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MOOCs, Completion Rate, Learning Satisfaction, Quantity and Quality of the Knowledge

Alireza TamjidYamcholo [1*]

1. PhD Information Technology Management Department, Parand Branch, Islamic Azad University, Tehran, Iran.

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Abstract

Purpose: This study uses TAM theory to better understand variables that are indicative of MOOCs' courses' completion rates; furthermore, this paper scrutinizes the quantitative relationship between MOOC platform usage and learning satisfaction.

Methodology: This was an applied research in a virtual community called Coursera where people all over the world participate. The research design was quantitative and the questionnaire link was posted on the Coursera, with convenience sampling. Data collection process started from November 12, 2020 until February 23, 2021, and 234 users of the selected MOOC platform (Coursera) participated to evaluate the proposed model. A multivariable systematic technique (PLS) was applied to analyze the model. To conduct the reliability test, individual item loadings and internal consistency were consulted. Convergent validity of the model was measured via the Structural Equation Model (SEM). The examination of the SEM was incorporated an evaluation of the path coefficients and R2 values.

Findings: The loadings of all measurement items are larger than 0.792, indicating sound internal reliability of the dataset. Moreover, the Cronbach's alpha values are all > 0.7 which proves the internal consistency of the research model. In this research, the range of CR is 0.838 to 0.947 and the range of AVEs 0.634–0.857, both exceeding the threshold values for desirable convergent validity. To obtain discriminant validity, the square root of AVE should be larger than the correlation among the constructs. The value of each AVE's square root is greater than the off-diagonal components. The model explains 21.1% of the variance in perceived usefulness, 20.9% in perceived ease of use, 26.9% in attitude to use, 20.0% in MOOC platform actual usage and 24.2% of the variance in learning satisfaction. The path coefficient from quantity and quality of knowledge (β=0.261, p<0.01) and perceived feedback (β=0.215, p<0.01) to PU are positive. The results show that perceived feedback (β=0.275, p<0.01), perceived complexity (β=-0.367, p<0.01) significantly and meaningfully affect PEOU. The PU showed a positive and strong effect on attitude to use (β=0.271, p<0.01), MOOC platform actual usage (β=0.360, p<0.01), and learning satisfaction (β=0.277, p<0.01).

Conclusion: The results indicated that the quantity and quality of the knowledge and perceived feedback have a positive and significant impact on the perceived usefulness of MOOCs. The perceived complexity as a negative construct was found to be an important indicator of MOOC platforms usage.

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* Corresponding author: itm.tamjid@gmail.com

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1. Introduction

Massive Online Open Courses (MOOCs) have become a dominant constituent of lifelong and distance learning technology for the past several years. MOOC platforms resolve the limitation of geographical and social boundaries and can provide access to world-class educational resources and teaching materials. Specifically, students can benefit from it, which live in less developed countries and have budget limitations for tuition and attendance in recognized universities of the world. MOOCs are distinguished as two distinct models: cMOOC model and xMOOC. The cMOOC (c for connectivity) underlines creativity, creation, and social networking learning, with a focus on knowledge generation and creation. On the other hand, the xMOOC highlights a more conventional learning strategy employing online video presentations and brief tests and quizzing stressing knowledge duplication (Elizondo-Garcia & Gallardo, 2020).

In other words, cMOOCs address knowledge creation and generation, while xMOOCs are concerned with knowledge duplication. These two types of MOOCs operate in a larger scale, display substantial rates of attrition, and share geographical diversity of participants. In recent years, xMOOCs, which is the focus of current research, has been employed by profit or non-profit corporations in partnership with individual scholars or educational institutions, and supplied services and learning materials; Coursera, edX, Udemy, Udacity, and Future learn are examples of the firms and consortia which adopt MOOCs. Even with universal enthusiastic learners and professional individuals to the MOOCs, there is a main issue regarding MOOCs: the number of dropouts for the presented courses is elevated and rate of completed courses from participants is typically less than ten percent compared to traditional online learning (Chen et al., 2019). The high dropout rate of MOOC courses is a problem and there is an imperative to resolve this issue. Sari, Bonk, and Zhu (2020) held that the completion behavior of current course users should be assessed to understand the logic behind the high dropout rate. The high rate of these dropouts has raised questions about MOOC usage end results on learning satisfaction. There are few empirical studies to find the effect of MOOC usage on learning satisfaction (Hew, Hu, Qiao & Tang, 2020). Thus, the current research sets out to answer two research questions: What factors influence the completion rate of presented courses in MOOC platforms? And, what is the effect of MOOC usage on learning satisfaction?

The initial TAM has been enhanced into an updated model: the first modified model TAM, the second modified model TAM2, and the third modified model TAM3. Since its inception, many researchers have used different variables to predict the behavior of technology users (Kamal, Shafiq & Kakria, 2020).

In this research, the original variables, including perceived ease of use (PEOU) and perceived usefulness (PU) have been used with other variables to predict the usage behavior of MOOC platform users. Moreover, the scope of knowledge, perceived feedback, and perceived complexity are used to analyze the completion behaviour of MOOC platform users. These variables will be elaborated in the following subsections. TAM suggested that perceived usefulness (PU) and perceived ease of use (PEOU) determine a person's attitude to use, intention to use, and actual usage of information systems. Attitude towards use is defined as users' consideration and assessment of the desirability of a certain application related to a computer system (Scherer, Siddiq & Tondeur, 2019). TAM emphasized that it is feasible to predict the attitudes of users about technology via PEOU and PU (Revythi & Tselios, 2019).

The PEOU was defined as the degree to which a person supposes that the execution of a particular computer system is straightforward directly affects the PU and users' attitudes (Kamal, Shafiq & Kakria, 2020). Earlier research revealed that if individuals think that a novel information system is easy to use, they are more likely to be an end-user of that system (Wu & Chen, 2017). The PU described the degree to which a person's usage of a technology will boost their productivity. The PU has both direct and indirect effects on the actual utilization of the system. Previous research illustrated the positive effect of the PU on attitude and actual use. Contrary to the original TAM, behavioral intention is not included in the current research model following the suggestions from Wallace and Sheetz (2014), considering that the emphasis on the current research is the real behavior (i.e., actual usage in MOOCs).

Internet has become an affordable means that allows millions of people worldwide to exchange information in virtual communities. The supply of knowledge and its quality is a major challenge of sustainable professional virtual communities (Gibbs, Kim & Ki, 2019). Online communities have less credibility without rich knowledge. Wei, Wang, Chen, Yang and Min (2018) pointed out that the king of online communities is content (i.e., knowledge). This is the reason why many scholars researched the determinants of knowledge sharing behavior in online communities (Wang, Yang, Chen & Tsai, 2016). Ruipérez-Valiente, et al (2020) explained that MOOCs are accelerators for learning via sharing knowledge and expertise and they assumed that MOOCs platform should have adequate quantity and quality of knowledge. If individuals have no confidence in the quantity and quality of knowledge in a voluntary setting like MOOC platforms, it is less likely for the participants to attend courses (Ruipérez-Valiente, et al, 2020). Quantity of knowledge is defined as the volume of knowledge posting and viewing in an online community (Lou, Fang, Lim & Peng, 2013), while the quality of knowledge is defined as the nature and helpfulness of content and knowledge shared in the virtual communities (Askell-Williams, Barr & Ngendahayo, 2019).

Quantity and quality of knowledge play an important role in the success of shared databases for knowledge exchange in groups and professional virtual communities (Chiu, Wang, Shih & Fan, 2011), but quantity and quality of knowledge has not been examined in MOOC platform settings. In this research, the knowledge quantity and quality are expected to be the main drivers of user-perceived usefulness in MOOC platforms and having a positive effect on the MOOC course's completion rate, accordingly. Perceived feedback is a key component in both behaviorist and cognitive theories (Wang & Zhang, 2020). In our context, it is regarded as a dialogic process and mainly provides information to learners about their course performance and platform-related questions. Therefore, in the current research, the perceived feedback is considered to have two aspects which are formatting the construct as a formative construct. The first aspect deals with the information that is conveyed to users in terms of performance and the learning process, to help them find the current gap between what has been obtained and the targets to be obtained in a given study (Wood, 2020). The second aspect is concerned with the information provided to the user about platform-related questions or problems and helps solve their MOOC platform-related issues. Studies on the perceived feedback have been conducted in various areas including students' perceptions of teachers' feedback (Vattø & Smith, 2019) and online learning (Hovardas, Tsivitanidou & Zacharia, 2014).

Recent years have seen a growing interest in the study of feedback in online learning environments because it has been identified as one of the key components for promoting and validating knowledge in this setting (Keil & Johnson, 2020). The feedback can either be positive or negative (Fishbach, Eyal & Finkelstein, 2010) and they found that feedback, whether positive or negative, has an encouraging effect on collaborative online information sharing. The determining effect of the perceived feedback has not been analysed in the MOOC domain; thus, this research assumed that the perceived feedback can support the participation and completion rate of MOOCs' courses. Perceived complexity is the degree to which an individual realizes that innovation is awkward to use and understand (Markowska & Wiklund, 2020). Rogers (2010) identified complexity as an important attribute that explains the reason for the application of innovation or its failure. However, the impact of complexity on the adoption of innovation has been thoroughly studied in other domains (Pierguidi, Spinelli, Dinnella, Prescott & Monteleone, 2019), so it is not assessed in the MOOC platform settings. Generally, complexity has been found to harm the adoption of information technologies. In an attempt to extend the work of previous studies in MOOC platform environments, we examined the effect of MOOCs platform complexity on MOOC courses' completion rate. According to the expectation–confirmation theory, a person's intention to continue using information technology relies upon the user's degree of satisfaction (Park, 2020). In addition, Liaw (2008) suggested that environmental satisfaction should be thought whenever establishing e-learning environments, given that environmental satisfaction would improve learners' perceptions of technologies which may promote their involvement in the learning processes. Earlier studies Alraimi, Zo & Ciganek (2015) illustrated a strong positive relationship between learning satisfaction and learning effectiveness. Furthermore, it was indicated

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that there is a positive link between learning satisfaction and the continuous use of e-learning systems (Pham, Limbu, Bui, Nguyen, & Pham, 2019). In other words, the usage of technology would influence users' learning satisfaction. Alqurashi (2019) illustrated that learning satisfaction is influenced by perceived usefulness and if the users find the technology useful, they would tend to be satisfied with the learning process. However, the relationship between MOOC platform usage and learning satisfaction as an important indicator of courses' completion rate in MOOC platforms has not been analyzed yet. Based on earlier research, the following hypotheses are formulated:

H1. Quantity and quality of knowledge presented in the MOOC platforms are positively associated with the perceived usefulness of MOOC platforms. H2: The perceived feedback of the MOOC platforms is positively associated with PU of the MOOC platform. H3: The perceived feedback of the MOOC platforms is positively associated with PEOU of MOOC platforms. H4: The perceived complexity of the MOOC platforms is negatively associated with PEOU of the MOOC platform. H5: The PEOU of the MOOC platforms is positively associated with the PU of the MOOC platform. H6: The PEOU of the MOOC platforms is positively associated with the attitude to use MOOC platforms. H7: The PU of the MOOC platforms is positively associated with the attitude to use the MOOC platform. H8: The PU of the MOOC platforms is positively associated with the MOOC platform's actual usage. H9: The attitude to use the MOOC platforms is positively associated with the MOOC platform's actual usage. H10: The MOOC platform usage is positively associated with user learning satisfaction. H11: PU of the MOOC platform is positively associated with user learning satisfaction.

2. Methodology

The constructed model for this study is shown in Figure 1. This model consists of nine variables and explains the relationship between the quantity and quality of knowledge, perceived feedback, and PEOU with PU. It displays a connection between perceived feedback and perceived complexity with PEOU. It also shows the relationship between PEOU and PU with attitude to use and the relationship between PU and attitude to use with MOOC platform actual usage. Furthermore, the figure illustrates the connection between PU and actual use of the MOOC platform with learning satisfaction. The quantity and quality of knowledge are determined as a second-order construct and perceived feedback is considered as a formative construct. The other constructs are specified by reflective indicators. Based on the model, eleven hypotheses have been tested. Every single hypothesis is represented simply by an H and a number. The plus marks point to an affirmative connection and the negative mark points to a negative connection. The arrows' directions indicate the hypothesized relationship. In the present study, the items used to operationalize the constructs were mainly adapted from previous studies for use in the MOOC platform context. The quantity and quality complexity were examined according to Pierguidi, et al.'s (2019) research; besides, the perceived ease of use was operationalized according to Wu & Chen (2017), and the perceived usefulness was measured with items adapted from Scherer, Siddiq and Tondeur (2019). The items used by Chen, Xu and Arpan (2017) were used to measure attitude to use, while actual usage items were operationalized according to Ooi and Tan (2016). Finally, the findings from Alraimi, et al (2015) and Liaw (2008) were incorporated to assess learning satisfaction. Table 1 illustrates the research constructs and questionnaires' items.

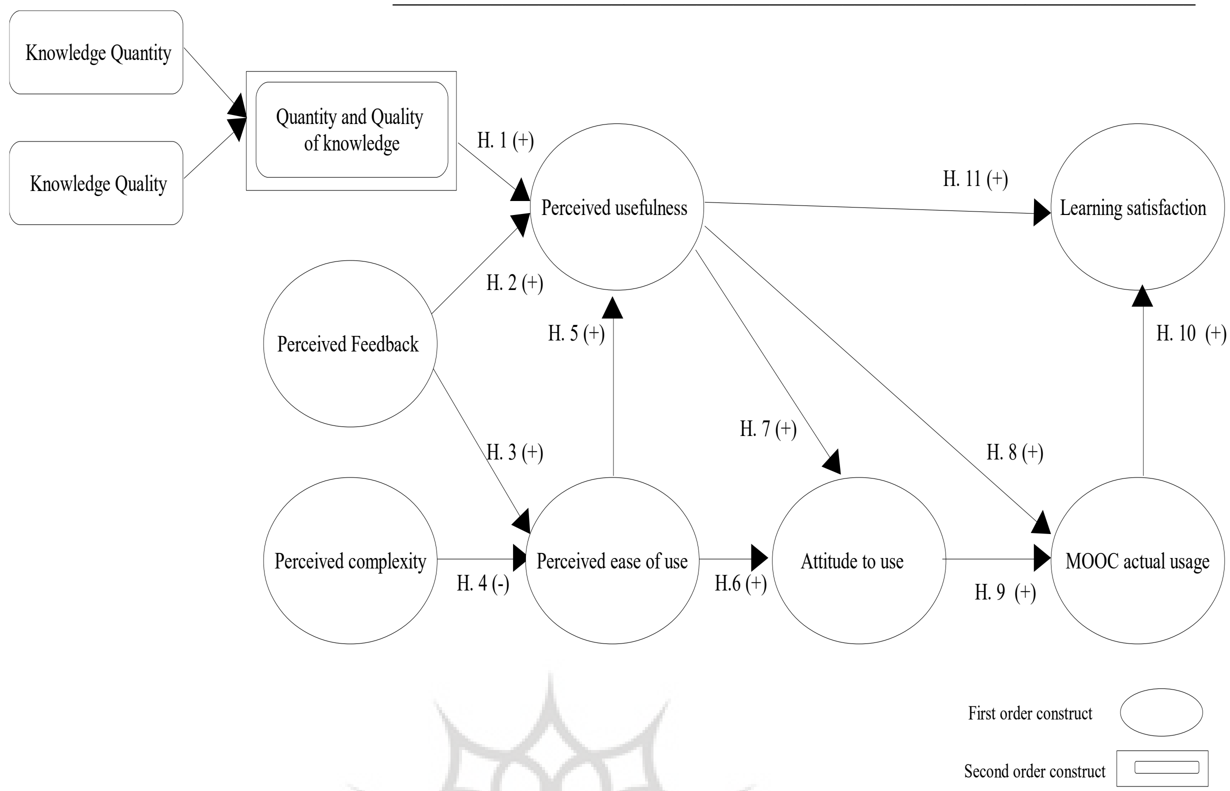

Figure1. The Research Model

Table1. Questionnaire items

Construct Name	Items	Alpha	Mean/S.D.
Knowledge Quantity	1. New content and knowledge are posted frequently in Coursera.	0.694	2.15/1.044
	2. Participants can obtain abundant content and knowledge from Coursera.		1.91/1.018
Knowledge Quality	1. The knowledge provided in Coursera is accurate.	0.782	1.66/0.739
	2. The knowledge provided in Coursera is reliable.		1.74/0.795
Perceived Feedback	1. Coursera provides a summary of participants' progress.	0.787	2.70/1.165
	2. Coursera provides a summary of participant's performance.		2.67/1.351
	3. Coursera immediately replies the participant's questions about platform usage.		2.76/1.321
	4. Coursera provides immediate feedback for participants' problems about the platform usage.		2.72/1.301
Perceived complexity	1. Learning Coursera takes a great deal of time.	0.766	4.55/1.712
	2. Using Coursera requires much mental effort.		3.96/1.896
	3. In general, Coursera is too complex to use.		5.59/1.436
Perceived ease of use	1. The process of using Coursera is clear, understandable and straightforward.	0.759	1.75/0.766
	2. It Is be easy to become skilful at using Coursera.		1.99/1.025

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	3. I find Coursera easy to use.		1.66/0.934
Perceived usefulness	1. Using Coursera helps me manage my studies.	0.833	2.29/1.189
	2. Using Coursera improves my productivity in managing tasks.		2.51/1.175
	3. Using Coursera improves my performance in conducting research.		2.61/1.210
Attitude to use	1. Using Coursera is a good idea.	0.715	1.53/0.689
	2. Using Coursera is unpleasant. (Reversed)		1.69/0.861
	3. Overall, my attitude towards the use of Coursera is positive.		1.44/0.712
MOOC actual usage	1. I use Coursera very intensively.	0.917	3.13/1.517
	2. I use Coursera very frequently.		3.05/1.549
	3. Overall, I use Coursera most frequently.		3.00/1.600
Learning satisfaction	1. My experience with Coursera is highly satisfactory.	0.87	1.79/0.916
	2. I am pleased with Coursera.		1.61/0.776
	3. Generalyy, I will definitely recommend Coursera to my friends.		1.37/0.852

The current research has been carried out in a massive online open course called Coursera. Coursera, in partnership with top universities, offers courses in physics, engineering, humanities, medicine, biology, social sciences, mathematics, business, computer science, and other subjects. To quantify and measure the research constructs, a group of subjects was chosen from the topics that were heretofore explained. The subjects were evaluated using a seven-point Likert scale. Prior to conducting the formal and final data collection process and to have a valid research instrument, a pretest and pilot-test were carried out. An associate professor and an assistant professor in the information system field along with two postdoctoral research fellows researching in virtual community settings pre-tested the questionnaire. Participants were required to remark on a list of subjects that correlate with each construct, containing logical consistencies, ease of understanding, contextual relevance, and sequence of questionnaires. Additionally, a pilot-test was carried out with twenty-five students who were involved in online learning systems in our university. Subsequently, the questionnaire was modified to incorporate a few comments made.

To collect data, courses from the Coursera groups on Facebook were chosen as targeted respondents. The selected group was a closed group. First, we requested to be a member of the groups. After obtaining the membership of the group, the questionnaire link was posted on the groups' page. Furthermore, the active members of the selected groups were identified and were subsequently sent a private message to participate in the survey. The message and post contained an online link to the questionnaire and a short description of the objectives of the research. For obtaining more responses, the participants were informed that they would have access to the study's results. A total of 248 responses were collected and after removing invalid replies, 234 valid responses were used for performing analysis. The detailed data of the participants is shown in Table 2.

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Table2. 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		Doctoral	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

Partial least squares (PLS) are a multivariable systematic technique which uses hidden construct for path analytic modeling. The PLS can develop a theoretical model and causal relational models can be examined simply and effectively through the PLS technique. Additionally, it is possible to construct both reflective and formative variables in PLS. Our research model was tested by Smart PLS version 3 (www.smartpls.de). Two steps were taken to analyse our model: first, the measurement model was assessed using reliability and discriminant validity. Second, the structural model was evaluated via the R2 values and path coefficients.

3. Findings

To ensure reliability, individual item loadings and internal consistency were used. Individual items with loadings > 0.7 are found to be strong and significant. As delineated in Table 3, the loadings of all measurement items were larger than 0.792. This proves that the dataset has sound internal reliability. Moreover, the Cronbach's alpha values are all > 0.7 demonstrating internal consistency of the research model. The PLS employed the hierarchical component model to examine second-order factors. A second-order factor is examined by applying the subjects of all its lower-order indicators. In this study, the quantity and quality of knowledge were used as second-order constructs and its lower-order constructs include knowledge quantity and knowledge quality. Convergent validity of the model was measured using Composite Reliability (CR) and Average Variance Extracted (AVE). The lowest suggested level of CR is 0.7, and the lowest recommended level of AVE is 0.5. In this research, the range of CR is 0.838 to 0.947 and the range of AVEs is 0.634–0.857, both exceeding the threshold values for desirable convergent validity. The square root of AVE had been employed to measure discriminant validity. To obtain discriminant validity, the square root of AVE should be higher than the correlations among the constructs. The diagonal elements in Table 4 are the AVE’s square root. This shows that the value of the square root of each AVE is greater than the off-diagonal components. Therefore, we concluded that there is an acceptable and logical extent of discriminant validity in all the research constructs.

Table3. Measurement analysis results

Measures	Items	Composite reliability	Average variance extracted	Loading	Standard Error	t-value
Knowledge Quantity	KN 1	0.867	0.765	0.874	0.023	37.72
	KN 2			0.876	0.024	36.606
Knowledge Quality	KL 1	0.902	0.821	0.899	0.026	34.488
	KL 2			0.913	0.015	60.161
Perceived Feedback	PF 1	0.875	0.702	0.757	0.059	12.76
	PF 2			0.883	0.042	20.986
	PF 3			0.893	0.045	20.886
	PF 4			0.867	0.047	18.276
Perceived complexity	PC 1	0.856	0.665	0.821	0.042	19.59
	PC 2			0.739	0.065	11.279
	PC 3			0.881	0.03	29.461
Perceived ease of use	PEOU 1	0.861	0.674	0.802	0.037	21.737
	PEOU 2			0.831	0.026	31.678

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	PEOU 3			0.829	0.037	22.424
Perceived usefulness	PU 1	0.9	0.75	0.841	0.027	31.167
	PU 2			0.892	0.017	51.981
	PU 3			0.864	0.025	34.576
Attitude to use	ATU 1	0.837	0.633	0.868	0.022	39.343
	ATU 2			0.691	0.068	10.104
	ATU 3			0.818	0.04	20.57
MOOC actual usage	MAU 1	0.948	0.858	0.889	0.023	38.709
	MAU 2			0.943	0.013	73.641
	MAU 3			0.945	0.009	109.96
Learning satisfaction	LS 1	0.919	0.791	0.93	0.013	69.909
	LS 2			0.937	0.014	65.684
	LS 3			0.793	0.098	8.125

Table4. Correlation between researches constructs

	(KN)	(KL)	(PF)	(PC)	(PEOU)	(PU)	(ATU)	(MAU)	(LS)
Knowledge Quantity(KN)	0.875								
Knowledge Quality (KL)	0.448	0.906							
Perceived Feedback (PF)	0.257	0.182	0.838						
Perceived complexity (PC)	-0.095	-0.123	0.007	0.816					
Perceived ease of use (PEOU)	0.45	0.392	0.272	-0.365	0.821				
Perceived usefulness (PU)	0.371	0.281	0.318	0.027	0.322	0.866			
Attitude to use (ATU)	0.409	0.377	0.17	-0.293	0.451	0.388	0.796		
MOOC actual usage (MAU)	0.399	0.206	0.284	0.008	0.342	0.422	0.299	0.926	
Learning satisfaction (LS)	0.452	0.463	0.225	-0.241	0.569	0.406	0.668	0.423	0.889

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

After ensuring reliability and validity in the preceding section, the research hypotheses were addressed. In the following 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, and the R2 values indicate the quantity of variance defined by the independent factors and reflects the predictive power of the model. In Figure 2, the R2 values are represented beside each dependent construct. The model explains 21.1% of the variance in PU, 20.9% in PEOU, 26.9% in attitude to use, 20.0% in MOOC platform actual usage and 24.2% of the variance in learning satisfaction. Figure 2 also illustrates the findings of the path coefficients. Regarding the efficacy of the determinants' variables in MOOC usage, we examined the path relationship between quantity and quality of knowledge, perceived feedback, perceived complexity, PU, PEOU, attitude to use and platform actual usage. In addition, we investigated the relationship between the MOOC's actual usage and PU with learning satisfaction. The path coefficient from quantity and quality of knowledge (β=0.261, $p<0.01$) and perceived feedback (β=0.215, $p<0.01$) to PU is positive, and it is statistically significant. This indicates that PU was effectively affected by the quantity and quality of knowledge and perceived feedback, thus confirming hypotheses 1 and 2. The results show that the perceived feedback (β=0.275, $p<0.01$) and perceived complexity (β=-0.367, $p<0.01$) significantly affect PEOU, which confirms hypotheses 3 and 4. The SEM analysis approved a positive and significant association between PEOU with PU (β=0.134, $p<0.05$) and attitude to use (β=0.364, $p<0.01$); therefore, hypothesis 5 and 6 were confirmed. As speculated, the PU showed a positive and strong effect on attitude to use (β=0.271, $p<0.01$), MOOC platform actual usage (β=0.360, $p<0.01$), and learning satisfaction (β=0.277, $p<0.01$). Thus, hypotheses 7, 8, and 11 were confirmed too. Consistence with our research assumption, the path coefficients indicated a positive relationship between the attitude to use (β=0.159, $p<0.05$) and platform actual usage, confirming hypothesis 9. Lastly, the result illustrated a positive and significant relationship between MOOC actual usage and learning satisfaction (β=0.306, $p<0.01$). Thus, hypothesis 10 was confirmed.

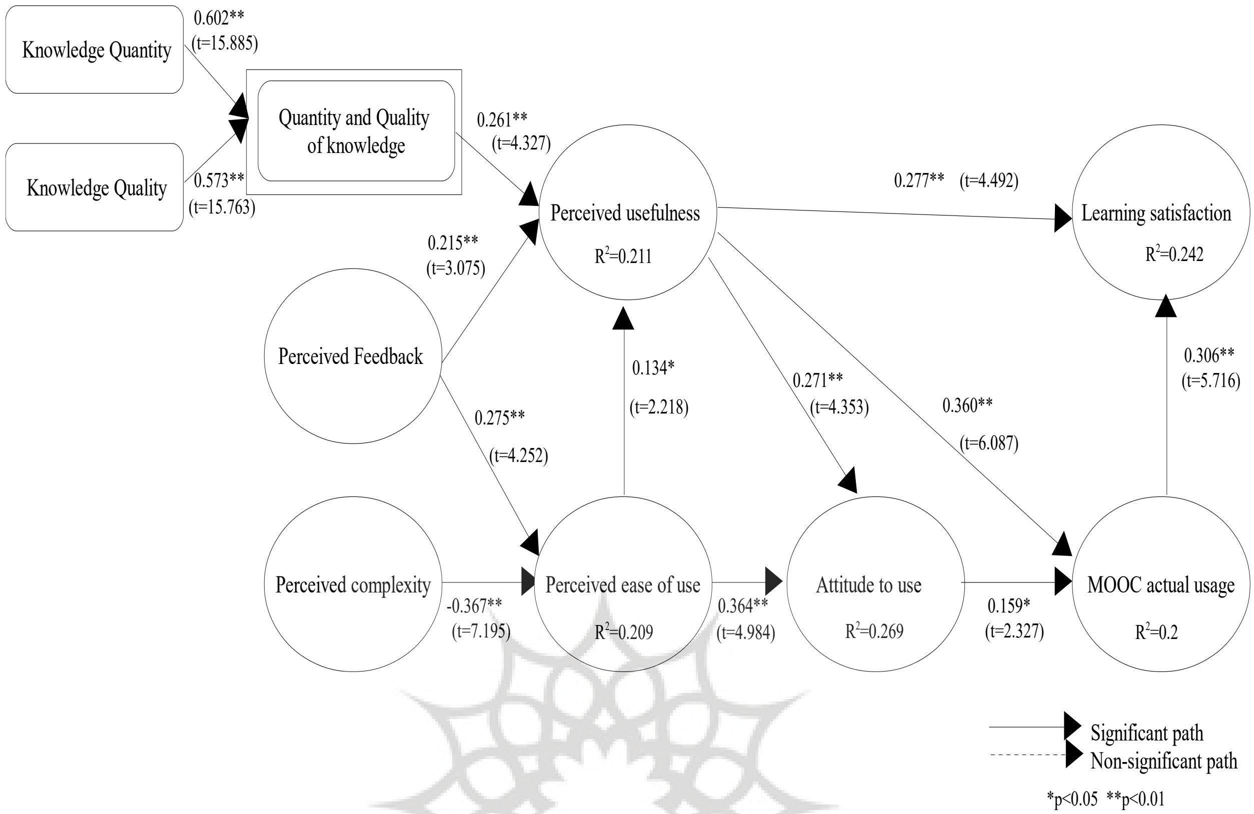

Figure2. SEM Analysis Model

4. Discussion

The primary objective of the current research was to identify the determinants which have a positive influence on MOOC platform courses' completion rate. In addition, we try to find the quantitative relationship between MOOC platform usage and learning satisfaction. An empirical study was conducted to test the research model. Parallel with the findings of Askell-Williams, et al (2019), the results of the present study indicated that quantity and quality of knowledge is a significant indicator of the MOOC platform perceived usefulness. The results of data analysis affirmed that the quantity and quality of knowledge could play a major role in the completion rate of MOOC platform courses; therefore, it can be inferred that as the quantity and quality of the provided knowledge in MOOC platforms increases, the dropout rate of the courses will decrease and completion rate will be enhanced. As it has been verified by the results of previous studies (Vattø & Smith, 2019), in which the perceived feedback played an important role in online involvement of users, the results of the present research showed that the perceived feedback has a positive impact on the PU and the PEOU of MOOC platform users. The result affirmed that when users of platforms receive feedback from their performance and platform related problems, they are more motivated to use the MOOC platform and complete their registered courses. The results of previous studies in e-learning study (Duan, He, Feng, Li & Fu, 2010) and knowledge-sharing behaviour (Ellahi & Mushtaq, 2011) confirmed that when the complexity in the provided technology is high, the intention to use and adoption of that technology is lower. In agreement with the previous findings, the result of this study illustrated that complexity has a strongly negative effect on the PEOU of MOOC platform users; therefore, if the presented the MOOC platforms are difficult to understand and use, it can lead to their lower usage and increase the dropout rate. In the core model of TAM, the PEOU was the direct determinant of the PU and the attitude to use. In line with earlier

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studies (Scherer et al., 2019; Kamal et al., 2020), it was found that the belief in PEOU has a significant effect on PU and using the attitude of the MOOC platform. This strongly verifies that potential users will use and finish MOOC courses when they find it convenient to use. This study reveals that PU has a significant positive effect on the attitude to use and actual utilization, and these findings are in agreement with previous studies (Revythi & Tselios, 2019). This result suggests that the usage and completion rate of the provided courses will further increase if the MOOC platform brings more tangible and practical benefits to the users. The path analyses showed that the attitude to use is a strong predictor of the final usage as found by Wallace and Sheetz (2014). Therefore, the attitude towards use acted as an important mediating variable between PEOU, PU and MOOC platform actual use. We found support for the salient effect of platform actual usage and PU to learning satisfaction, which is consistent with the findings of Park (2020) and Alqurashi (2019). It demonstrated that effective and efficient MOOC platforms can help promote learners' satisfaction; thus, the administrators and providers of the MOOC platforms should continuously enhance and improve the platforms, which in turn, leads to an increase in users' participation and a decrease in the dropout rates of users.

From a theoretical perspective, the research model offers several important theoretical contributions. Firstly, we analysed MOOC platform utilization by incorporating the factors from the well-established theory acceptance model. In light of the earlier discussion, PU, PEOU and attitude to use were identified as significant factors in explaining the platform usage behaviour. Secondly, according to the literature, this study developed new external variables for the PU, and the PEOU construct, including quantity and quality of knowledge, perceived feedback of platform and performance as a formative construct, and perceived complexity to fit the MOOC usage context. The results imply that users of the platform believe that the quantity and quality of knowledge, perceived feedback, and perceived complexity have impacts on their online learning activities. Thirdly, we have statistically examined the influence of MOOC platforms' actual usage and PU on learning satisfaction. The relationship between MOOC platform actual usage and learning satisfaction had not previously been studied. Our findings indicate that MOOC platform utilization and PU can enhance learning satisfaction.

From the practical perspective, to activate the usage of the MOOC platform and decrease the dropout of participants, the providers of platforms need to pay attention to the different motivational dimensions and create a suitable support system to intensify each motivation dimension. Therefore, managers of the community should offer intrinsic and extrinsic motivations to improve and retain the participants. This research suggests the following recommendations to assist practitioners to administer and design better MOOC platforms to attract, maintain and increase users. The results indicated that the knowledge quantity and quality had a significant effect on the expected usefulness of MOOC platforms. From the practitioners' standpoint, the MOOC platforms administrator needs to establish a setting where the users can discover the community serviceable and rich in qualified knowledge content. In doing so, they should enhance the quality and quantity of community knowledge via presenting enough courses and also through inviting experienced lectures to teach designed courses. The findings of this study imply that perceived feedback has a positive impact on both the PU and the PEOU of platform usage. Therefore, the administrators of the MOOC platforms need to enhance the feedback mechanism of their community in both platform side questions and performance side questions. The provided feedback should be delivered on time, in a precise manner and have enough quality and clarity to fulfil users' requirements. By confirming the effect of PU, PEOU, and perceived complexity on MOOC platform usage, the community providers should create an environment through which participants receive enough usefulness, understand and use without spending much time learning the MOOC platform and its facilities, and with a less complex system. Finally, the findings of the current study approved a positive and significant association between platform actual usage and learning satisfaction. The community managers could employ these findings to expand and develop their MOOC community and to encourage and market the utilization of the MOOC platform. Given the importance of the

MOOCs' platform in learning accessibility and blooming, we hope that the findings of the present research are useful for the practitioners and those involved in the theory of this field.

As MOOCs grow in popularity, the relatively low completion rate of the provided courses in MOOC platforms by the learners has turned into a central concern. We believe by observing the completion rates, a deeper understanding can be achieved of the reasons behind the high dropout rates in a voluntary usage setting. To understand this phenomenon, a research model was developed to investigate MOOC platform utilization in which many important factors were taken into consideration. These factors and constructs are presumed to enhance usage behaviour in massive open online courses. Additionally, the connection between perceived usefulness and platform actual usage with learning satisfaction has been assessed in the research model. For testing the theoretical model, an empirical study was designed. To evaluate the presented model, two hundred and thirty-four users from the selected MOOC platform (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 consists of path coefficients and R2 values. The analysis of the model was satisfactory and underpinned the validity of the proposed model. Consistent with our initial assumption, the findings indicated that the quantity and quality of knowledge have a significant effect on the perceived usefulness of MOOC platforms. Furthermore, the results illustrated that both platform-based feedback and performance-based feedback influenced the perceived ease of use and perceived usefulness. As it was assumed, complex designs and construction of the platform have a strong negative impact on the perceived ease of platform usage. The results indicated that the perceived usefulness and attitude to use the MOOC platforms were significantly affected by the perceived ease of use. The findings of this study suggest that the perceived usefulness exhibits a positive influence on the attitude, actual usage of the platform, and learning satisfaction of users; thus, the study suggests the perceived usefulness as a robust and salient indicator of MOOC utilization. Finally, the hypotheses regarding the influence of MOOC platform utilization to learning satisfaction were confirmed; consequently, the satisfied learner will continue using and completing MOOC platform courses.

Like all studies, there were a number of limitations in this study. First, it is not completely clear whether or not the findings of this study can be generalized to all MOOCs' platforms. This is because this study's findings are restricted to Coursera users; therefore, more research is needed to increase the generalizability of the findings of this research. Second, the sample of the study consists of active members of MOOCs. Thus, it was not possible to acquire the perceptions of individuals who do not take part in virtual communities anymore. Such individuals may provide alternative suggestions about the determinants. In addition, the reasons why they have withdrawn from the MOOCs provide invaluable information for the administrators of MOOCS. Accordingly, the results of the study can only be used to elucidate the current activities in virtual communities. Further studies can focus on the reasons why some individuals either do not take part or have less active participation in MOOC platforms.

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