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Examining the Perceived Consequences and Usage of MOOCs on Learning Effectiveness

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Abstract
Massive Open Online Courses (MOOCs) have recently received a great deal of attention from the academic communities. However, these courses face low completion rates and there are very limited research pertaining to this problem. Therefore, this study uses Triandis theory to better understand variables that are indicative of MOOC completion. Furthermore, this study scrutinizes the quantitative relationship between MOOC usage and learning effectiveness. Two hundred and thirty-four users from selected Coursera participated in this study to evaluate the proposed model. The partial least squares (PLS) were used to analyze the collected data and test the research hypotheses. The results indicated that perceived consequences (including knowledge growth, social interaction, and compatibility) and affect have a significant impact on intention to use MOOC. In contrast, social factors delineated the insignificant effects on intention to use MOOC. The findings indicated that facilitative conditions and intentions to use MOOC have a strong and positive impact on the actual use of MOOC. Hypotheses regarding the influence of perceived consequences and the actual usage of MOOC on learning effectiveness were upheld.

Keywords
MOOCs, Dropout rate, Completion rate, Triandis theory, Learning effectiveness.

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1. Introduction

In the past several months, Massive Online Open Courses (MOOCs) have emerged as a dominant constituent of lifelong and distance learning technology. MOOCs are defined as online courses without any prerequisites other than Internet access and interest, no participation limit, and free of charge (Aparicio, Oliveira, Bacao, & Painho, 2019). Using the contemporary growth in the development and advancement of educational sources equally in industry and academia, MOOCs have quickly transferred into a position of dominance in the scholarly publications, in the minds of the public, and in the mass media. This new advancement will precipitate the vision of having fair access to lifetime learning possibilities within functional reach. MOOCs present several useful learning activities to learners, including readings, video clip lectures, assignments, and assessments. It provides opportunities for learners to form connection and collaboration with each other via threaded community discussion forums and other Web 2.0 technologies. Goel, Sabitha, Choudhury, & Mehta (2019) expressed that tens of thousands encouraged learners all over the world who cannot attend elite institutions have been discovering the MOOCs, without spending college tuition or obtaining a college degree, to be on a path towards advanced expertise and high-paying careers. MOOCs have experienced an extraordinary capability to attract many more motivated learners to the online learning community. The participants have rapidly grown from a small number of learners to quite a large number of learners with the classes getting primary registrations of > 150K participants. The MOOCs have attracted students and learners from 100 to 200 countries at the same time and they easily go beyond national boundaries. Ma and Lee (2019) postulated that the MOOCs possess a couple of basic distinctions from prior educational technologies. First, MOOCs can be found anytime/anywhere within small devices that enable learners to learn simply and under a multitude of places, situations, and times (ubiquitous or mobility learning). Second, the MOOCS are socially active virtual communities of participants who support other learners' learning, resolve questions, and add additional materials and knowledge to the class.

Despite the worldwide enthusiastic interestof learners, educational institutions, and professional individuals in MOOCs, there are several challenges against MOOC. The first challenge is that developing, updating, and delivering online classes are undertaking intensive resources (Siemens, 2019). However, the MOOCs have yet to obtain a sustainable and worthwhile revenue model. Concerns remain around the activity and growth of MOOC until a revenue model is established (Reich & Ruipérez-Valiente, 2019). The second challenge is that some top universities in Germany, such as Berlin, Munich, and Freiburg have started accepting some presented courses on Udacity─MOOCs in their regular curricula (Berman et al., 2017). Subsequently, the MOOCs are progressively challenging long-established teaching institutions and methods (Siemens, 2015). The third challenge, which is the focus of the present study, is that, on average, the completion rate of MOOC courses is less than ten percent and the number of dropouts for these courses are very high compared to traditional online learning (Chen et al., 2019; Jacobsen, 2019; Koutsakas, Karagiannidis, Politi & Karasavvidis, 2020). To some degree, this issue can be owed to courses that are free of charge, do not award credits, and thus many learners may have signed up for them out of curiosity. However, the current low completion rates are of concern to scholars and there is a need to understand and explore this problem. Sari, Bonk, & Zhu (2020) and Xie (2019) pointed out that the completion rates of the presented courses should not be neglected and scrutinizing them will give input for better understanding of the logic behind them, and how online classes could be enhanced for both course leaders and students. Moreover, Reich (2015) suggested that the succeeding research on MOOC needs to adopt a wide range of designs with special attention to understand the causal factors that boosts student learning, as the participation and engagement of the learners in an MOOC setting is voluntary. These low rates do raise questions regarding MOOC's effectiveness (Koutsakas et al., 2020; H Hone & El Said, 2016). Yet, there is very little empirical research into MOOCs and their effectiveness for learning (Weinhardt & Sitzmann, 2019; Romero-Rodríguez, Ramírez-Montoya, & González, 2020). Thus, it is important to better understand variables that are indicative of MOOC completion. If academics and practitioners could find the primary motivations and reasons for the MOOC usage, they could obtain more precise and intuitive information on ways to enhance the MOOC completion rate and decrease dropouts. Although various studies have attempted to examine the MOOC, research on the perceptions of users pertaining to MOOC usage are scarce. In addition, there are only few empirical studies to identify the relationship between MOOC usage and learning effectiveness. The objective of the present study is to answer two research questions:

- What are the determinants contributing to the completion of MOOCs' courses?
- What is the effect of MOOCs' use on learning effectiveness?

2. Literature Review and Hypothesis Development

2.1. Triandis Model

Harry C. Triandis (1980) presented a thorough model to study interpersonal behavior. The effectiveness of the model in assessing broad range of intentions consisting of analyzing intentions of social trading platforms (Reith, Fischer & Lis, 2019), understanding the determinants of digital distraction (Chen, Nath, & Tang, 2020), and identifying the determinants of environmental behavior (Yuriev, Dahmen, Paillé, Boiral & Guillaumie, 2020). In general, the selected theory has been widely considered to be a base for studies in the information system field (Al-Shanfari, Yassin & Abdullah, 2020; Sanco, Harmein, & Rahim, 2019; Jeon, Kim, & Koh, 2011). The current study has employed only a subsection of the theory; therefore, it is not necessary to explain the details of the model and its thirty-four related hypotheses (which are not related to this study). The main notion of the presented model is that factors such as expected consequences, affect, and social issues have an impact on the intentions of people, and, consequently the intention impacts genuine behavior (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019). In our study, a subsection of the theory is applied to the context of MOOC utilization. Specifically, the direct effect of perceived consequences, affect, social factors on intention are examined. Moreover, the effects of facilitating conditions on the actual behaviors were examined. This study, similar to other studies, set aside habits from the model (Jeon et al. 2011), given that habits (in previous uses) were within the context of MOOCs usage, and displayed a tautological link with the existing use. The following sections will discuss the details and foundations of our research constructs.

2.1.1. Perceived Consequences

According to the base theory, expected consequences comprise an important indicator that affects behavior, later on renamed as perceived consequences (Teo, Sang, Mei, & Hoi, 2019). The perceived consequences originated from the expectancy theory of motivation that was expounded by Vroom (1964). This specific concept was additionally developed by Porter and Lawler (1968). The concept "consequences" manifests the expected merit of behavior. The perceived consequence is interpreted as the likelihood that a particular consequence might take place as an outcome of behavior (Vaterlaus, Spruance,Frantz, & Kruger, 2019). Kim, Cho, and Kim (2019) asserted that a person will be more readily involved in an action if the expected value of that action rises. Nguyen, Nham and Hoang (2019) described that the frequency and degree of knowledge sharing will rise whenever the perceived consequences have higher power and intensity. Perceived consequences have been thought to have several dimensions. Alves (2011) conceded that the perceived consequences probably contain many components and they are not unidimensional. This point is consistent with the empirical results and theoretical discussions of various studies that suggest the perceived consequences comprise several dimensions. Previous studies that employed our base theory in the context of information technology utilization identified perceived consequences to be complexity, long-term consequences, and near-term consequences (Chang & Cheung, 2001). Additionally, Jeon et al. (2011) launched novel multi-dimensions for the perceived consequences factor to investigate knowledge sharing in organizations. They included member-member, member-work, and organization-member aspects as the sub-dimensions of perceived consequences. Expected reputations, expected social interactions, and expected usefulness had been considered multidimensional perceived consequences to analyze the knowledge sharing behavior of information security experts in online communities (Tamjidyamcholo, Baba, Shuib, & Rohani, 2014). However, with respect to online learning and the MOOC literature, in the present study, the perceived consequences are introduced as a second-order construct including knowledge growth, social interaction, and compatibility.

Knowledge growth is explained as the knowledge seeker's perceived benefit of augmenting his or her personal learning and experience (Aleven et al. 2018). In fact, the main reason users were willing to participate in virtual communities is their attitudes and insights towards such communities, which ultimately lead to the exchange and generation of new knowledge and expertise (He & Wei, 2009). The ERP knowledge update was examined by Darban, Kwak, Deng, Srite, & Lee (2016). Their study explained that team collaboration and individual effort positively influence perceived knowledge update. Italian mathematic teachers used MOOCs for developing a new theoretical framework (Taranto & Arzarello, 2019). Some scholars suggested that only a small proportion of MOOC participants go on to complete their courses and relatively little is known about the MOOC influential factors that influence the participants' course completion (Hone & El Said, 2016). Therefore, the current study assumes that knowledge growth is an aspect of perceived consequence of the MOOCs completion.

Nahapiet and Ghoshal (1998) maintained that the basic assumption of the Social Capital Theory is actually that network connections furnish access to resources and information. Social networking or interaction ties have been identified as paths to the circulation of resources and information (Tsai & Ghoshal, 1998). Prior research have presented experimental support for the effect of social interactions on group cohesiveness (Huang, 2009), reinforcement learning (Hackel, Mende-Siedlecki, & Amodio, 2020), human needs and satisfaction with Life in Facebook (Houghton, Pressey, & Istanbulluoglu, 2020), and the quantity and quality of the distributed knowledge (Chang & Chuang, 2011). In this research, social interaction is explained as the strength of connections, the period of time passed, and the scope of the relationship happening among MOOC participants. Thus, we presume that social interaction is a first order factor for perceived consequence construct.

Perceived compatibility is the extent to which the innovation is recognized as being consistent with the potential user's existing values, previous experiences, and needs (Rogers, Singhal, & Quinlan, 2019). Rogers (2019) pointed out that high compatibility leads to preferable adoption and usage. Perceived compatibility has been proven to have significant influence on e-learning utilization (Islam, 2016), information system success model (Isaac, Aldholay, Abdullah, & Ramayah, 2019), is considered as a driving factor in the adoption of smart home technology (Nikou, 2019), and has a key linking mechanism between omni-channel experience and omni-channel shopping intention (Shi, Wang, Chen, & Zhang, 2020). To have an understanding of the participants of MOOCs utilization and completion behavior, we assume perceived compatibility as another aspect of the perceived consequences. Thus, the aforementioned explanation directs us towards the first hypothesis of our research as follows:

> Hypothesis 1: There is a positive relationship between perceived consequences (knowledge growth, social interaction, and compatibility) and the intention to use MOOC.

2.1.2. Affect

Affect is defined as a person's experience of hatred, dissatisfaction, happiness, joy, or thrill toward a particular behavior (Kim et al., 2019). Positive feelings accentuate the motivation to show a certain behavior, while negative feelings diminish the behavior motivation (Taherdoost, 2018). Anwar (2019) mentioned that there is an affirmative link between behavior and affect. Basically, it is more likely that behaviour will take place when the satisfaction and thrill of behavior are high. It is shown that pleasure and enjoyment, which are regarded as variables like affect, have a positive influence on knowledge sharing behavior of SMEs in communities of practice (Tan & Ramayah, 2018). In addition, the results of the study of Kgasago and Jokonya (2018) shows that affect has a significant effect on the users' acceptance of business intelligence systems. Furthermore, it is believed that affect can be effective on predicting other behaviors, such as ERP system adoption (Chang, Cheung, Cheng, & Yeung, 2008), internet piracy (Ramayah, Chin, & Ahmad, 2008), and knowledge sharing behavior (Jeon et al., 2011). Therefore, it is rational to examine the hypothesis that regards a positive relationship between affect and MOOC utilization.

> Hypothesis 2: There is a positive relationship between affect and the intention to use MOOC.

2.1.3. Social Factors

Garay, Font, and Corrons (2019) highlighted that intentional behavior is directly affected by social norms, and this link relies on the messages that individuals receive from other people. Rejón-Guardia, Polo-Peña, and Maraver-Tarifa (2019) mentioned that the social norms notify others about what to do. The basic theory underscored this concept and suggested the word 'social factors' for this connection; propounding that the individual's internalization of the reference groups' subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations. A subjective culture includes a category of beliefs, attitudes, ideals, experiences, roles, values, and norms, which is often recognized as the characteristic way that a human group views the human-made part of its setting (Jia, Guo, & Barnes, 2017). The subjective norm construct in the theory of reasoned action (TRA) behaves like social factors in the Triandis model (Ajzen & Fishbein, 1980). In their theory, Ajzen and Fishbein presumed that social norms could have an impact on behavior. The result of several empirical studies showed a positive connection between intentional behavior and social factors. In particular, the effects of social factors studied in online purchase intention and findings demonstrated that the social factor positively influenced the purchase intention (Tsai, Hung, & Yang, 2020). Yang and Lin (2019), using the TRA model, illustrated that social factors are the significant determinants of the intention to continue playing mobile game apps. In addition, Lo and Qu (2015) and Larue, Rakotonirainy, Haworth, and Darvell (2015) exerted that social norms have a positive impact on tourists' shopping intentions and the drivers' acceptance of intelligent transport systems, respectively. In this study, social factor describes the effect of friends, colleagues, subordinates, and superior individuals on an individual's utilization of MOOC. According to our base theory and findings from prior empirical findings, the next hypothesis that needs to be analyzed is:

> Hypothesis 3: There is a positive relationship between social factors and the intention to use MOOC.

2.1.4. Facilitating Conditions

Faulkner, Jorgensen, and Koufariotis (2019) assumed that there is an affirmative connection between facilitating conditions and behavior. Facilitating conditions are generally believed to be an impetus to the users in the context of individual usage of information systems (Peñarroja,Sánchez, Gamero, Orengo & Zornoza, 2019). The current research utilizes this specific viewpoint as a reference viewpoint. Triandis (1980) defined facilitating conditions as objective factors, out there in the environment, that several judges or observers agree that it makes an act easy to do. Prior empirical studies on the relationship between facilitating conditions and learning management system (Khechine, Raymond, & Augier, 2020), social enterprise consumer behaviors (Tsai et al., 2020), building information modeling acceptance (Son, Lee, & Kim, 2015), the Internet banking utilization (Zolait, 2014), and e-learning usage (Tarhini, Teo, & Tarhini, 2015) were supported. However, cultivating online communities without having suitable facilitating conditions may produce unforeseen negative outcomes, because the communities are generally vulnerable (Hao & Tan, 2019). In the present study, the facilitating conditions contain instructions or guidance that enable users to have access to the MOOC anytime they like, plus the support and assistance supplied through the community provider to make the usage of the MOOC easier. Hence, the following hypothesis is developed:

> Hypothesis 4: There is a positive relationship between facilitating conditions and the MOOC utilization.

2.1.5. MOOCs usage and learning effectiveness

Zulfiqar, Sarwar, Aziz, Ejaz Chandia, and Khan (2019) postulated that actual behavior is influenced by what people have usually done (habits), by their behavioral intentions, and by facilitating conditions. They contended that the anticipated behavior could occur if there is a high strength of intention and motivation. According to the TRA (Ajzen & Fishbein, 1980) and TAM (Venkatesh & Bala, 2008), the intention to use or behavioral intention can accurately predict behavior. The intention to use could help figure out the strength of an individual's intention to commence behavior and illustrate an action. The intention to execute behavior is an individual's intention to perform a certain behavior (Hwang, Lim, Neary, & Newton, 2018). Intention could be a very accurate construct when it comes to anticipating actual behavior (Hagger, Polet, & Lintunen, 2018). Since the quantity of online training and education programs have been boosted, practitioners and researchers are interested in examining ways to develop and design effective e-learning programs. The low rates of MOOC course completion raise questions regarding MOOC's effectiveness. The effectiveness of interactive video on e-learning (Zhang, Zhou, Briggs, & Nunamaker, 2006), mobile learning in the form of podcasting (Evans, 2008), and e-learning in construction safety (Ho & Dzeng, 2010) have been proven. Yet, there is very little empirical research into MOOCs and their learning effectiveness (Haggard et al., 2013; Weinhardt & Sitzmann, 2019). Thus, this study is focused on empirically investigating the relationship between MOOC usage and its effectiveness on learning. With respect to the preceding discussion and our base model, the following hypotheses would be tested:

> Hypothesis 5: There is a positive relationship between the intention to use MOOC and MOOC actual usage.
> Hypothesis 6: There is a positive relationship between the actual usage of MOOC and learning effectiveness.
> Hypothesis 7: There is a positive and direct relationship between perceived consequences and learning effectiveness.

3. Research Model

The model (Figure 1) is formed based on the preceding explanation and discussion. It incorporates seven factors: perceived consequences, affect, social factor, intention to use, facilitating conditions, MOOC utilization, and learning effectiveness. It indicates the link between perceived consequences, affect, and social factor and the intention to use MOOCs. The figure shows the connection between the intention to use MOOC and the actual usage of MOOC, and the perceived consequences with learning effectiveness. Furthermore, it displays the effects of perceived consequences and the actual usage of MOOC on learning effectiveness. With the exception of perceived consequences, which have been modelled to be a formative construct, all remaining constructs are formulized to be reflective.

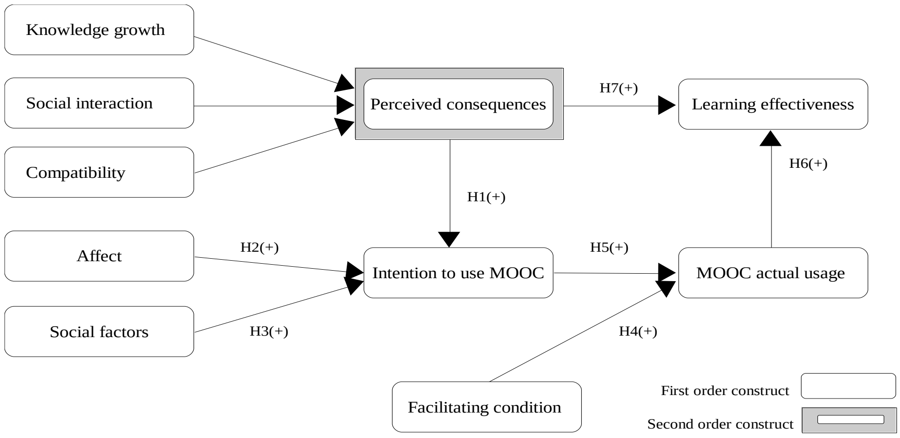

Fig. 1. Research model

Seven hypotheses have been proposed. The letter H and a number are used to depict each hypothesis. The plus marks point to an affirmative connection and the arrow directions indicate the hypothesized connections. In this research, the subjects that are applied to operationalize the constructs were extracted from prior research and adjusted for use in the MOOC usage context. Knowledge growth-based consequence, social interaction-based consequence, and compatibility-based consequence were used as factors to construct the superior perceived consequences construct. The knowledge growth-based perceived consequence was operationalized by He and Wei (2009). The social interaction-based perceived consequence was measured with items taken from Huang (2009) and Chang and Chuang (2011). The compatibility-based perceived consequence was operationalized according to Nikou (2019), and Isaac et al. (2019). The findings and concepts of Kim et al. (2019) were employed to analyze affect. The social factor was examined according to Lo and Qu (2015). The intention to use was measured based on the items extracted from Fang and Chiu (2010), and the facilitating conditions were assessed through items extracted from Khechine et al. (2020). Lastly, the measures and items used to assess learning effectiveness were extracted from Ho and Dzeng (2010) and Liaw (2008). The questionnaire items for the study constructs are illustrated in Table 1.

Table 1. Questionnaire items

Construct Name	Items	Alpha	Mean/S.D.
Knowledge growth	1. Using Coursera can promote my knowledge growth and development.	0.786	1.72/0.785
	2. Using Coursera helps me strengthen my concepts in my field.		1.91/1.019
	3. Using Coursera can sharpen my knowledge.		1.63/0.732
Social interaction	1. I spend a lot of time interacting with some participants in Coursera.	0.914	4.42/1.685
	2. I have frequent communication with some participants in Coursera.		4.51/1.822
	3. I maintain close social relationships with some participants in Coursera.		4.88/1.758
Perceived compatibility	1. Learning material provided by Coursera is compatible with my needs.	0.792	2.15/1.035
	2. Courses provided by Coursera meet my personal learning needs.		2.05/0.95
	3. The knowledge and information shared in Coursera' forum fits my current needs.		2.45/1.217
Affect	1. Using Coursera to learn new things would be enjoyable and interesting.	0.87	1.79/0.916
	2. Learning with Coursera is fun.		1.61/0.776
	3. 3. I feel good to use Coursera for learning.		1.37/0.852
Social factors	1. People who are important to me think that I should use Coursera.	0.915	2.99/1.599
	2. People who influence my behavior encourage me to use Coursera.		3.19/1.633
	3. My colleagues think that I should use Coursera.		3.18/1.633
Facilitating conditions	1. Coursera offers technical support when needed.	0.762	2.89/1.272
	2. Specialized instruction, concerning Coursera usage, is available to me.		2.99/1.399
	3. I can get technical support by email if I have problems using Coursera.		3.21/1.407
Intention to use	1. I intend to use Coursera in my learning in the future.	0.715	1.53/0.689
	2. I predict that I would use Coursera.		1.69/0.861
	3. I plan to use Coursera in the next (n) months.		1.44/0.712
MOOC actual usage	1. I use the Coursera very intensively.	0.917	3.13/1.517
	2. I use the Coursera very frequently.		3.05/1.517
	3. Overall, I use the Coursera a lot.		3.00/1.600
Learning effectiveness	1. I believe Coursera can assist learning efficiency.	0.835	1.81/0.831
	2. I believe Coursera can assist learning performance.		1.84/0.904
	3. I believe Coursera can assist learning motivation.		1.87/0.868

4. Research methodology

4.1. Data collection

The present study is conducted using a massive online open course called Coursera (https://www.coursera.org). Before conducting the formal and final data collection process and for having a valid research instrument, a pre-test and a pilot-test were carried out. One associate professor and an assistant professor in the information system field along with two postdoctoral research fellowships who were doing research in virtual communities pre-tested the questionnaire. Participants were required to remark and comment on a list of subjects that correlate with the constructs, the inclusion of logical consistencies, the ease of understanding, contextual relevance, and the sequence of questionnaires. Additionally, the pilot-test was carried out by twenty-three students in research and development building in our university. A few small modifications had been applied to the questionnaire after conducting the pre-test and pilot-test; accordingly, four unnecessary subjects were deleted from the questionnaire. After the application of the minor modifications, the questionnaires were distributed for the purpose of collecting research data. Three sources were selected from Coursera groups on Facebook to collect data, including a Coursera closed group, Internet Technology and Security (UMich—Coursera) group, and Modern & Contemporary American Poetry (Coursera ModPo) group. First, we requested to be a member of the groups. After obtaining the membership of the groups, the questionnaire link was posted on the page of the groups. The message and post contained an online link of the questionnaire that was developed using Google form technology, and a short description about the objectives of the study. The participation in this study was voluntary and data collection process started from July 12, 2018 until September 23, 2018. In total, 241 responses were collected. After removing seven invalid responses, 234 valid responses remained for the main research analysis. The characteristics and detailed information of participants have been shown in Table 2. The questions were assessed by a Seven-point Likert scale starting from ‘‘totally disagree’’ (1) to ‘‘totally agree’’ (7).

Table 2 . Characteristics of respondents

Measure	Items	Frequency	Percent (%)	Measure	Items	Frequency	Percent (%)
Gender	Male	159	68.0	Education	High School	36	15.4
	Female	75	32.0		Bachelor	116	49.6
					Master	61	26.0
Age	Less than 25	109	46.6		PhD holder	21	9.0
	25-30	50	21.4	Occupation	Student	116	49.6
	31-40	44	18.8		Employee	73	31.2
	Over 41	31	13.2		Professor	13	5.6
					Other	32	13.6

4.2. Data analysis

As a multivariate analytic method, partial least squares (PLS) uses latent variables for path analytic modeling. The PLS technique is appropriate for theoretical development; consequently, causal models can simply and effectively be examined by PLS. It is additionally feasible to formalize both reflective and formative constructs in PLS (Hair, Howard, & Nitzl, 2020). SmartPLS version 3 (www.smartpls.de) was used to test the current research model. The model was analyzed in two steps. First, the evaluation of the measurement model was done, which consisted of the reliability and discriminant validity. Second, the evaluation of the structural model was undertaken, which consisted of the path coefficients and the R2 values.

5. Results

5.1. The Measurement Model

The test of reliability was conducted by individual item loadings and internal consistency. Individual item loadings that are =>0.5 are believed to be sufficient. It is shown in Table 3 that loadings for all measurement subject were greater than 0.69. This demonstrates the existence of sound internal reliability. In addition, Cronbach's alpha was applied to assess internal consistency. As it is shown in Table 1, the Cronbach's alpha for each variable was => 0.7. The PLS used the hierarchical component model to analyze the second-order factors. Each item of the lower-order factors was used to measure second-order factors. In this study, the perceived consequences were used as the second order constructs.The lower order constructs include knowledge growth, social interaction, and perceived compatibility. In order to assess convergent validity, Composite Reliability (CR) and Average Variance Extracted (AVE) were measured. Based on the suggestion of PLS, the recommended degree of reliability is CR=>0.7, and the recommended level of AVE is AVE=> 0.5. In the present study, the range of CRs were 0.838 to 0.947, and the range of AVEs were 0.634–0.857, where both exceeded the threshold values, and thus, the convergent validity is approved. The square root of AVE was employed to measure discriminant validity. In order to obtain discriminant validity, the square root of AVE should be more than the correlations among the constructs. The diagonal elements in Table 4 are the AVE's square root. This indicates that the value of each AVE's square root is greater than the off-diagonal components. Therefore, we conclude that there is an acceptable and logical extent of discriminant validity in all of the constructs.

Table 3. Measurement analysis results

Measures	Items	CR	AVE	Loading	Standard Error	t-value
Knowledge growth	KG 1	0.875	0.7	0.845	0.024	35.089
	KG 2			0.811	0.035	23.417
	KG3			0.854	0.025	34.424
Social interaction	SI 1	0.946	0.853	0.922	0.222	4.158
	SI 2			0.944	0.234	4.03
	SI 3			0.904	0.212	4.259
Perceived compatibility	PC 1	0.879	0.708	0.821	0.031	26.161
	PC 2			0.906	0.015	61.848
	PC 3			0.792	0.043	18.439
Affect	AF 1	0.92	0.794	0.919	0.014	63.907
	AF 2			0.92	0.024	39.086
	AF 3			0.832	0.066	12.655
Social factors	SF 1	0.943	0.847	0.948	0.045	20.925
	SF 2			0.939	0.076	12.311
	SF 3			0.873	0.118	7.419
Facilitating conditions	FC 1	0.863	0.677	0.822	0.035	23.458
	FC 2			0.807	0.041	19.503
	FC 3			0.84	0.031	27.079
Intention to use	ITU 1	0.838	0.634	0.859	0.021	40.26
	ITU 2			0.698	0.073	9.522
	ITU 3			0.823	0.035	23.57
MOOC actual usage	MAU 1	0.947	0.857	0.888	0.022	39.493
	MAU 2			0.943	0.013	72.479
	MAU 3			0.946	0.009	107.017
Learning effectiveness	LE 1	0.901	0.752	0.867	0.034	25.17
	LE 2			0.896	0.02	44.071
	LE 3			0.843	0.028	30.476

Table 4. Correlation between research constructs

	(KG)	(SI)	(PC)	(AF)	(SF)	(FC)	(ITU)	(MAU)	(LE)
Knowledge growth (KG)	**0.837**								
Social interaction (SI)	0.059	**0.924**							
Perceived compatibility (PC)	0.533	0.194	**0.841**						
Affect (AF)	0.59	0.099	0.55	**0.891**					
Social factors (SF)	0.211	0.318	0.35	0.357	**0.921**				
Facilitating conditions (FC)	0.312	0.296	0.343	0.216	0.328	**0.823**			
Intention to use (ITU)	0.62	-0.093	0.487	0.669	0.183	0.2	**0.797**		
MOOC actual usage(MAU)	0.326	0.285	0.381	0.412	0.238	0.357	0.299	**0.926**	
Learning effectiveness (LE)	0.682	0.219	0.556	0.549	0.236	0.293	0.495	0.437	**0.867**

Note: the bold numbers in the diagonal row are square roots of the average variance extracted.

5.2. The structural model

Obtaining satisfactory results for the reliability and validity test in the preceding segments lead us to examine our research hypotheses. In this section, the proposed model and its hypotheses are assessed using the Structural Equation Model (SEM). The examination of the SEM incorporates an evaluation of the path coefficients and R2 values. The path coefficients represent the relationships between the endogenous and independent factors. The R2 values indicate the quantity of variance defined by the independent factors, and reflect the predictive power of the model. Table 5 summarizes the results of the hypotheses. In Figure 2, the R2 values are represented beside each dependent construct. The model describes 50.1% of the variance in the intention to use MOOC, 17.4% of the variance in the MOOC actual usage, and 53.7% of the variance in learning effectiveness.

Table 5. Results of hypothesis testing

Hypotheses	Results
Hypothesis 1. There is a positive relationship between perceived consequences and the intention to use MOOC.	Supported
Hypothesis 2. There is a positive relationship between affect and the intention to use MOOC.	Supported
Hypothesis 3. There is a positive relationship between social factors and the intention to use MOOC.	Not-supported
Hypothesis 4. There is a positive relationship between facilitating conditions and the MOOC utilization.	Supported
Hypothesis 5. There is a positive relationship between intention to use MOOC and MOOC actual usage.	Supported
Hypothesis 6. There is a positive relationship between MOOC actual usage and learning effectiveness.	Supported
Hypothesis 7. There is a positive and direct relationship between perceived consequences and learning effectiveness.	Supported

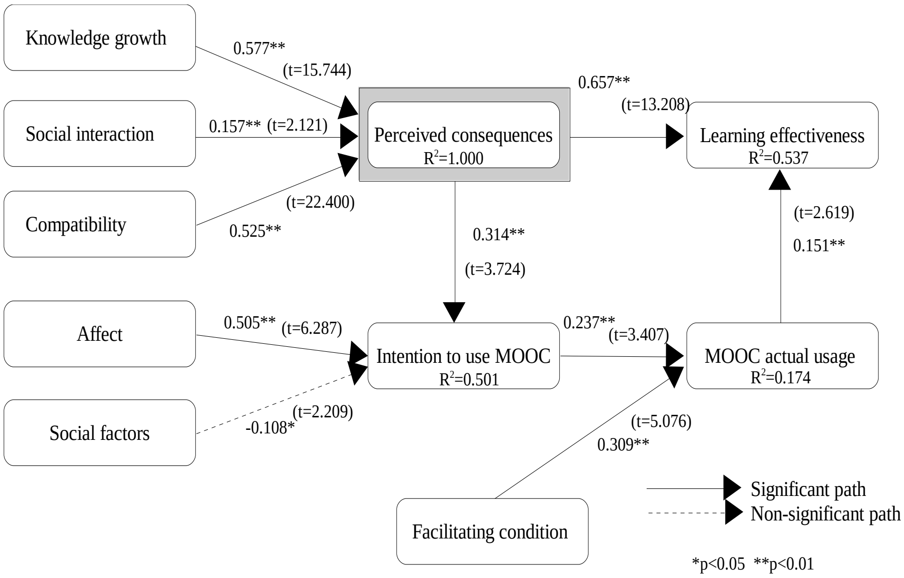

Fig. 2. SEM analysis results

Figure 2 also indicates the findings of the path coefficients. The path coefficient from perceived consequences to intention to use MOOC is affirmative, and indicates a significant relationship ($\beta=0.314$, $p<0.01$). This demonstrates that the intention to use MOOC was statistically affected by the perceived consequences; hence confirming hypothesis 1. The findings illustrate that affect ($\beta=0.505$, $p<0.01$) and facilitating conditions ($\beta=0.309$, $p<0.01$) have a meaningful and significant impact on the intention to use MOOC and the actual usage of MOOC respectively, which verifies hypotheses 2 and 4. Contrary to the initial assumption of this study, the social factor showed a negative impact on the intention to use MOOC ($\beta=-0.108$, $p<0.05$). Thus, hypothesis 3 was not supported. The SEM analysis approved a positive and significant link between the intention to use MOOC and the MOOC actual usage ($\beta=0.237$, $p<0.01$); therefore, hypothesis 5 is confirmed. Consistent with our research hypotheses, the path coefficients illustrate the strengths of the links between the perceived consequences as well as the actual usage of MOOC and learning effectiveness ($\beta=0.657$, $p<0.01$; $\beta=0.151$, $p<0.01$). Therefore, hypotheses 6 and 7 were validated.

6. Discussion

The primary objective of the current study was to reveal and identify the determinants of the MOOCs usage and also to find the quantitative relationship between MOOC usages and learning effectiveness. To test the research model, an empirical study was carried out. The findings indicated that perceived consequences can be a significant indicator of intention to use MOOC. The data analysis verified that perceived consequences are a major component in the completion rate of massive open online courses; thus, it can be concluded that if the amount of perceived consequences are boosted, the dropout rate of the courses will decrease and the completion rate will be enhanced. Three types of consequences have been defined by the study model, including the knowledge growth, social interaction, and compatibility.

As verified by the results of previous studies (Jung & Lee, 2019; Darban et al., 2016; Chan & Chan, 2011; He & Wei, 2009), in which knowledge building plays an important role in the online involvement of users, the results of the present research showed that knowledge growth has a positive impact on the intention of MOOC users. The results confirmed that the users of MOOC intend to enhance their own learning and experience and to have access to new knowledge or innovations. The conclusion of other relevant studies indicate that social interaction ties among the users of a specific community could be augmented via social interaction, and it is believed to be a meaningful indicator of collective action (Doty et al., 2020). These ties could be initiated among individuals with similar and exact resources and interests rather than different individuals (Nguyen & Schumann, 2019). Thus, as proven by the result of the research model, these ties and bonds help with the engagement and activity of the MOOC users. For instance, for the participants of MOOC to have easy interactions in discussion forums and also to have strong connections, they have created a special group in other virtual communities such as Facebook. The results of previous studies of online knowledge sharing (Oyemomi, Liu, Neaga, Chen, & Nakpodia, 2019), e-learning utilization (Islam, 2016), information system success model (Isaac et al., 2019), and the adoption of smart home technology (Nikou, 2019) confirm that when the compatibility in the provided technology is high, the intention to use and adopt that technology is higher. In line with the past findings, the result of this study illustrated that compatibility has a strong and significant effect on the usage intentions of MOOC; therefore the presented courses and materials should be compatible and consistent with the expectation and needs of the MOOC users. Similar to the results of Anwar (2019) and Kgasago and Jokonya (2018), the findings of this research confirmed that the utilization of MOOC is stronger when users have affirmative sentiments toward it. The intrinsic motivations of using and adopting a new technology are embodied in its affect (Kim et al., 2019). Affect can have various impacts on the users, including energy, happiness, joy, and enthusiasm, indicating that the intrinsic motivations of users can substantially influence the MOOC utilization and completion rates of the provided courses. The social factor was not found to be an instrumental construct in MOOC utilization. This is consistent with the findings of Hsu and Lin (2008) and contradictory to the results of Tsai et al. (2020) and Yang and Lin (2019). One possible reason for this result can be that MOOC is seen as a community to improve learning and knowledge. However, when someone receives a suggestion to join it, they see themselves as being unknowledgeable in the eyes of others and need to enhance their skills, hence they might reject the suggestion. The second plausible reason may be due to the fact that MOOC is a type of professional virtual community and the participants of this community completely know their own benefits, and know where and how to attain the information and knowledge they require. This can be a reason why social factors were not found to have any effect on the indivisible behaviors. The third reason might be that there is no obligation or commitment to join and use MOOCs, and any action in this setting is voluntary. According to the findings of other researchers, intention to use (Hwang et al., 2018; Hagger et al., 2018) and facilitating conditions (Tarhini et al., 2015; Zolait, 2014) are important indicators of MOOC actual usage. Hagger et al. (2018) asserted that intention would be the right factor to look at when it comes to anticipating behavior; accordingly the present study proved that when people have the intention to use MOOC, they would actually use MOOC. The results of facilitating conditions indicated that when an individual believes that there is an appropriate guidance, instruction, and technical support, they are more interested to use

MOOC. Lastly, as was explained in the preceding data analysis section, the results delineated that the actual utilization of the MOOC and perceived consequences positively and significantly affect the learning effectiveness. These findings are in agreement with the results of previous studies (Chen & Chen, 2015; Evans, 2008; Ho & Dzeng, 2010; Zhang et al., 2006). Therefore, the low rates of MOOC course completions are not because of the learning effectiveness. The authors believe that the MOOC providers should consider factors such as knowledge growth, social interaction, compatibility, affect, and facilitating conditions which have been confirmed to be the determining factors in the context of MOOCs.

6.1. Implications

From a theoretical perspective, the research model offers several important theoretical contributions. Firstly, we analyzed the MOOCs utilization by incorporating the important factors from the well-established model of Triandis. In light of earlier discussions and arguments, perceived consequences, affect, and facilitating conditions were identified as the significant constructs in defining the MOOC usage behavior. Secondly, based on the literature, the present study established a novel multi-dimension for the perceived consequences construct, including knowledge growth, social interaction, and compatibility to fit the MOOC usage context. The findings illustrate that the users of MOOC confirm the whole dimensions of consequences (knowledge growth, social interaction, and compatibility) in their online learning activity. Thirdly, we statistically analyzed the influence of MOOC actual usage and perceived consequences on learning effectiveness. The relationship between the actual usage of MOOC and learning effectiveness has not been formerly examined. The results of this study show that MOOC utilization and perceived consequences can enhance learning effectiveness. The assumption that a high dropout rate and low completion rate are caused by the lack of effectiveness of the MOOC would be a barrier to the MOOC development and usage. Thus, there would be good opportunity and motivation for the MOOC usage to expand while this false assumption is rejected.

From a practical perspective, in order to increase the usage of MOOCs and decrease the dropout rate of the participants, the providers of MOOCs need to pay special attention to different motivational dimensions and create a suitable support system to intensify each motivation dimension. Hence, the administrators of the learning community can enhance and retain the participants by offering intrinsic and extrinsic motivations. This research suggests the following recommendations to assist practitioners in administering or designing better MOOCs in order to attract, retain, and increase the number of users. First, the research findings demonstrate that the knowledge growth, as one dimension of perceived consequences, has an influential impact on the MOOC usage. MOOCs administrator needs to establish a setting where the users could enhance the quantity and quality of the presented knowledge by presenting enough courses and also through inviting experienced lecturers. The findings of this study imply that social interaction has a positive impact on MOOC usage. Therefore, the administrators of the communities need to enhance the social interaction mechanisms of their community by creating user friendly discussion forums, blogs, and personal message boards as social interaction tools for improving virtual interaction and connection among users. The findings of this research show that compatibility is a significant element of the perceived consequences. Thus, MOOC developers should present courses that are compatible with the needs of users, industries, or organization. If the provided courses fulfill the current needs of users, they would be more motivated to use them. Additionally, the influence of the affect construct on MOOC utilization has been affirmed. Thus, the providers of MOOCs should engage the users’ sentiments and affection through building a community spirit. This might be attained via various activities such as establishing online quizzes and online competitions. Moreover, when there are not enough facilitating and supporting systems, MOOC utilization and activities could not be promoted and extended. Thus, it is imperative for MOOC providers to furnish resources, such as special guidance and instructions as well as supplying a support group to foster participation of people. Finally, the findings reject the main assumption that the low completion rate or high dropout rate is because MOOC is an ineffective method for learning, since the erroneous assumption could impede the motivation of MOOC providers along with its users. Thus, community providers can employ this important result to expand and develop their community and also encourage the utilization of the MOOC. Given the importance of MOOC in learning accessibility and thriving, it is the goal of our study and its findings to be of benefit to others who are involved in this field theoretically and practically.

7. Conclusion

While MOOCs grow in popularity, the relatively low completion rate of learners has become a central concern. We believe that looking at completion rates is a starting point for a better understanding of the reasons behind the high dropout rate in a voluntary usage setting. In order to understand this phenomenon, a research model was developed to investigate MOOC utilization in which many important factors were taken into account from the Triandis model. These factors were believed to encourage and promote usage behavior in massive open online courses. In addition, the relationship between perceived consequences and the actual usage of MOOC with learning effectiveness was studied in our research model. To test our model, an empirical study was conducted. To evaluate the research model, 234 users from the selected MOOC (Coursera) participated in the survey. The conceptual model was examined via the measurement model and the structural equation model. The measurement model includes reliability and discriminant validity. The structural equation model was consists of path coefficients and R2 values. The analysis of the model satisfactorily confirmed the validity of the proposed model. The results corroborate that the perceived consequences, including knowledge growth, social interaction, compatibility, and affect, have an instrumental impact on the intention to use MOOC. Contrary to our initial assumption, the social factor shows an inconsiderable impact on the context of MOOC utilization. Furthermore, the intention to use MOOC and facilitation conditions exhibited a positive influence on the actual usage of the MOOC. The findings of this study suggest that the perceived consequences and MOOC actual utilization have positive effects on learning effectiveness and significantly enhance the learning process.

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