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The Impact of Massive Open Online Courses (MOOCs) on Knowledge Management Using Integrated Innovation Diffusion Theory and the Technology Acceptance Model

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Abstract: MOOCs have grown in popularity in universities, but the agents that influence users' acceptance of MOOCs are little understood. The large and open nature of MOOCs puts the student in charge of their own learning. As a result, it is critical to comprehend learner behavior. The research is conceptually founded on the innovation diffusion theory (IDT), as well as knowledge management (KM) and the technological adoption paradigm (TAM). In theory, eight separate factors were discovered as contributing to perceived usefulness, as well as perceived ease of use toward attitude toward utilizing MOOC systems and MOOC use intention. A survey questionnaire based on the innovation diffusion theory (IDT), knowledge management (KM) components, and the technological acceptance model (TAM) was used to collect data from 284 university students who were randomly selected. SPSS and SEM-Amos were used for data analysis. The findings show that perceived technology fit, perceived enjoyment, perceived compatibility (PC), trialability (TR), observability (OB), perceived usefulness (PU), perceived ease of use (PEOU), and attitude towards using the system (MOOCs) are the most important predictors of university students' continued intention to use MOOCs (MOOCs). Through attitudes toward utilizing systems, perceived utility and perceived ease of use have an indirect impact on sustained intention (MOOCs). Both effort-perceived utility and perceived ease of use impact knowledge application, knowledge access, perceived technology fit, perceived pleasure, perceived compatibility (PC), trialability (TR), and observability (OB). Perceived compatibility (PC) has no bearing on perceived ease of use, while perceived technological fit (PTF) has no bearing on perceived utility. The findings will aid researchers and practitioners in better understanding university students' intentions to use MOOCs in the future. This study's ramifications and shortcomings are also discussed.

Keywords: massive open online courses (MOOCs); knowledge management; innovation diffusion theory; technology acceptance model; SPSS; SEM-Amos

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1. Introduction

The COVID-19 outbreak has raised enrollments in massive open online courses (MOOCs) in recent years [1]. MOOCs are a collection of ego web-based learning materials [2,3]. According to Cope and Kalantzis [4], MOOCs are one of the numerous instruments afforded by ICTs applied to education. MOOCs are a relatively new learning phenomenon, blending eLearning and open education [5]. Their name comes from the concept of multi-player online game (MMOG) [4]. They are not the same as open or distant learning. In 1995, Mr. Jerrold Maddox of Penn State University in the United States offered the first online "Commentary on Art" course. Only four years later, the term "eLearning" was developed. The UK government made loans accessible to students enrolled in bachelor distance learning programs for the first time in 2013. It is important to distinguish between eLearning and MOOCs. Electronic technology and digital media are being used to supplement or even totally supplant in-class educational experiences with fully online learning [6,7]. MOOCs, on the other hand, can only benefit a student's learning experience if they are not administered according to strict guidelines. Significant elements, such as finance, advertising, legal problems, scaffolding, learner connection, and alignment with learning aims, must all be considered when implementing MOOCs [8,9]. MOOCs must guarantee that those that have registered keep learning from the courses that are available to them as the number of persons participating in MOOCs expands [10].

Previous studies have identified many reasons for individuals quitting MOOCs as a learning medium [3,9,11–13]. MOOC completion rates are low, demonstrating a lack of self-control and motivation compared to what is expected of students [3,11,14]. As students go through the course material, their efficiency drops [14]. Furthermore, these MOOCs do not ensure the effectiveness of educational elements, nor do they give any support and funding for entrant motivation or social connection formation [13,15,16]. Finally, MOOCs are founded on students' dedication to their learning goals, prior knowledge and abilities, and shared support [17,18]. Though the benefits and drawbacks of MOOCs have been debated [19,20], the effect of MOOCs on institutions of higher learning cannot be ignored. As a result, researching the viability and advantages of massive open online courses (MOOCs) as part of an academic program is crucial. MOOCs are a divisive topic, both in terms of their utilization and the possible consequences for advanced learning. MOOCs, according to a group of professors, do not suit the needs of students [18]. One instance is the poor student turnover rate in these programs. Another theory is that MOOCs might cause severe worries about higher education, especially in terms of research and development [19,20]. Because of their economic model, MOOCs have the potential to destabilize higher-education institutions by disrupting the relationship between the three parts that make up university operations: teaching, research, and program consumer lending. MOOCs, according to some experts [21], offer a huge potential for helping people since they enable flexible, inexpensive access and speedy completion for anybody who wants to learn [22]. One of the most crucial problems discussed during COVID-19 [19] was academic recognition, a community conversation concerning the influence of MOOCs on higher education. Additionally, even if there is a possibility that MOOCs will have a detrimental influence on higher education, it appears that there is a willingness to analyze the advantages and reach judgments during the height of the MOOC discussion. The benefits include promotion of the university's national objectives, which are connected to online classes and internet core skills at Saudi Arabian universities, as well as advancement of the institution's global status, international student appeal, and promotion of the university's nationwide aims. The role of King Faisal University in integrating MOOCs into the academic curriculum is examined in this paper, which aims to make suggestions for further MOOC incorporation in Saudi Arabian higher education.

As a consequence, by examining the links between TAM variables' originality, knowledge management (KM) characteristics, and innovation diffusion theory (IDT) in a comparable model, this work contributes to the TAM literature. Using KM as a contextual theory, the study aims to assess the impact of inspirational variables on IDT and TAM ideas. As a result, eight factors were discovered to be determining factors of perceived usefulness and ease of use, different values, attitude toward using MOOC systems, and intention to use MOOCs: subjective norm, applying new fit, perceived suitability, trialability, quantitative measurements, awareness, knowledge application, and knowledge sharing. The empirical study could help academics and practitioners create and sell MOOC systems by assisting them in designing and testing concepts to scheme recognition.

The Impact of MOOC Use in Saudi Higher Education

The Kingdom of Saudi Arabia is determined to stay up to date with the advancement of global higher-education institutions. As a result, the Ministry of Higher Education held the first international conference on massive open online courses (MOOCs) and remote learning [23]. The spread of COVID-19 prompted the closure of educational facilities across the world in 2020, as a result of the COVID-19 pandemic. As a result of the shutdown, those schools' online learning environments improved, and learning and teaching were no longer disturbed [24]. During the COVID-19 pandemic, the Saudi university's preparation for a complete MOOC system shift experience is put to the test, addressing obstacles students have when attending MOOC courses by comparing Saudi student challenges to the findings of several studies. According to the research, judging students' work is challenging, and speaking into a vacuum owing to the lack of rapid student reaction, being burdened by large time and financial obligations, and confronting a lack of student engagement in online forums are all issues [25,26]. The biggest difficulty that MOOC providers confront is poor adoption rates, particularly in developing countries [27]. Meanwhile, Saudi Arabian colleges have embraced MOOCs; for example, King Khalid University (2012) provides MOOCs so that all of its lectures are accessible online. MOOCs have the ability to update the Saudi workforce and improve the education system by providing high-skilled training programs [28], but only if students accept the MOOC approach. As a result, it is important to establish what elements influence learners' adoption of MOOCs. A MOOC is a free, open access online course, in which students follow a well-defined syllabus with stated learning goals while watching recorded videos or participating in asynchronous learning activities. Ego and freedom in deciding to engage in MOOCs due to self, as well as self-assessed preparedness of past knowledge and abilities [4], are the key concepts behind MOOCs. Because of the growing popularity of these MOOCs, some institutions and universities have decided to include them in their curricula [8].

2. Theoretical Background and Hypotheses

Knowledge management (KM), IDT, and TAM are equivalent in several aspects when it comes to monitoring the usage of information systems, and they complement each other. Davis [29] extended Fishbein and Ajzen's "Theory of Reasoned Action" by including perceived usefulness (PU), perceived ease of use (PEOU), and attitude toward using systems (MOOCs) as important drivers of massive open online course system utilization intention. TAM asserts that the attitude predicted by PU and PEOU also predicted a role. According to Venkatesh and Davis [30], PU and PEOU show direct relationships with attitudes about utilizing the system (MOOCs). TAM has also been thoroughly tested and proven to be useful in understanding technology acceptance and adoption [31,32]. As a consequence, TAM is used as a model in this study to explain MOOC acceptance among students at King Faisal University. The new TAM now includes perceived compatibility, trialability, observability, knowledge access, knowledge application, and knowledge sharing, as well as organizational learning and innovation diffusion theory (IDT). Figure 1 depicts the suggested research model.

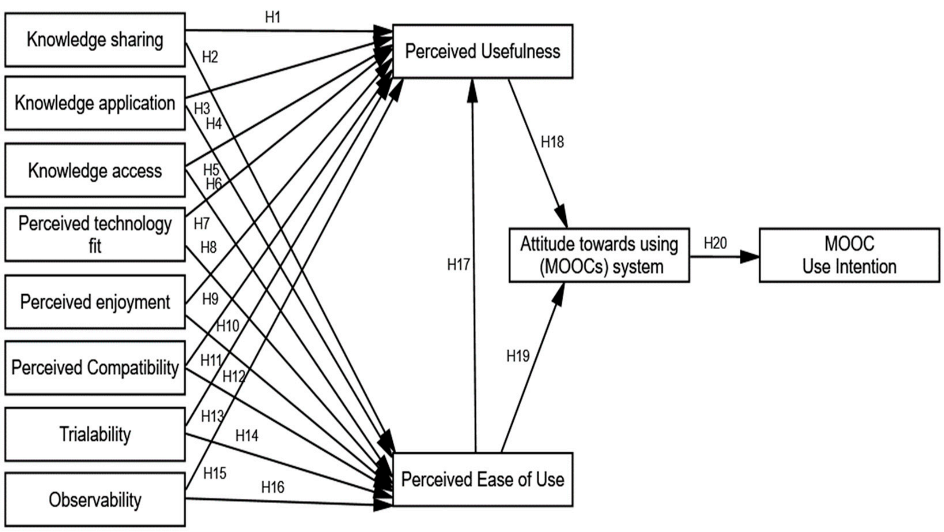

Figure 1. Research model.

2.1. Knowledge Management (KM)

2.1.1. Knowledge Sharing (KS)

"The process of disseminating varied resources among individuals engaged in particular tasks" [33] is how knowledge sharing is defined. The desire to share information and skills is a fundamental requirement for technological breakthroughs to be accepted and implemented. According to [34], knowledge sharing is defined as the exchange of experiences, ideas, and data between students and instructors through MOOCs. Between 2001 and 2018, Al-Emran et al. [35] analyzed the research literature on knowledge management and discovered that sharing information was the most often stated component in the KM literature and a strong predictor of technological innovation acceptance and adoption. Using a variety of technical instruments, researchers identified a link between information exchange and the PU and PEOU in a prior study [36–38]. Furthermore, Ali et al. [36] and Arpaci [37] found that when perceived usefulness and ease of use improve, so do perceived utility and ease of use. Knowledge exchange may have an impact on the PU and PEOU in the setting of this investigation. As a result, the scientists proposed the following hypotheses:

H1. *Knowledge sharing has a significant influence on MOOC PU.*

H2. *Knowledge sharing has a significant influence on MOOC PEOU.*

2.1.2. Knowledge Application (KAP)

"The mechanism that enables people to access knowledge effortlessly utilizing current efficient storage and retrieval systems" [35] is how knowledge application is described. Knowledge application, in other terms, is the process of allowing individuals and businesses to conveniently conduct research (ResearchGate) via effective backup and recovery mechanisms [34]. Meaningful learning is one of the most prevalent KM methodologies in the literature, according to Al-Emran et al. [35]. Furthermore, several studies have indicated that applying knowledge to technical advances increases their adoption and implementation [36–38]. Furthermore, Ali et al. [36] suggested that the more knowledge is used, the more beneficial it is judged to be. As a consequence, the researchers came up with the following hypotheses:

H3. *Knowledge application has a significant influence on MOOC PU.*

H4. *Knowledge application has a significant influence on MOOC PEOU.*

2.1.3. Knowledge Access (KA)

"The process of obtaining and exchanging knowledge and information from a specific system", is how knowledge access is defined [39]. The current study defined information access as the acquisition and transmission of knowledge and expertise from engineering students' use of MOOCs. MOOCs can help professors and students share fresh or updated knowledge and skills, ensuring that all students have access to high-quality content [40]. The usage of MOOCs enhances the retrieval and accessibility of information. As a result, MOOCs strive to make information accessible to all users, including students and teachers. According to Arpaci [37], the behavioral inclination to use mobile cloud computing for educational purposes is positively related to information extraction and accessibility. According to this study, engineering students' expectations for information access may have a major impact on MOOCs' perceived value and simplicity of use. As a result, the following theories are proposed:

H5. *Knowledge access has a significant influence on MOOC PU.*

H6. *Knowledge access has a significant influence on MOOC PEOU.*

2.2. Technology Acceptance Model

2.2.1. Perceived Technology Fit

The perceived technological fit of learners has been demonstrated to be a predictor of learning performance and future use [41,42]. According to research on procedural learning through YouTube [6,43], the task technology fit of learners impacts perceived utility and perceived ease of use. In MOOCs, task technology fit has a substantial impact on perceived ease of use and usefulness [44]. Because MOOCs provide free access to everyone who wants to participate, a wide range of learners can obtain knowledge tailored to their specific interests. Learners complete personalized tasks that are tailored to their unique interests. Learners examine perceived technology fit to attain their own goals before embracing system technology [45,46]. As a result, the following hypotheses have been proposed:

H7. *Perceived technology has a significant influence on MOOC PU.*

H8. *Perceived technology has a significant influence on MOOC PEOU.*

2.2.2. Perceived Enjoyment (PE)

In this study, enjoyment is defined as the extent to which the activity of using MOOCs for learning is "perceived to be delightful in its own right, free from any performance implications that may be predicted", as characterized by Davis, Bagozzi, and Warshaw [44] (emphasis on the original). Perceived enjoyment, according to this definition, is a sort of intrinsic motivation that can result in emotional arousal. Several studies have emphasized the importance of incorporating intrinsic motivation into the explanation of technology acceptance and usage [47]. The intrinsic motive for using MOOCs was provided in our study as perceived delight. MOOC acceptability is heavily influenced by users' perceptions of MOOC enjoyment. MOOCs, unlike traditional classrooms, provide users with not just a creative and useful platform for learning, but also a hedonic purpose, resulting in an enjoyable learning experience [48,49]. Interactive learning approaches, engaging activities, and the utilization of multimedia technologies differentiate today's MOOCs [50]. Consequently, in this research, perceived enjoyment refers to a student's belief that their academic performance would increase if they have fun in a massive open online course (MOOC). As a result, the following alternatives have been proposed:

H9. *Perceived enjoyment has a significant influence on MOOC PU.*

H10. *Perceived enjoyment has a significant influence on MOOC PEOU.*

2.3. Innovation Diffusion Theory (IDT)

2.3.1. Perceived Compatibility (PC)

Perceived compatibility (PC) refers to when society believes an invention effectively communicates data about "existing values, past experiences, and wants of potential consumers" [9]. Perceived compatibility is defined by Moore and Benbasat [51] as the degree to which an observable MOOC system adheres to current standards, criteria, and student experiences [52,53]. As a result, this study defined perceived compatibility as a student's belief that utilizing a MOOCs system would help them learn more successfully. Perceived compatibility was used as a predictor of attitude toward utilizing MOOC systems and behavioral control to use in research on information system adoption [54]. Furthermore, according to recent research on perceived compatibility from multiple viewpoints, it affects perceived utility, usefulness and ease of use, attitude toward adopting MOOC technologies, and behavior control to use [55,56]. Some of the hypotheses that have been offered include:

H11. *Perceived compatibility has a significant influence on MOOC PU.*

H12. *Perceived compatibility has a significant influence on MOOC PEOU.*

2.3.2. Trialability (TR)

TR refers to how confident society is in its ability to experience innovation before deciding whether or not to adopt new technologies. A trialable idea suggests less doubt to anybody looking at it for execution or executing it to learn [57]. As a result, in this study, this is defined as the degree to which a student considers the acceptability of MOOC system usage to have an influence on their learning performance. Several studies [56,58] have revealed an experimental link between effort expectancy and attitudes toward using the MOOC system as a method of instruction. The following hypotheses were developed:

H13. *MOOCs' trialability (TR) has a significant influence on MOOC PU.*

H14. *MOOCs' trialability has a significant influence on MOOC PEOU.*

2.3.3. Observability (OB)

The degree to which "the invention's consequences are visible to others" is referred to as observability (OB) [56]. Because friends and neighbors usually question innovation appraisal, this exposure stimulates peer discussion of a unique concept [57]. As a result, "observability" is defined in this study as the amount to which a student's perspective supports the usage of MOOC systems, which influences their learning achievement, using a variety of techniques and gathering a broad group of people with different specialties [9,57]. According to some experts, the system's observability influences users' attitudes toward it and their plans to utilize it [59]. In an empirical study, it was shown that observability had a significant effect on perceived ease of use, attitude toward using the MOOC system, and behavioral control of utilizing the MOOC system. The following were the ideas that were developed:

H15. *Observability has a significant influence on MOOC PU.*

H16. *Observability has a significant influence on MOOC PEOU.*

2.4. Perceived Ease of Use (PEOU)

PEOU is "the degree to which a person believes that putting in place a particular system would be painless" [60]. The PEOU concept is related to the DOI (Rogers, 2010) and the UTAUT's "complexity" and "effort expectancy", as demonstrated by Venkatesh et al. [54]. PEOU is defined, in this study, as the degree to which an engineering student views MOOCs to be effort-free and to help them learn more effectively [61]. PEOU has a good and considerable effect on the PEOUU and ATU, according to a current study on MOOC adoption and use [62–64]. As a result, the following hypotheses are presented:

H17. *The perceived ease of use has a significant influence on MOOC PU.*

H18. *The perceived ease of use has a significant influence on MOOC ATUM.*

2.5. Perceived Usefulness (PU)

Davis (1989) defined perceived usefulness (PU) as the degree to which an individual believes that adopting a certain technique will increase job performance [44]. Consequently, in this study, perceived utility is defined as a student's view that completing MOOCs would help them learn more effectively. According to a recent study on MOOC utilization, perceived usefulness has a major impact on attitudes about using the system [65–68]. The following is a hypothesis that was proposed:

H19. *The perceived usefulness has a significant influence on MOOC ATUM.*

2.6. Attitude towards Using MOOCs (ATUM)

Some researchers believe that classroom components [69], as well as students' commitment to and acceptance of tasks [70], impact students' perceptions about MOOC learning. Perceived ease of use and TAM, according to Davis [44], influence perceived attitudes and, as a consequence, the user's attitudes towards adopting information technology. According to [71,72], perceived ease of use has an effect on a student's attitude toward and intention to utilize an online learning system such as MOOCs. The following is a hypothesis that was proposed:

H20. *Attitude towards Using MOOCs has a significant influence on MUI.*

3. Research Methodology

Following a manual review, 16 of the 300 questionnaires were found to be incomplete, indicating that students did not complete the survey; as a result, they had to be eliminated, leaving 284 questionnaires usable (See Appendix A). According to [73], this is a valid reason for exclusion, stating that outliers might lead to erroneous statistical conclusions and should be avoided. Massive open online courses (MOOCs) were used as the study's sample, and the perceived ease of use, predicted benefit, and attitude toward utilizing the MOOC system were all studied. The sample size of this study consisted of 284 bachelor's and master's degree students in the age range of 18 to 46 and higher from King Faisal University located in Saudi Arabia. This study utilized a quantitative method for the sampling technique, and the respondents were selected from three specializations and others. The questions were scored on a 5-point Likert scale and included aspects of TAM and assessment knowledge management (KM) with innovation diffusion theory (IDT). Participants were given the questionnaire in person and instructed to return it once they had finished it. The poll focused on perceived usefulness and ease of use, perceived utility, opinions about MOOC platforms, and participants' plans to utilize them. SPSS was used to analyze the data, and structural equation modelling was used (SEM-Amos). The research is divided into two parts: convergent and discriminatory validity, and structural model evaluation. Refs. [74,75] advocated for these techniques.

3.1. Participants

Gender, age, and expertise were all covered in the demographic profile section of the survey. From a total of 284 questionnaires, 377 (70.4%) were completed by male participants, and the remaining 84 (29.6%) were completed by female participants. The survey data showed that 56 (19.7%) of the respondents were aged between 18 and 24 years, while 104 (36.6%) were aged between 25 and 29 years. Additionally, 68 (23.9%) of the respondents were aged between 30 and 34 years, 20 (7.0%) were aged between 35 and 39 years, and 36 (12.7%) were above 40 years of age. Based on demographic factors related to specialization, 113 of the participants were affiliated with the management field (39.8%), 77 were from science and technology (27.1%), 52 were from engineering (18.3%), and 42 were from other specializations (14.8%) (See Table 1).

Table 1. Summary of the demographic profile of the respondents.

Items	Description	N	%	Cumulative %
Gender	Male	200	70.4	70.4
	Female	84	29.6	100.0
Age	18–24	56	19.7	87.3
	25–29	104	36.6	36.6
	30–34	68	23.9	60.6
	35–39	20	7.0	67.6
	40 and above	36	12.7	100.0
Specialization	Management	113	39.8	66.9
	Science and Technology	77	27.1	27.1
	Engineering	52	18.3	85.2
	Others	42	14.8	100.0

3.2. Measurements

According to [76–78], a 15-item scale was designed to assess people' knowledge management practices. Information access (five items), knowledge sharing (five items), and application of knowledge (five items) are the three dimensions of the measure (five items). The measurement items, i.e., perceived (five items), indicated that overall use (five items), perceived technological fit (five items), perceived enjoyment (five items), attitudes towards the use of the system (five items), and massive open online course system usage intention (five items) were adapted from TAM [44,79,80]. The items measuring perceived compatibility (PC) (five items), trialability (TR) (five items), and observability (OB) (five items) were adapted from [76,80–83]. The final measure had 60 items listed in Appendix A, each of which was assessed on a 5-point Likert scale ranging from 1 to 5, with 1 indicating "strongly disagree" and 5 indicating "strongly agree".

4. Results and Analysis

The associated issues with knowledge management (KM) factors, TAM, and innovation diffusion theory (IDT) influenced students' attitudes toward using MOOC schemes and intention for helping students learn in higher education. Cronbach's alpha reliability coefficient was 0.911.

4.1. Measurement Model Analysis

In AMOS 23, structural equation modeling (SEM) was integrated with confirmatory factor analysis as the major statistical technique for evaluating data (CFA). Hair et al. [74] evaluated the model's unidimensional reliability, discriminant validity, goodness of fit, and convergent validity. The goodness-of-fit indices are summarized in Table 2, and the measurement model is shown in Figure 2. Finally, normality was based on the values of the variance inflation factor (VIF < 10) and tolerance (>0.1) as well as Pearson's product-moment correlation coefficients of less than 0.90 (see Table 3). The values of VIF should not be greater than 3, as values exceeding 3 are often considered to indicate multicollinearity problems. As depicted in Table 3, all VIFs are below 3.

Table 2. The measurement model of Goodness-of-fit indices.

Type of Measure	Acceptable Level If Fit	Values
Root–Mean residual (RMR)	near to 0 (Perfect fit)	0.054
Incremental Fit Index (IFI)	= or >0.90	0.914
Tucker Lewis Index (TLI)	= or >0.90	0.900
Comparative Fit Index (CFI)	= or >0.90	0.913
Root- mean square error of approximation (RMSEA)	<0.05 indicates a good fit.	0.045

Table 3. Correlation analysis.

Coefficients		
(Constant)	Tolerance	VIF
KS	0.314	2.181
KAP	0.164	2.111
KA	0.285	1.511
OB	0.125	3.013
TR	0.139	2.172
PC	0.662	1.510
PTF	0.562	1.779
PE	0.515	1.942
PU	0.318	2.143
PEOU	0.133	1.540
ATUM	0.304	2.294

Dependent Variable: MUI.

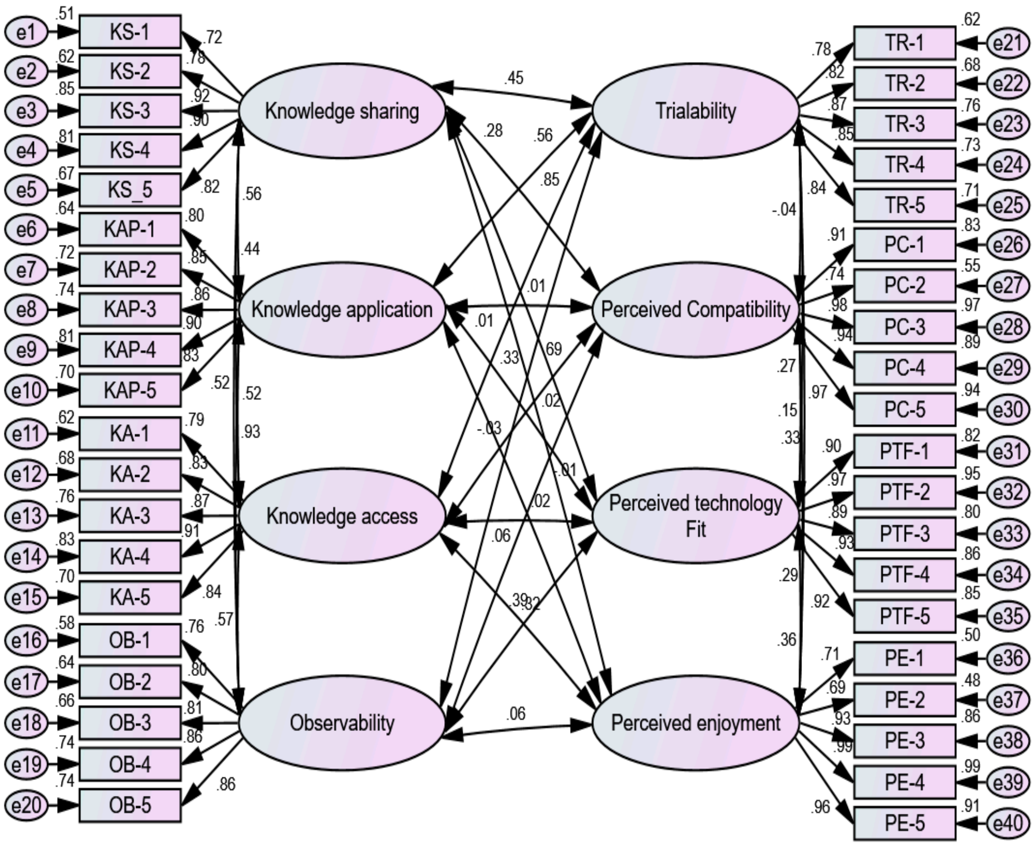

Figure 2. Independent result measurement.

4.2. Validity and Reliability of Measures Model

The validity and reliability tests are outlined in Table 4. All of the results for the overall composite reliability (CR), Cronbach's alpha (CA), and average variance extracted (AVE) values were accepted, demonstrating discriminant validity. The acquired (CR) values are also displayed, ranging from 0.837 to 0.967, all of which are greater than the cut-off value of 0.70. All of the CA values were greater than the cut-off of 0.70, ranging from 0.883 to 0.966. Additionally, the AVE values varied between 0.721 and 0.962, all of which exceeded the desired threshold of 0.50, indicating that the entirety is significant and greater than 0.50, therefore, meeting Hair et al. [74].

Table 4. Overall validity and reliability, AVE, CR, and CA for students.

	PE	PTF	PC	TR	OB	KA	KAP	KS	PEOU	PU	ATUM	MUI	AVE	CR	CA
PE	0.984												0.748	0.935	0.933
PTF	0.386	0.939											0.853	0.967	0.966
PC	0.240	0.210	0.736										0.962	0.837	0.963
TR	0.296	0.152	0.023	0.848									0.699	0.921	0.918
OB	0.043	0.352	0.009	0.552	0.857								0.672	0.911	0.908
KA	0.301	0.076	0.014	0.720	0.493	0.945							0.719	0.927	0.926
KAP	0.035	0.311	0.001	0.465	0.760	0.470	0.887						0.721	0.928	0.927
KS	0.026	0.006	0.220	0.358	0.422	0.376	0.455	0.810					0.692	0.918	0.916
PEOU	0.304	0.128	0.004	0.722	0.531	0.704	0.555	0.405	0.807				0.636	0.897	0.896
PU	0.081	0.011	0.183	0.388	0.389	0.367	0.325	0.578	0.319	0.733			0.602	0.883	0.883
ATUM	0.116	0.378	0.018	0.489	0.725	0.500	0.661	0.379	0.497	0.352	0.922		0.758	0.940	0.939
MUI	0.001	0.024	0.261	0.361	0.365	0.404	0.314	0.570	0.341	0.588	0.367	0.852	0.774	0.945	0.945

4.3. Structural Model Analysis

Throughout the hypothesis-testing argument, the findings are presented and contrasted using the MOOC method. To test the hypotheses offered, the CFA was used as the following step in the structural equation modeling (SEM). This is seen in Figures 2–4. All hypotheses pertaining to the twelve key constructs are depicted in Figure 3. Eighteen hypotheses were found to be valid, while just two were found to be false. Table 5 shows the results of the hypothesis testing. The outcomes of this study support the TAM hypotheses in their entirety, and they are in line with the bulk of prior studies that have demonstrated reported enjoyment, usefulness, and simplicity of use. MOOCs increase students' attitudes and behavioral intentions toward using them for learning. Children's academic performance increases as a result [84–86]. As a consequence, the current model reveals that MOOCs benefit all students and are beneficial to their learning.

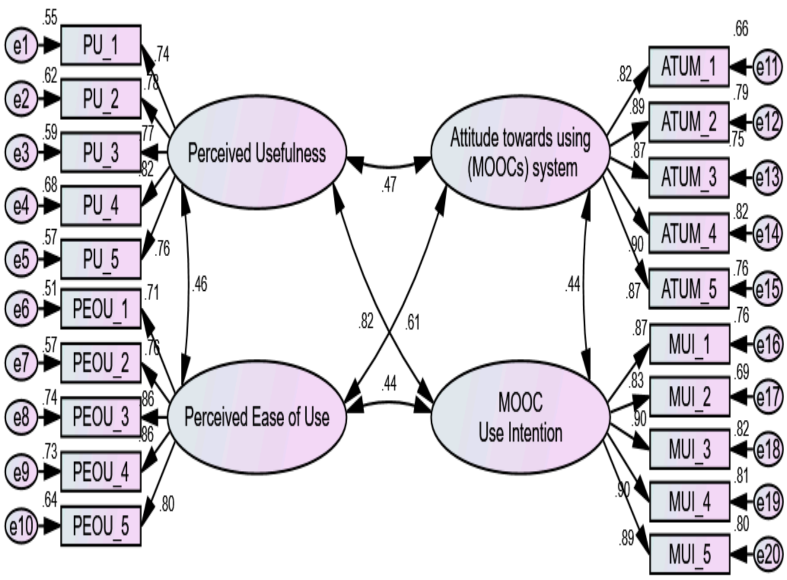

Figure 3. Measurement of mediator and dependent values.

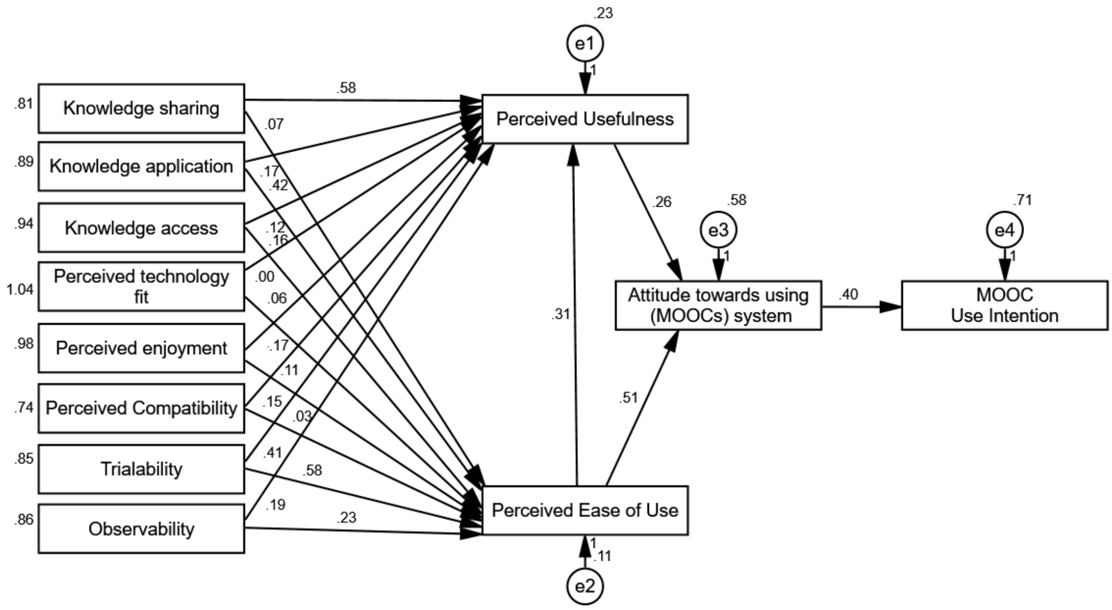

Figure 4. The proposed model's results for the system of MOOCs.

Table 5. Structural model for hypothesis-testing results.

	Independent	Relationship	Dependent	Estimate	S.E.	C.R.	*p*	Result
H1	KS	→	PU	0.585	0.045	12.934	0.000	Accepted
H2	KS	→	PEOU	0.068	0.031	2.194	0.028	Accepted
H3	KAP	→	PU	0.167	0.075	2.224	0.026	Accepted
H4	KAP	→	PEOU	0.418	0.046	9.183	0.000	Accepted
H5	KA	→	PU	0.117	0.054	2.152	0.031	Accepted
H6	KA	→	PEOU	0.157	0.036	4.307	0.000	Accepted
H7	OB	→	PU	0.186	0.078	2.387	0.017	Accepted
H8	OB	→	PEOU	0.235	0.052	4.501	0.000	Accepted
H9	TR	→	PU	0.408	0.079	5.141	0.000	Accepted
H10	TR	→	PEOU	0.585	0.043	13.753	0.000	Accepted
H11	PC	→	PU	0.145	0.040	3.608	0.000	Accepted
H12	PC	→	PEOU	0.028	0.028	−0.013	0.311	Rejected
H13	PTF	→	PU	0.004	0.037	0.109	0.913	Rejected
H14	PTF	→	PEOU	0.056	0.025	2.190	0.029	Accepted
H15	PE	→	PU	0.165	0.039	4.208	0.000	Accepted
H16	PE	→	PEOU	0.111	0.026	4.206	0.000	Accepted
H17	PU	→	ATUM	0.257	0.058	4.437	0.000	Accepted
H18	PEOU	→	PU	0.310	0.086	3.606	0.000	Accepted
H19	PEOU	→	ATUM	0.514	0.055	9.308	0.000	Accepted
H20	ATUM	→	MUI	0.399	0.052	7.666	0.000	Accepted

5. Discussion and Implications

MOOCs provide students with ubiquitous access to a variety of materials in "anytime, anywhere" situations. MOOCs give sufficient storage capacity for students to save their content. Students can also exchange material content with their classmates through MOOCs. Management, engineering, and science and technology students may use what they have learned in MOOCs for decision-making and problem-solving tasks. Nonetheless, there are a number of elements that may influence students' decision to use MOOCs. Due to the cultural backgrounds of the pupils, these elements differ from one nation to the next. The goal of this study was to develop and test a model by looking into KM, IDT, and

TAM theories, such as expertise access, application of knowledge, knowledge sharing, user satisfaction, perceived advantages, viewed compatibility, tangibility, observability as dimensions of PEOU, PU, and attitude toward using MOOC system on students' intention to use MOOCs across different cultures, specifically Saudi Arabia.

The hypothesized correlations were evaluated using SEM analysis using SPSS-AMOS 23. Knowledge sharing (β = 0.585, t-value = 12.934; $p < 0.001$; β = 0.068, t-value = 2.194, $p < 0.001$), knowledge application (β = −0.167, t-value = −2.224 $p < 0.001$; β = 0.418, t-value = 9.183 $p < 0.001$), and knowledge access (β = 0.117, t-value = 2.152, $p < 0.001$) were shown to be the most common As a result. H1, H2, H3, H4, H5, and H6 were shown to be viable options. The findings revealed a positive and substantial association, supporting hypotheses (H1–H6) that students value MOOCs for knowledge sharing, knowledge application, and information access, and anticipate utilizing them to improve their educational performance. These results support previous research [81,82], which revealed that ease of use utility boosted students' active learning, application, and sharing.

According to TAM, students' perceptions toward MOOCs and their motivation to participate in MOOC programs were influenced by perceived enjoyment, perceived technical fit, perceived utility, and considered ease of use. This was the case in this study, where users of MOOC systems thought that a higher perceived usefulness equaled a greater willingness to use the MOOC systems. Perceived technology fit does not have a positive and significant impact on the perceived usefulness (β = −0.004, t-value = −0.109, $p < 0.001$). Therefore, hypothesis (H7) indicates that there is not a relationship between perceived technology fit on perceived usefulness; thus, H7 was unsupported. However, perceived technology fit was positively associated with the perceived ease of use (β = −0.056, t-value = −2.190, $p < 0.05$) and, therefore, H8 was accepted. Moreover, perceived enjoyment has a significant beneficial effect on perceived usefulness (β = −0.165, t-value = −4.208, $p < 0.001$) and PEOU (β = 0.111, t-value = 4.206, $p < 0.001$). Thereby, H9 and H10 were supported. These outcomes were similar to those in [54].

The results of the path coefficients are shown in Figure 4 and Table 3. For hypotheses (H11–H16), observability has an influence on perceived usefulness (β = 0.186, t-value = 2.387, $p < 0.001$) and perceived ease of use (β = −0.235, t-value = −4.501, $p < 0.001$), trialability on perceived usefulness (β = 0.408, t-value = 5.141, $p < 0.001$) and perceived ease of use (β = 0.585, t-value = 13.753, $p < 0.001$), and perceived compatibility on perceived usefulness (β = 0.145, t-value = 3.608, $p < 0.001$) for MOOCs. These findings are in line with a prior study [87,88], which found that perceived ease of use and perceived utility increased students' observability, trialability, and perceived compatibility. Perceived compatibility, on the other hand, was negatively linked with the PEOU (β = −0.028, t-value = −1.013, $p < 0.001$); hence, H12 was rejected. Perceived compatibility, on the other hand, had no positive or substantial influence on PEOU; consequently, H12 was not supported.

This research also showed that perceived ease of use had a positive effect on perceived usefulness. Therefore, hypothesis (H17) demonstrated that there was a positive relationship between perceived ease of use and perceived usefulness (β = 0.257, t-value = 4.437, $p < 0.001$); thus, H17 was supported. Similarly, the relationship between PEOU on PU (H18) was (β = −0.310, t = −3.606, $p < 0.001$). Thereby, the hypothesis was accepted. Moreover, H19 was supported. PEOU has a significant positive effect on the attitude towards using MOOC systems (β = 0.514, t = 9.308, $p < 0.001$). Nonetheless, the test findings were the same as in previous reports [87,88].

Finally, attitude towards using MOOC systems was positively associated with the MOOCs (β = 0.399, t = 7.666, $p < 0.001$) and, therefore, H20 was accepted. On the other hand, the attitude toward utilizing the MOOC system has a favorable and significant influence on the intention to utilize MOOCs; hence, H20 was endorsed. These findings back a prior study [89,90], which found that students' views on utilizing MOOC platforms were all impacted by their parents. This research presents three pieces of evidence. Perceived usefulness and ease of use were the first empirical evidence of the MOOC system, and the second was evidence of attitude toward using the MOOC system, as measured through perceived usefulness and ease of use, which may influence the intention to use MOOCs. Knowledge sharing, knowledge access, and knowledge application provided the last empirical proof that perceived usefulness and ease of use of MOOC systems may impact students' perceptions about utilizing MOOC systems. In the educational environment, there was a substantial theoretical addition to prior knowledge management components (KM), IDT with TAM [76,91,92]. Education must open the door to questioning the entire concept of sustainable development as the proper way and motivate today's and tomorrow's students to build new ideas and paradigms in order to make the world a better place [93,94].

Limitations and Future Work

In addition to contributions in determining the antecedents of knowledge management (KM), IDT, and TAM and their influence on MOOC use intention, there are some limitations in this study. First, the sample size of the research was limited to one university in Saudi Arabia. Therefore, the results may not reveal the performance of private universities, militaries, or school teachers. Second, this study excluded the UTAUT factors (performance expectancy, social influence, and facilitating conditions), and the participants in this study were selected randomly from one university. Future studies must take into account a number of important restrictions. To begin, only questionnaire surveys were employed to gather information. As a result, future attempts may look into employing qualitative methods, such as interviews or focus groups, to better understand and confirm the quantitative findings. Second, the model should be expanded to include other components such as contentment with the system and confirmation. Third, the three moderators (age, gender, and experiences) were not included in this study, and the participants were chosen at random from one institution; future studies should use diverse samples from different universities to investigate the impact of these moderators on the model. Finally, while the sample size was enough for examining the model and performing the structural equation model analysis, bigger sample sizes should be used in future investigations.

6. Conclusions

This study explains the elements that influence students' use of MOOCs and proposes twenty hypotheses based on a model that combines knowledge management factors, the TAM model, and IDT theory with computer self-efficacy and attitude. Only two of the twenty possibilities are accepted. The study model explained a significant portion of the variance in the intention to use MOOCs in the future. To the best of our knowledge, this study was conducted only at one university. We used KM factors, the TAM model, and IDT theory in the research model, which included completing the relevant knowledge application, knowledge sharing, user satisfaction, perceived advantages, perceived suitability, tangibility, and quantitative measurements. Finally, the findings of this study contribute significantly to the establishment of a new paradigm for MOOCs as a form of higher education. The model presented in this research contributes to the existing literature on MOOC adoption, and it may motivate institutions and MOOC designers to produce successful MOOCs that are also sustainable. The role of faculty in the acceptance of MOOCs as a long-term educational solution will be the subject of a future study. As a result, a future study into the linkages between e-learning system complexity and MOOC systems and other educational technology systems, as well as research into the ties between MOOC systems and other educational technology systems, is required. Furthermore, the roles of knowledge access, application, and sharing in MOOCs should be examined, particularly in terms of adaptability and sustainability in developing countries' higher education.

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Informed Consent Statement: This research did not apply to human and animal participants.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

	Knowledge sharing (KS)
1.	MOOCs allows me to share knowledge with my instructor and classmates.
2.	MOOCs supports discussions with my instructor and classmates.
3.	MOOCs facilitates the process of knowledge sharing at anytime anywhere.
4.	MOOCs enables me to share different types of resources with my class instructor and classmates.
5.	MOOCs facilitates the collaboration among the students.
	Knowledge application (KAP)
6.	MOOCs provides me with an instant access to various types of knowledge.
7.	MOOCs enables me to apply the knowledge in performing the learning activities and assignments.
8.	MOOCs allows me to integrate different types of knowledge.
9.	MOOCs can help us for better managing the course materials within the university.
10.	MOOCs system facilitates the process of acquiring knowledge from the course material.
	Knowledge access (KA)
11.	MOOCs enable me to access video lectures anytime and anywhere.
12.	MOOCs facilitate my access to video lectures.
13.	MOOCs enable me to quick access to video lectures and learning materials.
14.	MOOCs enables me to acquire the knowledge through various resources with lectures
15.	MOOCs enable me to ubiquitous access to learning materials and video lectures
	Observability (OB)
16.	I have seen people around me using MOOCs.
17.	It's easy for me to find others sharing and discussing the usage of MOOCs.
18.	I can quickly feel that MOOCs could bring me some benefits.
19.	I have seen my coworkers or friends using MOOCs.
20.	I have seen the demonstrations and applications of MOOCs
	Trialability (TR)
21.	I can try any kind of function before using MOOCs officially.
22.	I know how to try it out before using MOOCs officially.
23.	I can quit it if I am not satisfied after trying MOOCs.
24.	I can try the technology provided by the MOOCs vendor to evaluate if it meets my work or research needs.
25.	I can accumulate useful experiences after trying the MOOCs
	Perceived Compatibility (PC)
26.	MOOCs is compatible with other systems/services I am using and consistent with my habits
27.	MOOCs is compatible with SPOC, a flipped classroom, and other application scenarios
28.	Using MOOCs is compatible with all aspects of my learning
29.	Using MOOCs is completely compatible with my current learning situation
30.	I think using MOOCs fits well with the way I like to conduct learning activities
	Perceived technology fit (PTF)
31.	MOOCs platform provides multiple evaluation functions.
32.	The services provided by MOOCs can meet my requirement.
33.	The functions of MOOC platform can meet my requirement.
34.	The quality of MOOCs can meet my requirement
35.	I think that using MOOC is well suited for the way to learn.
	Perceived enjoyment (PE)
36.	Using MOOCs is pleasurable.
37.	I have fun using MOOCs.
38.	I find using MOOCs to be enjoyable.
39.	I believe that using MOOCs will be interesting to me
40.	I believe that using MOOCs system will not be intimidating.

	Perceived Usefulness (PU)
41.	Using MOOCs would improve my academic performance.
42.	Using MOOCs would improve my effectiveness.
43.	Using MOOCs would improve my skills.
44.	Using MOOCs would improve my efficiency.
45.	Using MOOCs will enhance my learning effectiveness".
	Perceived Ease of Use (PEOU)
46.	Using MOOCs would be easy for me.
47.	Using MOOCs, I can easily watch a video lecture.
48.	Using MOOCs, I can easily share learning materials.
49.	MOOCs would help me study my courses anywhere and anytime.
50.	MOOCs makes it easy to access course material for my learning
	Attitude towards using (MOOCs) system (ATUM)
51.	I believe that using MOOCs is a good idea.
52.	I believe that using MOOCs is advisable.
53.	I am satisfied with using MOOCs.
54.	Studying is more interesting with MOOCs
55.	I am happy when I am able to answer the practice questions in the MOOC.
	MOOC Use Intention (UMI)
56.	I intend to continue to use MOOCs for learning in the future.
57.	I plan to use MOOCs for learning in the future
58.	I will insist on using MOOCs to study the courses I registered for.
59.	I will recommend other students to use MOOCs system.
60.	I predict I will use the MOOCs system in the future.

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