continuance intention or the intention to complete MOOCs (Hsu et al., 2018; Subramaniam et al., 2019).

Despite the fact that only some individuals complete MOOCs and a significant number drop out, only a few studies have considered the factors that influence individuals' intention to complete or cancel MOOCs (Joo et al., 2018; Li & Moore, 2018). The relationship between these three e-learning behaviour intentions – which can, in fact, be closely connected – has not been analysed at all. Furthermore, studies focusing on the reasons for dropping a course have typically analysed learners' motivations and the elements of the course content that impacted their decision to do so (Liu & Li, 2017).

However, for the successful implementation of MOOCs, it is equally important to disclose the factors that motivate learners to continue studying or complete a course, as well as those that lead to the decision to drop out. Based on this, the aim of the current study is to expand the body of knowledge related to factors that impact continuance intention, the intention to complete or cancel MOOCs by employing the TPB and TAM. First, it analyses three different e-learning behaviour intentions. The existing articles in the literature have each analysed only one e-learning behaviour intention: continuance intention (Wu & Chen, 2017; Shao, 2018), the intention to complete (de Souza & Perry, 2021) or the intention to cancel MOOCs (Aldowah et al., 2020; Dikcius et al., 2021). Second, this study proposes a clear mechanism of how the specific factors of TPB (self-efficacy; participants' support) and TAM (perceived usefulness, perceived ease of use and perceived enjoyment) influence each of the three e-learning behaviour intentions, suggesting that learners' motivations are different (process- versus result-oriented). Lastly, it confirms that there is a relationship between the three different e-learning behaviour intentions.

2. Theoretical Background and Hypotheses

2.1. Theoretical Frameworks for Studying MOOC/e-learning Behaviours

Analysis of previous research confirms that different theoretical frameworks have been used to study MOOC/e-learning behaviour and determine the major factors affecting it. However, different versions of TAM and TPB have been applied most often in this context (Lin et al., 2014; Song et al., 2017; Wu & Chen, 2017).

Since its development, TAM has been often applied to explain technology adoption. This model proposes that an individual's perceptions regarding the ease of use and usefulness of technology condition the general attitude of the person toward its usage as well as behavioural intention to use it. Finally, the attitude and intention to use the technology determine the actual behaviour, whether one accepts or rejects the information technology (Davis, 1989). The extended version of TAM incorporates not only perceived ease of use and perceived usefulness but also perceived enjoyment, describing the degree to which individuals understand the use of technology as enjoyable, pleasant, and interesting (Teo & Noyes, 2011).

TPB contains three major concepts: attitude, subjective norms, and perceived behavioural control. Attitude toward behaviour can be conceptualized as an individual's evaluation of behaviour, while the subjective norm refers to how an individual evaluates the social pressure regarding the performance of behaviour (Ajzen, 1991, p. 188). Perceived behavioural control describes the individuals' perception of the ease or difficulty to perform a certain behaviour (Ajzen, 1991, p. 188). Furthermore, the three mentioned factors predicting behavioural intention can be influenced by indirect determinants named as sets of beliefs (Ajzen, 1985; Lee et al., 2010).

Most of the studies on e-learning have employed only one of these theories to explain students' online learning behaviour (Bazelais et al., 2018; Samed Al-Adwan, 2020). Only a few have analysed this type of behaviour using both frameworks (Lee, 2010; Song et al., 2017; Wang et al., 2020). Furthermore, the majority of these studies have focused on the continuance intention as an initial e-learning behaviour intention (Lee, 2010; Buabeng-Andoh, 2021), although other e-learning behaviour intentions (intention to complete, intention to cancel) are equally important and can be successfully studied using these theoretical frameworks.

In summary, using both the TAM and TPB in one study not only helps to clarify the dispositional (long-term) factors of students' intentions towards e-learning but also includes factors related to specific e-learning situations. Furthermore, it is important to understand that even though the motivation for these three different e-learning behaviour intentions can be explained based on these two theoretical frameworks, it is very different.

2.2. TAM Antecedents of Different E-learning Behaviour Intentions

The TAM and its different extensions are widely used to explore technology adoption in various contexts, including studies online (Bazelais et al., 2018; Samed Al-Adwan, 2020) and more specifically learning behaviour in MOOCs (Wu & Chen, 2017; Joo et al., 2018; Tao et al., 2019). Based on this, this study considers not only the impact of initial TAM factors – perceived usefulness and ease of use (Davis, 1989) – but also perceived enjoyment, which relates to the emotional aspects of MOOCs (Davis et al., 1992; Salloum et al., 2019; Alyoussef, 2021). Furthermore, most studies have analysed the impact of TAM-related variables only on one e-learning behaviour intention, mainly the continuance intention (Safsouf, 2020). This study analyses three different e-learning behaviour intentions and how they are impacted by TAM factors.

In the prior technology acceptance literature, it has been many times revealed that perceived usefulness and ease of use of the targeted system will lead to continuance intention of it (Li & Shi, 2012; Wu & Chen, 2017). MOOCs are also considered a novel technology that could provide individuals with useful content and functions making them easy to use as discussed by Tao et al. (2019) and Alraimi et al. (2015). Furthermore, previous studies have confirmed that intrinsic motivation (i.e., enjoyment, entertainment, fun, and playfulness) has an impact on individuals' intention to apply new systems (Venkatesh et al., 2012). Studies by Tao et al. (2019) and Shao (2018) confirmed that perceived enjoyment significantly affected continuance intention to use MOOCs. Therefore, the following hypotheses were developed:

H1: *Perceived usefulness has a positive impact on MOOCs continuance intention.*

H2: *Perceived ease of use has a positive impact on MOOCs continuance intention.*

H3: *Perceived enjoyment has a positive impact on MOOCs continuance intention.*

Furthermore, the positive impact of perceived usefulness, perceived enjoyment, and perceived ease of use on the intention to complete the course was observed by Tao et al. (2019), these factors were also found to have a positive impact on actual course completion rates (Aharony & Bar-Ilan, 2016; Jung & Lee, 2018). As stated by Tao et al. (2019), MOOCs platforms not only provide useful and innovative approaches to the learning process, but they also have a hedonic purpose. Following this, the more favorable learners perceive the learning system in terms of its usability, ease of use, and enjoyment, the more favorable outcome of the intention to complete the course is expected. Therefore, three additional hypotheses were also developed:

H4: *Perceived usefulness has a direct positive impact on the intention to complete a course.*

H5: *Perceived ease of use has a direct positive impact on the intention to complete a course.*

H6: *Perceived enjoyment has a direct positive impact on the intention to complete a course.*

In terms of course cancellation, Onah et al. (2014) has revealed that specific course related factors, such as course design, its time and course difficulty, are critical to the high student dropout rate of MOOCs. Aldowah et al. (2020) added that the course cancellation behaviour is also impacted by the learner's motivation, skills, and course difficulty. These factors in a way are related to learner's perceptions regarding the course usability, ease of use and enjoyability. The implication of TAM-related factors on course cancellation was explored by Dikcius et al. (2021), who suggested that perceived usefulness, perceived ease of use and perceived enjoyment impact the overall learner's satisfaction, which is then negatively related to the intention to cancel the course. Therefore, it is assumed that perceived usefulness, perceived ease of use and perceived enjoyment, on the contrary, may lead to the desire to complete a course and have a negative impact on the intention to cancel a course. Therefore, the following hypotheses were created:

H7: *Perceived usefulness has a direct negative impact on the intention to cancel a course.*

H8: *Perceived ease of use has a direct negative impact on the intention to cancel a course.*

H9: *Perceived enjoyment has a direct negative impact on the intention to cancel a course.*

2.3. TPB Antecedents of Different E-learning Behaviour Intentions

Previous research has confirmed that the TPB model and, specifically, the factors such as subjective norms and perceived behavioural control, may enhance understanding of students' e-learning behaviour. Therefore, different extensions of the TPB model have been developed to explain educational innovations' adoption intentions (Clutterbuck et al., 2015). Based on the TPB model, students' behaviour can be influenced not only by intrinsic motivation and technology-related factors but also social influence.

Previous research has confirmed that most online courses require the acceptance of the developed competencies by employers or other professionals (Dikcius et al., 2021). This acceptance may impact participants' perception of the course as well as their continuance intention or intention to complete the course (Spiller & Tuten, 2019). Furthermore, it has been confirmed that the opinions of close peers or family members can influence a learner's perceptions of a course and motivation, as well as positive intentions (Wu & Chen, 2017; Hsu et al., 2018) or the decision to cancel a course (Rosé et al., 2014). However, social interaction with other course participants exerts the most significant impact on participants' perceptions of a course, which is related to social norms (Zhang et al., 2016; Wu & Chen, 2017; Hsu et al., 2018). In addition, some studies have reported that poor feedback provided by instructors or other course participants is an important predictor of student dropout in MOOCs (Halawa et al., 2014; Onah et al., 2014). Therefore, the following hypotheses were developed:

H10: *Participants' support has a positive impact on MOOCs continuance intention.*

H11: *Participants' support has a direct positive impact on the intention to complete a course.*

H12: *Participants' support has a direct positive impact on the intention to cancel a course.*

As previously stated, e-learning participants' perceived behavioural control can be also a clear predictor of their continuance intention, the intention to complete or cancel a course (Teo et al., 2019; Maya-Jariego, 2020). However, this study includes self-efficacy, which refers to confidence in one's ability to organise and implement the actions needed to achieve a desired outcome (Bandura, 1997), instead of perceived behavioural control. Several previous studies have presented closely-related definitions of these two constructs (Greenslade & White, 2005; Droms & Craciun, 2014). Furthermore, while it seems that self-efficacy and perceived behavioural control are quite similar, previous research has suggested that self-efficacy is a better predictor of behaviour and intentions (Manstead & Eekelen, 1998; Trafimow et al., 2002; Parkinson et al., 2017).

Self-efficacy has been extensively studied in learning contexts, including online learning. According to the reasoned action approach (Fishbein & Ajzen, 2011) and self-determination theory (Ryan & Deci, 2000), learners' self-efficacy and level of motivation directly impact learning behaviour. Previous studies have confirmed the positive impact of self-efficacy on learners' attitudes, engagement and persistence (Zimmerman, 2000; Tsai et al., 2011; Milligan et al., 2013; Wang & Baker, 2015; Kuo et al., 2021). In addition, Hodges (2016) has revealed that learner self-efficacy can be enhanced in MOOCs through course elements designed to address vicarious experiences and verbal persuasion. A few studies have even found that students who reported high academic self-efficacy at the beginning of a MOOC course were more likely to complete the course (Wang & Baker, 2015). It has also been revealed that self-efficacy has a positive impact on attitude towards MOOCs (Luang-Guang, 2019) and the continuance intention (Shao, 2018). Therefore, it can be presumed that course participants' self-efficacy negatively affects their intention to drop out (Lee et al., 2013). Therefore, the following hypotheses have been developed:

H13: *Self-efficacy has a positive impact on MOOCs continuance intention.*

H14: *Self-efficacy has a direct positive impact on the intention to complete a course.*

H15: *Self-efficacy has a negative impact on the intention to cancel a course.*

2.4. Different E-learning Behaviour Intentions and their Relationships

As previously mentioned, unlike past research, this study analyses three different e-learning behaviour intentions: continuance intention, the intention to complete and the intention to cancel a course. Even though each of these e-learning behaviour intentions has different motivations, there are relationships among them. Previous research reveals that behavioural intention is a strong predictor of practice. Action is unlikely if intention is absent; therefore, intent precedes action (Krueger, 1993).

First, individuals have the intent to try something and then create a mental model of what they want to do (Krueger, 2000). Therefore, it is common to believe that learners who intend to continue studying in MOOCs are also motivated to complete them and, conversely, are not inclined to cancel them. Tao (2009) has confirmed this by stating that the continuance intention using e-learning resources has a positive impact on their usage. Gupta and Maurya (2022) revealed that the intention to adopt MOOCs significantly predicts the intention to complete them. However, to the best of our knowledge, no other studies have proven the relationships indicated in this research. Therefore, the following hypotheses were proposed:

H16: *MOOCs continuance intention has a positive impact on the intention to complete a course.*

H17: *MOOCs continuance intention has a negative impact on the intention to cancel a course.*

3. Method

3.1. Questionnaire Design

The questionnaire included scales that have been used successfully in other studies. Perceived usefulness and perceived ease of use were measured using separate four-item scales, both adapted from Wu and Chen (2017) and Liu and Li (2010). A three-item perceived enjoyment scale was taken from Alraimi et al. (2015). A three-item scale to measure participants' support was taken from Wu and Chen (2017). To measure self-efficacy, a six-item short version scale was adapted from Rigotti et al. (2008). Finally, a three-item 'intention to complete' and a two-item 'intention to cancel' scale were adapted from Shin (2003). Continuance intention was measured using a two-item scale adapted from Alraimi et al. (2015). All statements in the aforementioned scales were assessed through a 7-point Likert-type scale, ranging from totally disagree to totally agree. The detailed information about the scale items used in this study is provided in the Appendix.

3.2. *Participants*

The data for this study were based on a convenience sample collected by the researchers as a part of a larger study in 2019. The study recruited participants from a list of BitDegree clients. BitDegree is an educational platform that supplies a variety of MOOCs for career development purposes in the IT field. The company has more than 70,000 clients from all over the world. To be included in the study, participants had to have taken a MOOC in the last 12 months with the intention to develop their professional skills. Excluding questionnaires with incomplete information or with low variance in answers, in total 299 valid questionnaires from 44 different countries were used for further analysis. Most of the respondents represented emerging economies, where India, followed by Pakistan, Indonesia, and Lithuania formed the largest part. The demographic characteristics of the sample are shown in Table 1. The total sample comprised 65% men and 35% women with average age M = 30 years; SD = 8.3.

Table 1

Socio-demographic Characteristics of the Sample

Variable	Categories	Total sample %
Gender	Female	35.2
	Male	64.8
Education	Unfinished high school	8.6
	High school	46.6
	College or professional school degree	25.3
	Bachelor's or higher degree	19.5
Continent	Europe	8.7
	Asia	60.2
	North America	21.1
	Latin and Central America	2.7
	Africa	3
	Middle East	4.3
Number of open online courses taken over the last 12 months for professional development	1–2	27.4
	3–4	49.2
	5–6	18.1
	7–8	2.3
	9 or more	3

4. Results

4.1. Reliability and Validity Test

Reliability and validity analysis was performed for all items measuring constructs in this study. Confirmatory factor analysis (CFA) utilizing AMOS (v.26) was conducted to determine the psychometric properties of the scales. The initial model was adjusted based on the examination of standardised factor loading and standardised residual covariance (Hair et al., 2010). In response to this, one item was removed from the perceived usefulness scale. Several fit indices such as the Chi-square/degrees of freedom (χ^2/df) test, the Goodness-of-Fit Index (GFI), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA) were employed to assess the final model. It is confirmed that χ^2/df values below 3, GFI, CFI and TLI values above 0.9 (Hair et al., 2010) and RMSEA values below 0.6 represent an adequate model fit (Byrne, 2010). Fit indices of the final model are χ^2/df =1.446 (χ^2 = 391.976, df = 271) $p < 0.001$; GFI = 0.909; CFI = 0.966, TLI = 0.959; RMSEA = 0.039, which indicate a good model fit.

Cronbach's alpha (CA) and composite reliability (CR) scores were applied to evaluate reliability, as shown in Table 2. The CA values of all constructs ranged from 0.75 to 0.90, exceeding the threshold value of 0.7 recommended in the literature (Fornell & Larcker, 1981). All CR estimates also exceeded 0.7 and ranged from 0.75 to 0.90. The mentioned values confirm high construct reliability. The average variance extracted (AVE) and the factor loadings of all indicators were examined to assess the convergent validity. The factor loadings were generated using confirmatory factor analysis (CFA). The AVE values ranged from 0.50 to 0.82, exceeding the recommended threshold value of 0.5 (Fornell & Larcker, 1981). A comparison of the square root of the AVE values for each construct with the inter-construct correlation estimates helped to confirm the discriminant validity (Fornell & Larcker, 1981). The values of the square roots of the AVE that are greater than the other values of the inter-construct correlation are indicated and highlighted in bold in Table 2. This suggests the presence of discriminant validity. In summary, the presented results show that the measurement model has good psychometric properties.

4.2. Testing of the Hypothesised Structural Model

Correlation analysis was implemented to develop hypothesised models for further path analyses. The correlation coefficients, means and standard deviations (SD) of key variables are presented in Table 3. Correlation analysis confirmed that variables had significant correlations with other variables (except intention to cancel and perceived enjoyment; $r = -0.025$, $p > 0.05$). Coefficients of correlation varied from $r = -0.155$ to $r = 0.576$, $p < 0.01$.

Table 2
Index Values of Reliability and Validity Measurement

	CA	CR	AVE	Intention to com-plete	Perceived usefulness	Perceived ease of use	Perceived enjoyment	Participants' support	Self- effi-cacy	Continu-ance intention	Intention to cancel
Intention to complete	0.763	0.762	0.517	**0.719**							
Perceived usefulness	0.762	0.763	0.518	0.659	**0.719**						
Perceived ease of use	0.818	0.818	0.529	0.706	0.687	0.727					
Perceived enjoyment	0.766	0.766	0.522	0.629	0.686	0.681	**0.722**				
Participants' support	0.75	0.752	0.503	0.415	0.388	0.330	0.567	**0.709**			
Self-efficacy	0.87	0.871	0.530	0.718	0.684	0.701	0.609	0.316	**0.728**		
Continuance intention	0.803	0.804	0.672	0.719	0.716	0.640	0.609	0.209	0.590	**0.820**	
Intention to cancel	0.904	0.904	0.825	-0.259	-0.245	-0.178	-0.037	0.328	-0.194	-0.337	**0.909**

Table 3

Descriptive Statistics and Correlations among Observed Variables

	Mean	SD	Perceived usefulness	Perceived ease of use	Perceived enjoyment	Participants' support	Self-efficacy	Intention to cancel	Intention to complete
Perceived usefulness	5.34	0.99	--						
Perceived ease of use	5.28	1.00	0.542**	--					
Perceived Enjoyment	5.20	1.04	0.523**	0.536**	--				
Participants' Support	4.97	1.21	0.303**	0.265**	0.438**	--			
Self-Efficacy	5.25	1.00	0.550**	0.597**	0.492**	0.261**	--		
Intention to cancel	3.77	1.85	-0.201**	-0.155**	-0.025	0.260**	-0.166**	--	
Intention to complete	5.30	1.01	0.496**	0.553**	0.475**	0.329**	0.576**	-0.193**	--
Continuance intention	5.30	1.16	0.568**	0.517**	0.478**	0.173**	0.488**	-0.282**	0.556**

Note. N=299; **$p<0.01$.

Path analysis, which is a specific case of SEM in which all variables are observed, and no latent variables are estimated (Diamantopoulos & Siguaw, 2011), was employed to test the hypotheses. IBM SPSS AMOS 26 was used for testing the relationships (see Figure 1). Next, the statistical significance of each structural path was assessed for testing the hypotheses. The non-significant paths were omitted to create the optimal mediation model. For the evaluation of direct and indirect effects, 5,000 bootstrapped samples were used, and two-tailed significances with bias corrections were presented in this analysis.

The model fit indexes proved a good initial model fit to the data set, with $\chi2 = 3.80$, df = 1, $\chi2/df = 3.80$ ($p=0.051$), GFI = 0.997, CFI = 0.997, TLI = 0.911 and RMSEA = 0.097, 90% CI [0.000, 0.208]. The RMSEA result is slightly above the expected value 0.6, but this could be due to the model complexity. Some previous studies reported that it could be positively biased because of RMSEA dependence on sample size and degrees of freedom (Hooper et al., 2007). Therefore RMSEA could be expected to be higher for this model due to relatively few degrees of freedom.

Table 4 presents the initial model with parameter estimates and significance. Only some of the pathways in the model were significant, while others showed no impact. Participants' support ($b = -0.09$, $p = 0.069$) had an insignificant effect on MOOCs continuance intention. Two variables – perceived usefulness ($b = 0.039$ $p = 0.495$) and perceived enjoyment ($b = 0.041$, $p = 0.468$) – had no direct impact on the intention to complete MOOCs. In addition, perceived ease of use ($b = -0.041$, $p = 0.569$), perceived enjoyment ($b = 0.071$, $p = 0.316$) and self-efficacy ($b = -0.07$, $p = 0.316$) had no statistically significant direct impact on the intention to cancel MOOCs.

Table 4

Summary of Parameter Estimates of the Initial Model

		Estimate	S.E.	Standardised Estimate	Z	P
Perceived usefulness-->	Continuance intention	0.381	0.068	0.327	5.623	<0.001
Perceived ease of use-->	Continuance intention	0.218	0.07	0.189	3.136	0.002
Perceived enjoyment-->	Continuance intention	0.202	0.066	0.182	3.068	0.002
Participants' support-->	Continuance intention	-0.086	0.047	-0.09	-1.816	0.069
Self-efficacy-->	Continuance intention	0.151	0.069	0.13	2.186	0.029
Perceived usefulness-->	Intention to complete	0.04	0.059	0.039	0.682	0.495

		Estimate	S.E.	Standardised Estimate	Z	P
Perceived ease of use-->	Intention to complete	0.18	0.058	0.178	3.091	0.002
Perceived enjoyment-->	Intention to complete	0.04	0.055	0.041	0.726	0.468
Participants' support-->	Intention to complete	0.115	0.039	0.138	2.941	0.003
Self-efficacy-->	Intention to complete	0.264	0.057	0.26	4.613	<0.001
Continuance intention-->	Intention to complete	0.237	0.048	0.271	4.972	<0.001
Perceived usefulness-->	Intention to cancel	-0.273	0.133	-0.146	-2.047	0.041
Perceived ease of use-->	Intention to cancel	-0.075	0.133	-0.041	-0.569	0.569
Perceived enjoyment-->	Intention to cancel	0.126	0.125	0.071	1.003	0.316
Participants' support-->	Intention to cancel	0.525	0.089	0.344	5.91	<0.001
Self-efficacy-->	Intention to cancel	-0.131	0.13	-0.07	-1.002	0.316
Continuance intention-->	Intention to cancel	-0.379	0.109	-0.237	-3.492	<0.001

Due to the lack of direct impact, these pathways were excluded from the model. The modified model fits the data better than the initial model since all fit indices met the criteria. It showed a great fit: $\chi^2 = 10.584$, df = 7, $\chi^2/df = 1.512$ ($p = 0.158$), GFI = 0.991, CFI = 0.996, TLI = 0.984 and RMSEA = 0.041, 90% CI [0.000, 0.089]. Figure 1 presents the final model with the significant paths and standardised parameter estimates. The final model shows that all the path coefficients were statistically significant. In addition, compared with the initial model, the final model was more parsimonious. According to Kelloway (1998), if two competing models have similar results, the parsimonious model should be adopted. Therefore, Model 2 was adopted in this study.

The significance of the mediating effects was tested using the bootstrap estimation procedure in AMOS (a bootstrap sample of 5,000 was specified; Preacher et al., 2007). The results of path analysis showed the significant direct positive effects of perceived usefulness ($b = 0.318$, $p < 0.001$), perceived ease of use ($b = 0.189$, $p < 0.05$) and perceived enjoyment ($b = 0.148$, $p < 0.05$) on the MOOCs continuance intention (see Table 5). Thus, the results confirm H1, H2 and H3 and fully correspond to the extended TAM.

Figure 1

Research Model

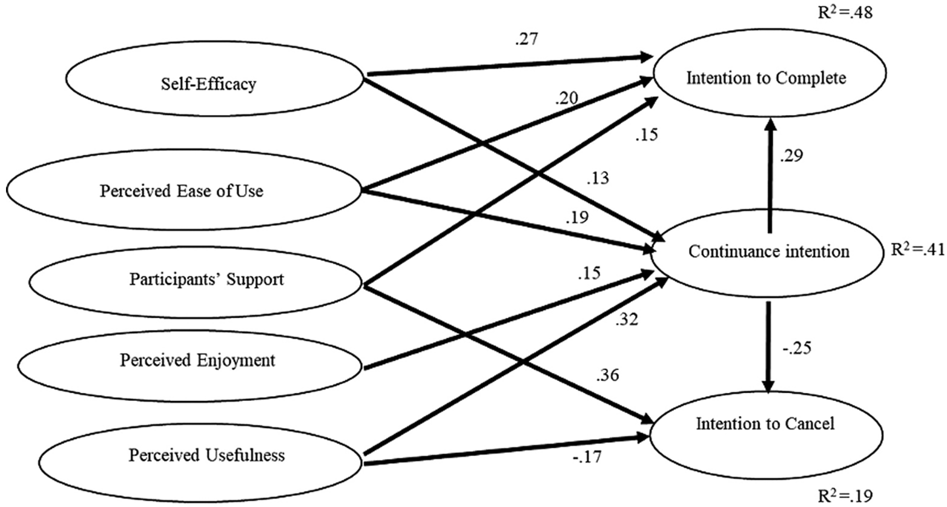

Table 5

Summary of Parameter Estimates and Hypotheses Testing Based on Two-tailed Significance with Bias Corrections (Total, Direct and Indirect Effects)

	Standardised Total Effects			**Standardised Direct Effects**			**Standardised Indirect Effects**	
	Continuance intention	Intention to cancel	Intention to complete	Continuance intention	Intention to cancel	Intention to complete	Intention to cancel	Intention to complete
Perceived usefulness	0.318***	-0.247***	0.093[a]	0.318***	-0.168*		-0.08*	0.093*
Perceived ease of use	0.189*	-0.047*	0.251**	0.189*		0.196**	-0.047*	0.055*
Perceived enjoyment	0.148*	-0.037*	0.043[a]	0.148*			-0.037*	0.043*
Participants' support	0	0.356***	0.154**		0.356***	0.154**	0	0
Self-efficacy	0.127	0.032	0.312**	0.127		0.275**	-0.032	0.037
Continuance intention	0	-0.25***	0.292***		-0.25***	0.292***	0	0

Note. ***p<0.001; **p<0.01; *p<0.05; [a] – impact is based on standardized indirect effect.

However, the TAM cannot fully explain the intention to cancel or complete a course. Only perceived ease of use had statistically significant direct ($b = 0.196$, $p < 0.01$) and indirect ($b = 0.055$, $p < 0.05$) impacts on the intention to complete MOOCs, allowing us to confirm H5. Two other elements of the extended TAM – perceived usefulness ($b = 0.093$, $p < 0.05$) and perceived enjoyment ($b = 0.043$, $p < 0.05$) – only had an indirect positive impact on the intention to complete the course, while the direct effect of these variables was statistically insignificant (perceived usefulness, $b = 0.039$, $p=0.495$; perceived enjoyment, $b = 0.041$, $p = 0.468$) (see Table 4). Due to this, H4 and H6 were rejected.

Only perceived usefulness had a direct impact ($b = -0.168$, $p < 0.05$) on the intention to cancel, as well as an indirect impact, partly mediated by continuance intention ($b = -0.08$, $p < 0.05$). Two other variables in the extended TAM had only an indirect impact on the intention to cancel MOOCs: perceived ease of use ($b = -0.047$, $p < 0.05$) and perceived enjoyment ($b = -0.037$, $p < 0.05$). Based on these findings, H7 was accepted, while H8 and H9 were rejected.

In terms of the TPB model, neither participants' support ($b = -0.09$, $p = 0.069$, see Table 4) nor self-efficacy ($b = 0.127$, $p > 0.05$) had an impact on MOOCs continuance intention, which caused us to reject H10 and H13. Meanwhile, self-efficacy had the strongest direct positive ($b = 0.275$, $p < 0.01$) effect on the intention to complete followed by participants' support ($b = 0.154$, $p < 0.01$). Hence H11 and H14 were confirmed. The factor to have the strongest and only direct impact on the intention to cancel was participants' support ($b = 0.356$, $p < 0.001$), while self-efficacy had neither a direct ($b=0.032$, $p>0.05$) nor an indirect impact ($b = -0.032$, $p > 0.05$) on the intention to cancel MOOCs. Therefore, H12 was confirmed, and H15 was rejected.

Finally, the intention to complete the course was directly positively influenced by continuance intention ($b = 0.292$, $p < 0.001$). Meanwhile, a direct negative impact of continuance intention on the intention to cancel MOOCs ($b = -0.25$, $p < 0.001$) was observed. These findings allowed us to confirm H16 and H17.

5. Discussion and Conclusions

The most general objective of the current study was to contribute to the body of knowledge regarding the factors that impact three different e-learning behaviour intentions in MOOCs – specifically the continuance intention, the intention to complete or cancel a course – by employing the TPB and TAM. Moreover, this investigation addresses gaps in the literature on the relationship between three different e-learning behaviour intentions. In addition, it should be stressed that most of the respondents in this study represented emerging economies, therefore the findings clearly represent the specifics of these countries. Based on this, several key conclusions are proposed.

First, the results confirm that the TAM can only clearly explain the learner continuance intention of MOOCs. Perceived usefulness had the strongest influence, followed by perceived ease of use and perceived enjoyment. These results are consistent with the results of previous studies (Alraimi et al., 2015; Shao, 2018; Tao et al., 2019). Contrary to our presumptions, the TAM could not explain the two-remaining e-learning behaviour intentions: the intention to complete and the intention to cancel a course. Perceived ease of use was the only TAM factor that had a direct positive impact on the intention to complete, while perceived usefulness was observed to have a negative direct impact on the intention to cancel MOOCs. This is not entirely consistent with existing literature, which has suggested that all three extended TAM factors lead to the intention to complete MOOCs (Aharony & Bar-Ilan, 2016; Jung & Lee, 2018), with the intention to cancel being negatively impacted by perceived ease of use, perceived usefulness (Goopio & Cheung, 2021) and perceived enjoyment (El Said, 2017). However, this can be explained by the fact that, in this study, three different e-learning behaviour intentions were analysed. No previous study has investigated all three intentions.

Interestingly, additional calculations on the indirect effects of the factors of the TAM on the intention to complete and the intention to cancel a course showed more promising results. Perceived ease of use had not only a direct impact on the intention to complete MOOCs but also an indirect impact, mediated by continuance intention. The indirect positive effects of perceived usefulness and perceived enjoyment on the intention to complete MOOCs were also confirmed. In the case of the intention to cancel, perceived usefulness had both a direct negative impact and an indirect negative impact, partly mediated by continuance intention. The indirect negative effect of perceived enjoyment and perceived ease of use were also revealed. These results suggest that respondents possibly linked continuance intention to their attitude about MOOCs because they were asked about their general MOOCs continuance intention in the questionnaire. Based on this assumption, continuance intention may represent attitude in the TAM.

Second, analysis of TPB factors, specifically participants' support and self-efficacy, also showed rather surprising results. Although it was hypothesised that these factors would have an effect, they had no impact on continuance intention, and only participants' support had a moderate positive impact on the intention to cancel MOOCs. Meanwhile, both factors had an impact on the intention to complete MOOCs; self-efficacy was revealed to be the strongest predictor. This is only partially consistent with previous studies. Shao (2018) suggested that self-efficacy influences continuance intention; however, this study does not confirm that. Nevertheless, the results of this study are consistent with previous research stating that self-efficacy positively impacts the intention to complete a course (Wang & Baker, 2015). The fact that self-efficacy has no effect on the intention to cancel MOOCs has not been confirmed unanimously by previous studies, either (Lee et al., 2013; Wang & Baker, 2015). In terms of participants' support, this study agreed with the results of previous studies that other course participants and interaction with them may impact the decision to cancel a course (Rosé et al., 2014; Goel & Goyal, 2020). According to Rosé et al. (2014), if course participants begin to see others in their course leaving, they may find the environment less supportive and engaging and may be more likely to drop out the course. The positive impact of participants' support on the intention to complete the course was also confirmed, concurring with previous research (Brooks et al., 2015).

Third, despite the fact that some of the obtained results were rather unexpected, they help to address the existing gap in the literature and suggest that the motivations for the three e-learning behaviour intentions may be different when they are analysed together. Continuance intention was driven by perceived usefulness, ease of use and enjoyment, allowing us to presume that, in this case, learners' motivation is process-oriented. Not only are the applicability and usefulness of the course important, but participation in the course should be accompanied by enjoyment and perceived ease of use, which strengthen the desire to be a part of the learning process. If the learner has a sufficient internal motivation, the influence of other individuals, including other course participants or close peers, does not impact it significantly. Meanwhile, the intention to complete it was impacted by perceived ease of use, self-efficacy and participants' support, prompting the idea that, in this respect, learners are more result-oriented. They are likely strongly motivated to obtain a certificate confirming their attendance in the course. Furthermore, the opinions of others play an important role; the learning process itself is not so important. Finally, the intention to cancel MOOCs was negatively impacted by perceived usefulness but positively by participants' support, suggesting mixed motivations of the two aforementioned e-learning behaviour intentions.

Lastly, the study results led us to conclude that the three analysed e-learning behaviour intentions are interrelated, meaning that continuance intention positively impacts the intention to complete a course and negatively impacts the intention to cancel it. This can additionally confirm the results of previous studies that individuals' intention may be a strong predictor of actual behaviour (Krueger, 1993, 2000; Tao, 2009). However, as previously stated, continuance intention may also have been evaluated by the respondents as an attitude. This supports previous research stating that attitudes may lead to behavioural intentions and actual behaviour. Since this type of influence has been tested for the first time in the context of MOOCs, these findings may cause speculation and outline promising directions for future research.

In summary, it can be said that motivation for three different e-learning behaviour intentions is different when analysing them together, which requires using two theoretical frameworks, more specifically TPB and TAM, for their better understanding. This can be explained by the fact that the e-learning process is not entirely focused on the use of technology but at the same time, it includes social influence and intrinsic motivation to do so. Finally, the analysed e-learning behavioural intentions are affected by each other, where understanding one behavioural intention leads to a better understating of another, and as a result, this helps in more effective planning of MOOCs.

6. Managerial Implications

The obtained results suggest concrete managerial implications regarding the ways to increase learners' motivation to continue, complete and not drop MOOCs. To increase learners' continuance intention, it is important to convince them of the usefulness of the course and applicability in practice. Therefore, course developers should communicate the value of the course regarding professional development and employer recognition through professional certification or references to well-known educational establishments. It is no less important to make the process of learning enjoyable. This can be done using gamification elements and the inclusion of innovative learning methods and tasks. Furthermore, the results of the study show that, for the completion of the course, perceived ease of use, self-efficacy and participants' influence play important roles. Therefore, when developing e-learning courses, companies should consider that the studying process, including different tasks, should be challenging but at the same time possible to accomplish. This can be done using different innovative learning methods, such as providing learning tips simplifying the study process and technical functionalities allowing interaction between e-learning participants. Elements of gamification can be considered to provide a great opportunity for learners' interactivity.

Lastly, to avoid participants dropping out of the course it is important to ensure that the course is relevant and can be useful in practice. By completing the course, the student can develop the skills required to be competitive in the market. Furthermore, no less important is participants' influence, which can be addressed via technical course functionalities allowing participants to interact with each other and share feedback.

7. Limitations and Future Research

While we believe that this research has provided important new knowledge regarding online learning, some limitations and future directions should be acknowledged as well. First, the actual participants of the specific career development course were included in this study; thus, the sample was limited to the number and type of this online course participants. Furthermore, respondents of this research involved individuals with similar career orientations (IT specialists) so the results might differ among participants in a course with different content. Therefore, future studies may seek to involve participants from courses on various topics and career aspirations. Second, this study included self-efficacy as a construct similar to perceived behavioural control. However, future studies may test if perceived behavioural control impacts the different e-learning behaviour intentions similarly. Furthermore, the results of this study showed that participants' support negatively influenced the intention to cancel the course, which was rather surprising. Therefore, future studies may seek to further analyse this relationship. Moreover, in this study, the selected variables explained only 20% of the intention to cancel the course, meaning that there are other factors that can better explain the intention to cancel it and should be further explored in the future.

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Appendix
Scale Items

Scales	Items
Perceived usefulness Source: Adapted from Wu and Chen (2017), Liu and Li (2010).	I believe MOOCs improve my learning performance. Using MOOCs will enhance my learning effectiveness. Using MOOCs will help me in the long run. Using MOOCs will contribute to my personal success in the future.
Perceived ease of use Source: Adapted from Wu and Chen (2017), Liu and Li (2010).	Learning to use MOOCs is easy. It is easy to become proficient in using MOOCs. The interaction with MOOCs is clear and understandable. I think that generally, MOOCs use is simple.
Perceived enjoyment Source: Alraimi et al. (2015).	Using open online courses is pleasurable. I think using open online courses has to be fun. I find using open online courses to be enjoyable.
Participant's support Source: Wu and Chen (2017).	Other participants' beliefs about open online courses encourage me to use them. Other participants' beliefs about open online courses influence my degree of usage of them. Other participants' beliefs about open online courses condition me to use them.
Self-efficacy Source: Adapted from Rigotti et al. (2008).	I can remain calm when facing difficulties in my job because I can rely on my abilities. Whatever comes my way in my job, I can usually handle it. My past experiences in my job have prepared me well for my professional future. I meet the goals that I set for myself in my job. I feel prepared for most of the demands in my job. When I am confronted with a problem in my job, I can usually find several solutions.
Intention to complete Source: Adapted from Shin (2003).	Finishing MOOCs is important to me. I am confident that I can overcome the obstacles encountered in the MOOCs. I will finish MOOCs no matter how difficult it may be.
Intention to cancel Source: Adapted from Shin (2003).	I am not likely to continue studying in MOOCs. I would like to quit MOOCs I am currently enrolled in.
Continuance intention Source: Adapted from Alraimi et al. (2015).	I will want to use (or continue using) MOOCs in the future. I will certainly enroll in for another MOOCs.