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Continued Intention to Use UCOM: Four Factors for Integrating With a Technology Acceptance Model to Moderate the Satisfaction of Learning

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ABSTRACT This paper investigates whether the universities' communication model and the technology acceptance model, which include four factors, namely, academic performance, student satisfaction, effectiveness, and support assessment, simultaneously enhance student satisfaction and improve the teaching method and academic performance level. This paper aims to adapt a model to improve the assessment method and improve the model of student satisfaction. This paper focuses on improving e-learning to activate the feedback of continued intention of using the model that helps to navigate the student understanding level and academic performance immediately. In this paper, surveys were distributed to (295) undergraduates in four universities in Oman to assess their feedback on e-learning. The partial least squares-structural equation model was used to calculate the measurement of all hypotheses proposed. The results of this paper prove that most of the hypotheses are a positive influence on the continuance of intention to use the proposed model.

INDEX TERMS Academic performance, e-learning, MOOC, student satisfaction, support assessment.

I. INTRODUCTION

Among the new teaching goals of universities and any educational institute are the learning goals that make institutions wish for their students to achieve with outcomes understand [1]. This method can be applied by faculty members when they use their courses and the university uses graduate proficiencies. Such outcomes need to be understandable and assessable and need to provide basics for curricula improvement and the development of all courses. To be sure of learning outcomes movement, this can foul by students who have been interested in the effects of the changing patterns of college attendance on the curriculum and real level of learning [2], [3]. Many studies have pointed to the use of massive open online courses (MOOCs) as online e-learning with unlimited learners. This platform model enables students and the faculty to connect easily and to progress the course requirement with the assistance of peer observation and automatic grading, which helps for time reduction and trusted assessment models [4]. Still, many challenges are presented during the use of MOOCs, such as lower faculty motivation to use the application of learning [5]. Because of the rapid technological changes, learners need to adapt to new methods of communication by using online chat, which involves the use of related PDF files, videos, and Google forms [6]. Maas *et al.* (2014) pointed to massive open online courses (MOOCs) as well-known platforms created after the year 2012. They are limited to direct relation feedback between faculty and students. They are concerned with the interactivity and support assessment to get the course objectives and continue to use the model [7]–[9]. Most of the new approaches used e-Learning concepts, of which MOOC is an evolutionary step, tightly coupled technologies of chat, files, and automatic exams to reach huge numbers of participants and teach interested skills. Most research focuses on the academic impact, while a few studies consider the personal satisfaction and student knowledge development of this step and their intention to use the university communication model (UCOM) [1]. The e-learning can pave the way for better teaching methodologies and can effectively support the development of technologies and improve learning outcomes in the universities [10]. The use of e-learning helps faculty members to be more professional with technological tools that facilitate self-assessment used to evaluate the faculty's teaching methods, students' performance levels, and course

material [3], [6], [11], [81]. The overall use of e-learning models could illustrate the level of satisfaction that students may reflect over their grades and the way of course content material with teacher subject knowledge with interactivity that provides effective learning skills freely without being committed to a specific space and time [12], [80]. The purpose of this study is to identify the E-learning factors that have an impact on the improvement of both the assessment method and the academic performance to achieve the continued intention of use. These factors include perceived usefulness, perceived ease of use, student satisfaction, interactivity, faculty subject knowledge, and integration technology. These factors help to distinguish the differences between individuals and the implementation of the play or role depending on a specific method of understanding.

As such, in recent studies on UCOM that work in ways similar to MOOC, these models attempt to go beyond the direct factors used in TAM. This research tries to shine light on the combination of learning requirement factors and TAM factors to produce a better comprehensive view of the characteristics of a unique model of use. First, there are many studies need to understand deeply focus on learning process of course content and teacher knowledge with technology integration [12], [13]. These studies position the focus on the teacher, learner, and technology of communication to play a critical part in the learning procedure to complete a course using an MOOC model. Some studies reveal that student learning progress needs some internal factors and other external factors to reach the teaching target [14]. The results of this work generate very valuable knowledge. However, the continued intention to use issue has infrequently been the point of these studies. Actually, initial and continued behavior share different characteristics [15]. For example, learners' initial adoption of the e-learning model can be assessed by peers' suggestions and teacher support, but their revisit behavior and continued use is more likely to be determined by their own experiences and evaluations of the model system [16]. If they have enough experiences and assess the model positively, they are more likely to have continued intentions to use the UCOM model. This paper is presented in different sections; the first section is a review of the literature related to each nominated factor of the continued intention to use the model; the second section is devoted to the development of the model hypothesis that has a combination of 16 relations between independent and dependent factors. The third section presents the results analysis of the outcome of UCOM and testing for student motivation and assessment acceptance. The fourth section includes the discussion of valuable targets, followed by limitations and future work.

II. LITERATURE REVIEW

The use of communication tools and application software provide the mechanisms for deciding which group members coordinate job requirements, save records, and impart knowledge achievements. These tools help students to be more confident and trained in the usage of technologies. Currently, academic staff relies heavily on communications that could redesign adopted courses. Therefore, a limited number of studies have investigated the relationship between support assessment and interactivity with satisfaction in the higher education field [17], [18]. As a recommendation, Cavanagh *et al.* (2014) states that research needs a reflection of a live audience in a more authentic classroom style, giving a group work impression to increase activities and participation [19]. They used a new method to improve communication performance by using a video-based application to improve students' understanding and activate the technology element in developing tools available to IT following university policies, but it is still based on faculty communication and suffers from less of an effect on support assessment.

TEL environments are recognized as effective facilitators that support student learning [20]. The different technologies and applications used currently in universities could directly or indirectly interfere with both the university academic performance and student satisfaction [83]. Schemed (2014) came to the conclusion that the average effectiveness and satisfaction was more in reduce control with technology, and they used a combined dataset and work in effective measure by self-evaluation assessment [21]. There are multiple innovative performances that have been developed to additionally and fully connect the students with the MOOC used in science education, and the development gives students the necessary skills and knowledge to assist faculty members [22]. Lee, Yeung, & Ip (2017) found that interactivity between learners yielded satisfaction with the use of computer devices and that computers with technology enhance the learning process and facilitate communication among the faculty members, between the faculty and learners, and among learners themselves. This variant of emerging e-learning systems can be adapted for managing online courses, MOOC and UCOM system [23]. These types of systems can serve the methodology improvement through different types of analysis of student actions, interesting, and students at risk to assess achievements of learning goals [24]–[26].

Mullen *et al.* [27] (2017) found two main options for assessment and satisfaction; one is called automated machine grading, which is suitable for grading quizzes and calculations if the outcome is well defined by use of course content and teacher knowledge. The second option is peer grading using an interactivity factor where UCOM or MOOC participants evaluate several achievements of other students and provide feedback on their quality and correctness [28], [81]. There are many key elements of these technologies, such as providing all content, assessment on the same platform, auto-graded assessment for immediate feedback, and discussion forums for questions and answers. Finally, these studies still work individually based on their factors but not in combination with a technology acceptance model and learning processing requirements.

Chmiel *et al.* (2017) used the behavioral intention factor as the main characteristic such that all the computational web-based survey models are appropriate and

widely accepted as important techniques for behavioral research. These computations were based on the interactivity and effectiveness of comprehensive factors for students and academic performance that has been adopted as new technologies [29]. This study is an attempt to establish how functions have influential effects on teaching assessment and academic performance. In addition, Dabbagh *et al.* [11] (2017), adopted the network between three keys of self-learning with interactivity, technology integration, and personal factors. The method uses a questionnaire built on three factors of self-management, desire learning, and self-control by use of a newly proposed multiple-indicator-multiple-cause (MIMIC) model. It is similar to multiple regressions. Still, this method suffers from how personal needs, course requirements and computer tasks affect self-development learning factors and outcomes. Alraimi, Zo & Ciganek, 2015 conducted a survey with different users on MOOC platforms to get the intention of using the model. They found that the result was significantly influenced by perceived usefulness, perceived ease of use, and user satisfaction based on academic performance [14]. At the same time and with the same scope, Greene, Oswald, & Pomerantz, (2015) found many cases from the start to the end of the first chapter that they dropped out [30]. DeBoer, Ho, Stump, & Breslow, (2014) argued that students join the MOOC without really participating in the course; this could make the statistics appear misleading [31].

This paper presents a new structure of (UCOM) model to implement a new approach. This research provides the chance to include the support assessment and effectiveness to work in parallel with the needed technology to enhance the development of the academic performance and student satisfaction as part of the continued intention to use UCOM that is part of the learning process. Most of the analyzed papers show that the work moved towards theoretical work in assessment more than toward use of the tool in an evaluation element. This result supports the aims that are suggested by the researcher of electronic support to support assessment and improve academic performance.

In summary, the main work used the perceived ease of use with perceived usefulness to affect student satisfaction and behavior intention. In addition, a technology integration factor was used to further enhance it [10]. In the second part, the paper combines course content and teacher subject knowledge with interactivity to affect the effectiveness and support assessment. All of these factors are used to improve the reality of undergraduate continued intention to use UCOM as the e-learning model.

This study tries to show the effectiveness of the combination of model factors on the degree of acceptance of the usage of UCOM technique or any LMS model as a supportive way to improve academic performance. The study measures the usefulness of the teaching knowledge of learning, the power of electronic assessment acceptance, and student satisfaction of grades and academic performance improvement.

III. RESEARCH METHOD

A. DIMENSIONS OF ONLINE LEARNING INTERACTIVITY AND SUPPORT

Most new models and technologies use the work on online learning, and therefore Peltier, Drago, and Schibrowshy (2003) reviewed and increased the effectiveness of the online learning experience [32]. They explained in the research two types of support for communication issues. The first type includes student-to-student, student-instructor and instructor mentoring. The second type focuses on course design, including course content, structure and delivered technology. All results show a significant effect on the perceived effectiveness of the course. Then, reanalysis of the data suggested that the course content was the most important factor for perceived usefulness of online learning. Additionally, Eom, Wen, & Ashill, (2006) examined course content, instructor knowledge and facilitation, as well as instructor feedback to participants, in both learning style and motivation. They used PLS with 397 data points of learners; they found that these elements predicted user satisfaction [33].

Marks, Sibley and Arbaugh (2005) argued that study should focus on student, instructor and content. In an empirical study, they found a significant effect between student and instructor interaction but course content had no effect [34]. This result was not right every time; if they applied it to a programming course, it was difficult to understand until the course credits were completed, while its work had a positive effect with other theoretical courses. They used two techniques, one with streaming audio and video and another with PowerPoint presentations, to help student's self-rate learning effectiveness [35].

B. RESEARCH MODEL AND HYPOTHESIS

In this section, we propose new complementary factors for our model of learning Management System (LMS) continuance that links the Technology acceptance model (TAM) in the theoretical background with our adopted important measurement. The major factors of work based on knowledge development and the effect of assessment method acceptance are used in the educational process. The relationships between these constructs are explained by the model design in Figure 1. Finally, it is noticed that previous studies provide knowledge that helps with continued intention to use the learning system. However, this learning is based on factors: student satisfaction, behavior intention, support assessment and effectiveness to confirm the continued intention. However, fewer studies address details of determining learning assessment and academic performance.

This study moves in the path of drawing the characteristics of UCOM as same as MOOC technology and to solve the complex of course assessment depend on course content, teacher subject knowledge level and interactivity. In addition, academic performance results of grade scores and student satisfaction feedback with student effectiveness and support assessment. This model is different from the traditional

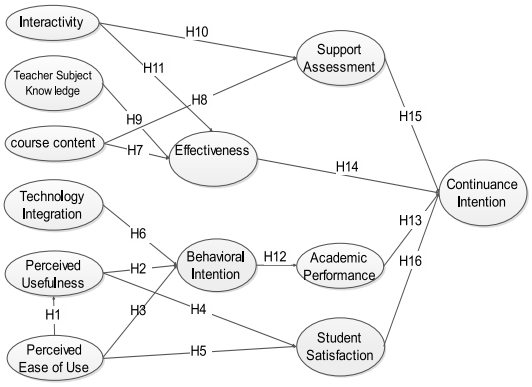

FIGURE 1. UCOM model factors test.

teaching model that is fixed on time and real class, in which students and teachers can directly connect online or outside of course time [13], [36], [84]. The proposed model can check the impact of system use on four factors that used survey filled with each assessment to confirm the assessment validity and match with student learning outcomes.

The aim of the use of the technology acceptance model (TAM) presented by Davis (1986) was to explain the user acceptance behavior for computer technology [37]. Davis used small keys related to the perception of usefulness and ease of use. In this study, we increase the keys to six measures, as shown in Figure 1. The TAM is adopted to measure the level of support assessment and evaluate the academic performance improvement using the UCOM model. Therefore, TAM is used as the background for the effectiveness of the adapted technologies' enhancement of learning that uses many factors to influence their decision [38].

1) THE TAM

Here tries to test the dependent variables of UCOM that are applied. In the context of UCOM, the model to test the relationship between student perception (perceived ease of use (PEOU)) and perceived usefulness (PU) of behavioral intention (BI) [38]. This connection affects the extra factors of interactivity, teacher subject knowledge (TSK) and course content (CC) on the effectiveness [13]. Both relations demonstrate an extra effect on support assessment, academic performance and student satisfaction on continued intention to use. In addition, technology integration (TI) with PEOU and PU affect the behavior intention and student satisfaction. The main factors of TAM plus the additional factors from another adapted models [12], [17], [84].

Starting with student perception, the PEOU goal is to believe that the model is free of effort and that it is easy to acquire skills using e-learning 2.0 [39], [40], [41], [82]. Our model defines PEOU as user belief that continued intention to use will be effortless [41], [42]. In addition, PEOU has a positive effect on PU by using the model system directly or indirectly through TAM factors Reference [43] where PEOU are working with PU toward using E-Learning. Davis (1989) defined PU as people's belief regarding how a new technology will enhance their learning performance. These factors can directly affect Student Satisfaction and behavioral intention and thus indirectly affect academic performance factor [1].

PU represents the subjective mechanism of using the system to assess the level of job performance enhancement and degree of student progress in a course. The PU of UCOM reveal which learner believes that application system can be a tool towards achieving learning goals. It represents the direct determinant of IS behavioral intention, where continued use of UCOM is significantly influenced by PU [14], [44].

Alternately, these two factors, PEOU and PU, are recommended with significant effect on satisfaction [17]. There are previous theories on TAM with participant initial acceptance and satisfaction. Therefore, we view satisfaction as a mediating factor between PU, PEOU and continued intention to use the UCOM model. Bhattacherjee and Anol [45] (2001) used an expectation confirmation model that uses acceptance factors to determine the satisfaction as initial acceptance. In this study, we focus on motivation as an influence of initial TAM on satisfaction. Most previous studies on this measurement have reported consistent findings. Studies show that PEOU between learners of e-learning has a significant effect on satisfaction. In addition, PU has a significant effect on satisfaction [17].

Previous studies have shown that the student perception has a positive effect on knowledge development of the use of systems [46]. Additionally, it reflects the user support assessment for enhancement of job performance, which means that the satisfaction level will indirectly affect the continued use [42]. Thus, we propose the first hypotheses:

H1: There is a significant positive relationship between perceived ease of use and perceived usefulness.

H2: There is a significant positive relationship between perceived usefulness and behavioral intention.

H3: There is a significant relationship between perceived ease of use and behavioral intention.

H4: There is a significant positive relationship between perceived usefulness and Student Satisfaction.

H5: There is a significant relationship between perceived ease of use and Student Satisfaction.

2) TECHNOLOGY INTEGRATION

Being able to understand the operations and limitations of technology could enable the mastering of technologies and types of technology integration. The UCOM application has covered some aspects of modern technologies from theoretical and practical viewpoints. This drives the UCOM learner to acquire deep support to do so effectively.

Therefore, strategies are needed to address the technologies that allow students to connect and improve these communication programs that humor confidence and improve support assessment because they engage learning effectiveness and academic performance and they are highly accepted in intention to use the model [47].

However, the course can be presented in different types, one as a student participant, another as teacher and slides only. While in the new generation of MOOC and UCOM, all-electronic material makes the technology integration more sufficient and makes it easy to access and share [14], [48]. Thus, we propose this hypothesis:

H6: There is a significant relationship between technology integration and behavior intention.

3) TEACHER AND COURSE CONTENT WITH EFFECTIVENESS

Many studies have proposed that course content is an important factor in determining the usefulness and quality of online learning [12], [49]. Adamopoulos and Panagiotis [50] (2013) and Peltier *et al.* [49] (2007) suggested the key role of course content and material in perceived effectiveness, which can be tested with the new MOOC and UCOM context. Adamopoulos's analysis results show that course material fails in proving the effect on the applied model. However, Peltier (2003, 2007) used both the course content effect and course structure to prove the suggested measures are positive for retention by continuous use of the model and measure the effectiveness through the level of interactivity achieved. In course content, they used an online survey that work positively with the applied model. Eom *et al.* [33] (2006) tested the effect of course content and teacher knowledge with other factors, as well as faculty feedback and participant feedback with self-learning in the e-learning context. They used PLS with a sample of 397 learners; they found that all results predict learner satisfaction for perceived effectiveness, which was also predicted for the learning outcomes. Many previous empirical studies [51] suggested whether any technology works well with the effectiveness and behavior intention values, i.e., the intention to use can be basement of utilizing technology to influence online learning effectiveness [39].

The impact of UCOM technology is shown by the comparison between the traditional educational mode and the use of E-Learning support. The course material used is greatly determined by the teacher knowledge [52]. For teacher subject knowledge, the faculty can help students to select the proper method of collecting data, presenting and achieving good performance based on each student's ability and confidence in presenting results in the best way of academic performance [53] . Additionally, we conjecture that the teacher knowledge is important in UCOM and any other electronic model that can be evaluated with high quality, thus leading to both academic performance and continued usage [13].

A teacher that is a subject expert in technology could encourage students' level of use. The expectation regarding technology integration development comes when a teacher's course and experience transferred on nice soft material, with an easily understandable method [12]. In addition, student links with peers and social media programs convinces more students [47]. Therefore, this relationship should be significantly positive for student satisfaction on a revisit of MOOC or UCOM [16]. Generally, in traditional education, the course description and material are determined by the teacher. Thus, we propose the following hypotheses:

H7: There is a significant relationship between course content and effectiveness.

H8: There is a significant relationship between course content and support assessment.

H9: There is a significant relationship between teacher subject knowledge and effectiveness.

4) INTERACTIVITY

For the next design, we considered that the interactivity could argue the education through electronic material by PowerPoint slides, files, and videos attached to the model is likely to affect the student academic performance and support the assessment of learner satisfaction. In the era of evolution step, the complementary use of Internet, email, wiki, and video conversations has enhanced distance learning and improved coursework teaching. Currently, all facilities used in parallel with attending classes and discussing in real-time or class off time with participants. This technology of attending classes can help in taking exams, accessing online libraries accessing globally huge electronic libraries and collaboratively completing assignments.

Marks *et al.* [34] (2005) explained the three aspects of interactivity: instructor-student, student-student, and student content interactions. An empirical study found a significant effect of interactivity on learning effectiveness and assessment support with faculty-student and student-student interactions that affect student presentation features and the use of technology samples.

The interactivity is defined as the degree of student influence on the sharing or high participation of presentations of interactions between peer students and the vividness of each group in the communication level; this interactivity can be fluid to the level of development knowledge [36], [17]. Additionally, it enables students to learn more of the knowledge between teacher and learner communication, followed by technical support to confirm the correct sequence and recorded orders. This interactivity encourages students to add skills with regard to developing ideas, attitudes, conversation and trust with teachers. Many models, such as MOOC and UCOM, have high interactivity when discussed frequently between teacher and students [54]. Thus, we propose the next hypotheses:

H10: There is a significant relationship between interactivity and support assessment.

H11: There is a significant relationship between interactivity and effectiveness

5) BEHAVIORAL INTENTION WITH ACADEMIC PERFORMANCE

The academic performance represents the student learning outcomes and the grade score of exams that transfer to high AP. These two methods of presentation can affect student attendance and their AP in learning [55].

The technology acceptance model (TAM) suggests that BI is significant to continued intention to use the UCOM model. The behavior intention of students determined by the perceived usefulness of full meaning uses the direct access to the model online and full material available with all types of connections between students and faculty of the course, which enhances the learner academic performance. Additionally, behavior intention determined by the perceived use indicates to the free follow of the practical part of UCOM. With all adapted TAM models that have been applied using MOOC, all studies refer to the significant influence and positive effect of PU and PEOU on behavior intention and adopted with another context look likes e-learning [38].

H12: There is a significant relationship between behavior intention and academic performance.

6) ACADEMIC PERFORMANCE, SUPPORT ASSESSMENT, EFFECTIVENESS AND STUDENT SATISFACTION

The impact of UCOM technology wholly influences the academic performance and assessment acceptance. These two dependent factors can generate the last step of performance, i.e., student satisfaction of the educational process and evaluation of each step of the assessment that accurate improves the AP of students by raising up the grade scores of assignments, presentations and online exams. Previous studies indicate the effect of games rules, a guideless video that can engage in learning activity [56], [57], [83]. In this research, these studies impression to motivate learner for feedback and attention to the needs of end users. In the high education context, they design the user's diverse needs and interests [58]. This approach is concerned with student learning and the teaching process. Additionally, a teacher assists students to meet learning goals of assessment and performance [59]. Research evidence has shown that academic performance increases student participation and satisfaction and academic performance success [60]. Both AP and support assessment focus on a learner that needs to determine the student satisfaction. Furthermore, both approaches aim to achieve faster feedback and flexibility for students and take on challenging learning tasks.

The students wanted analyses regarding the state of knowledge and SS. They enabled revision beyond the assessment content, and they asked for preference recommendation by supporting assessment and satisfaction feedback. The students also want the system to offer exercises to examine their status (AP). It appeared that chat, video, and online teamwork can realize their needs. The academic performance evaluates to a relationship with satisfaction. It examines the structure, processes and achievements. Structure includes all equipment, facilities, verities of material and assessment used though the semester work, and the support for more clarifications and knowledge development. Processes include data influenced by student answers and communications, such as downloads, tests, technical competence, use of guidelines, etc.; achievement includes the number of participants, satisfaction level, improvement of performance, enhancement of knowledge and evaluation of assessment acceptance attitudes and satisfaction [61].

One possible explanation for the succession of this model environment is based on student satisfaction(SS), which could be on course material to help students accomplish the objectives and the assessment transparency of learning outcomes [62]. In other words, the high SS level may be because there was a good relationship between academic performance, assessment acceptance and knowledge development that fitted with expectations and student needs [63]. Thus, we proposed the last level of hypotheses:

H13: there is a significant relationship between academic performance and continued intention to use.

H14: there is a significant relationship between effectiveness and continued intention to use.

H15: there is a significant relationship between support assessment and continued intention to use.

H16: there is a significant relationship between student satisfaction and continued intention to use.

C. OPERATIONAL WORK OF CONSTRUCTS

All the items used to measure the constructs were adapted from previous studies to ensure their validity [64]. Items measuring students' continued intention to use were adapted from [15]: 1) ''What is the possibility that you would learn with UCOM more than MOOC?'' 2) ''How probably are you to learn with a UCOM e-learning model?'' and 3) ''I think I will learn with UCOM.'' Items measuring the course content factor were adapted from [36], and [13]: 1) ''Practice course content instruction on UCOM is dynamic''; 2) ''Practice instructional content on UCOM is lively''; and 3) ''I can acquire Practice instructional content on UCOM from different sensory programs.'' The construct of teachers' subject knowledge was measured by items derived from [53]: 1) ''The teacher knows the content that he/she teaches very well''; 2) ''The teacher makes good decisions regarding the depth, scope, and extension of concepts taught''; 3) ''UCOM application is trusted by faculty to enhance learning'' and 4) ''The teacher does a good job of controlling the mechanism of concepts explained in class.'' Items measuring interactivity were adapted from [34], [13], and [52]: The interactivity of teacher and students in UCOM 1) ''I felt free to express and explain my own views throughout UCOM application''; 2) ''I had sufficient opportunity to interact with other students using UCOM application''; 3) ''The Faculty provided timely feedback on assignments, exams or projects''; and 4) ''UCOM application facilitates the collaboration among the students.''The items measuring academic performance were derived from [65]. Item measuring students' satisfaction and behavior intentions of the service, using technology-acceptance models as derived from [38], and the intention to use can be based on utilizing technology integration to influence online learning effectiveness [39]. However, the behavior intention factor has a positive effect on support assessment [66].

In the hypothesized model, we posit learner-level variables, namely, perceived usefulness and perceived ease of use as a mediating variable. Additionally, we use course content, teacher subject knowledge and interactivity to examine the effectiveness, and in the results, we examine how these variables affect students' satisfaction and behavior intention with academic performance to use UCOM. In summary, the research model aims to test the extended technology acceptance over a longer time scale by examining the continued intention of using UCOM in the future**.**

IV. RESULTS

A. DATA COLLECTION

The data collected for this model were from four different universities in Oman. These universities' students were chosen as the main sample focus of this study because, in these universities, students are trained on using Google classroom in **BUC** and MOODLE in **SohU** and **SQU**. In **UoB**, they only use email for communication and the university website. Using a convenience sampling method, we proposed that our UCOM model be implemented in parallel with these two applications. Therefore, the knowledge of this test may affect the generalization ability of our findings. Still, the total numbers of samples are ideal, the groups were selected with different courses, but student was undertaken in classes plus the UCOM use. The procedure starts in the classes where UCOM was used during the course, and it show the importance of UCOM in class learning and in self-motivation by level of satisfaction and agreement of assessment support and discussion announced through class meeting and UCOM chat course. Additionally, they told students that this model is a supplementary tool for the education process to improve student learning outcomes and increase the confidence of students. Furthermore, students were informed that some of the uploaded material in the model will be included in the final exam to evaluate the involvement of students with this model. Then, the compound mixture between materials used between different universities depends on the specific course that matched between two program studies. Even when students present their assignments, the connection between different groups to discuss and moderate the answers with also joined between faculties to moderate the assessment process. Ultimately, 392 questionnaireswere distributed, and only 307 replies were collected, with 12 records having missing answers.

The tested system is used by two different groups, which are the undergraduates in diploma and bachelor's degree whose age range between 18 to above 26 years old, in traditional course and class work time with soft material, and interaction in class time with faculty. All students filled out a hard copy of the survey (in paper format) that asks about the UCOM application and student satisfaction level. In total, from AlBuraimi College (BUC), 96% filled out the survey in BUC (100 out of 104). In addition, from Sohar University (SohU), 99% percent of students answered the questionnaire (83 out of 84). In Sultan Qaboos University (SQU), the participants included (54 out of 59) that give 92% percent of the total samples. Lastly, in University of Buraimi, the questionnaire was distributed to 60 students, and only 58 responded and filled it out, which means that97% participated in the survey. See Table 1 for the demographic information on participants. The survey consists of two phases. The first phase is general information, including: institute (university) name, major, degree, gender, scholar and age.

B. DATA ANALYSIS

This analysis shows student interest to add more updated communication tools and to encourage teamwork among students. This in turn can motivate weak students to learn and add learning skills when they know the weakness of their evaluation by the faculty and moderator through the sequence of assignment assessments. The new process and control can monitor their outputs and finalize the conclusion of AP and SLO in a short amount of time and efficient values. This is supposed to reduce the wasted time and update the applications, which are easy to access, use, and develop by the users of this technique.

TABLE 1. Demographic characteristics of respondent participants.

Field	Description	Number	BUC	SohU	SQU	UoB
Participant	Total	307	104	84	59	60
	Valid	295	100	83	54	58
	Missing data	12	4	1	5	2
	Percent	96%	96%	99%	92%	97%
Major	IT	105	88	3	9	5
	Engineering	136	0	62	36	38
	LAW	54	12	18	9	15
Degree	Diploma	134	57	53	0	24
	High diploma	29	12	6	0	11
	Bachelor	132	31	24	54	23
Gender	Male	112	25	37	35	15
	Female	183	75	46	19	43
Scholar	Government	206	70	30	54	52
	Private	89	30	53	0	6
Knowledge of computer	Very High	114	60	20	24	10
	High	148	35	59	30	24
	Low	33	5	4	0	24
How often UCOM used	Often	156	53	42	31	30
	Sometimes	106	32	30	19	25
	Never used	33	15	11	4	3
Age	18-21	123	38	31	39	15
	22-26	93	32	20	10	31
	Above 26	79	30	32	5	12

Table 1 show that SohU has 99% valid participants, and a total percentage of active results of 96%. BUC has (34%) the highest number of surveys distributed on UCOM learners. BUC has the highest number of participants (100); engineering major students (136) comprised the highest percent of participants with 46.2%. The diploma degrees (134) have the highest percentage of interested students with 45.4%. Most of the participants were female (183, 62%). The governmental scholars (206) have a high percentage of 70%. Additionally, the knowledge of computers was high (148, 50%), while how often UCOM used options were often (156) with (53%). In addition, the high numbers of participant age average (18-21) were (123) percent was (41.7%). All students

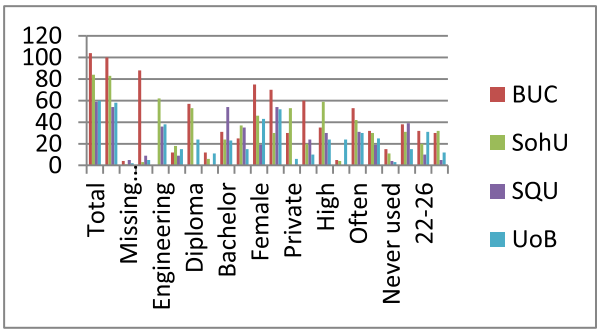

FIGURE 2. Demographic information diagram.

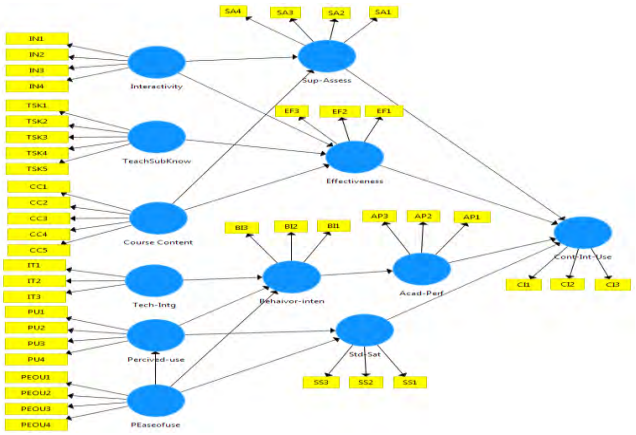

FIGURE 3. Model item distribution.

are registered for coursework semester. This sample was from (semester 1, 2017-2018), with 17 academic weeks and 3 credit hours per week.

The second phase used the different factors of the survey that measure the level of support assessment, perceived effectiveness, academic performance and student satisfaction, and all affect the continued intention to use the UCOM model. These factors help in improvement through the testing of SLO, student perception (perceived ease of use, perceived usefulness), interactivity, technology integration, teacher subject knowledge, and course content to conclude the level of student satisfaction. The second phase of the survey is shown in the Appendix. The questionnaire employed the Likert scale method of creating a 5-point scale for the responses. The distribution of each scale was as follows:1 for strongly disagree to 5 for Strongly agree. The SmartPLS program was preferred as the best statistical application to analyze the responses from the random participant.

C. DATA DISCUSSION

The result of the accredited program was analyzed with this model to activate, facilitate and help teachers in guiding the students and increase their level of communication and link with their learning outcomes and program satisfaction [67], [68], [69]. The result of the questionnaires distributed to the different university members gave insight on the development of UCOM and their reflection on the graduated students with satisfaction results. The questionnaire includes 44 specialist questions distributed between 12 factors, as shown in Figure 3.

D. CONSTRUCT VALIDITY

1) EVALUATION OF RELIABILITY AND CONVERGENT VALIDITY

Reliability was assessed using Cronbach's alpha. All multi-item constructs should meet the guidelines for a Cronbach's alpha of greater than 0.70. Convergent validity was assessed based on the criterion that the indicator's estimated coefficient was significant on its posited underlying construct factor. We evaluated the measurement scales using three criteria: all item factor loadings (k) should be significant and exceed 0.7; composite reliabilities (CR) for each construct should exceed 0.7; and the average variance extracted (AVE) for each construct should be greater than 0.50 [70].

Table 2 demonstrates the data analysis of questionnaire items, including item, number, missing values, Mean, Median, Minimum, Maximum, Standard deviation, Excess Kurtosis and Skewness. The mean should be above 2.5, the Median should be 2.5, and the standard deviation should be significant at more than 0.5 to be sure that all item results are truly accepted. In Kurtosis, the guidelines should be not more than $+1$ or less than -1 to be in a normal distribution (not peak or flat). Even for skewness, the guidelines should not exceed $+1$ or be less than -1 to be normal [71].

Table 3 demonstrates that item loading, the AVE, CR and Cronbach's alpha values for all constructs in the measurement model exceeded the recommended threshold values. In summary, the adequacy of the measurement model indicated that all items were reliable indicators of the hypothesized constructs.

2) DATA SCREENING AND MEASUREMENT MODEL

The initial data screening identified the Academic Performance scale as problematic, with low Cronbach's alpha < 0.7 of all participants to most items on the scale, so this construct was eliminated to one item to be accepted in further analysis. Although initial examination of the support assessment needs to exclude two of the items to keep a high degree of design, factor constructs showed these to be reliable (all with Cronbach's alphas > 0.7). Additionally, in teacher subject knowledge, we need to exclude some items to be in reasonable result affect. Exploratory factor analysis confirmed high cross loadings between many of the constructs. After removal of cross-loading items, a clean two-factor model was obtained, consisting of Course Content (retaining three out of five items from the original scale) and teacher subject knowledge (formed by retraining one only out of five items). In addition, academic performance was redesigned to one item out of three in the original scale. In the final stage, all constructs used in this model showed a high degree of validity and reliability (see Table 3).

TABLE 2. Data analysis indicator of participants.

Item	No.	Miss	Mean	Min	Standard Deviation	Excess Kurtosis	Skewness
PU1	1	0	4.208	2	0.788	-0.857	-0.508
PU2	2	0	4.117	2	0.88	-1.024	-0.462
PU3	3	0	4.28	2	0.731	0.519	-0.843
PU4	4	2	4.367	2	0.694	-0.147	-0.758
CC1	5	0	4.238	2	0.689	0.159	-0.591
CC2	6	0	4.303	2	0.663	0.234	-0.631
CC3	7	4	4.211	1	0.737	0.416	-0.303
CC4	8	4	4.251	1	0.701	0.745	-1.086
CC5	9	0	4.306	2	0.618	-0.208	-0.395
PEOU1	10	0	4.023	1	0.606	2.473	-0.628
PEOU2	11	0	4.231	1	0.677	0.368	-0.905
PEOU3	12	0	4.316	1	0.783	0.365	-0.807
PEOU4	13	0	4.55	2	0.547	0.286	-0.8
IN1	14	0	4.195	3	0.492	0.221	0.39
IN2	15	0	4.176	2	0.611	1.089	-0.461
IN3	16	0	4.199	2	0.494	1.114	0.216
IN4	17	0	4.257	3	0.537	-0.372	0.112
TSK1	18	0	4.28	1	0.774	1.319	-1.082
TSK2	19	0	4.072	1	0.572	0.591	-0.94
TSK3	20	0	4.16	2	0.585	1.979	-0.532
TSK4	21	0	3.717	1	0.749	-0.263	0.051
TSK5	22	0	4.046	2	0.618	0.509	-0.278
IT1	23	0	4.362	2	0.776	-0.784	-0.771
IT2	24	0	4.182	2	0.794	-0.255	-0.652
IT3	25	2	4.19	2	0.731	-0.7	-0.414
SA1	26	0	4.081	1	0.742	0.46	-0.565
SA2	27	0	4.313	2	0.615	0.712	-0.567
SA3	28	0	4.081	2	0.579	0.175	-0.309
SA4	29	0	4.326	2	0.674	0.186	-0.694
EF1	30	0	4.101	2	0.68	0.726	-0.566
EF2	31	0	4.443	1	0.717	0.896	-0.425
EF3	32	0	4.257	2	0.763	-0.08	-0.738
CI1	33	0	3.987	1	0.803	-0.424	-0.318
CI2	34	0	4.414	2	0.589	-0.082	-0.527
CI3	35	0	4.316	1	0.736	0.957	-1.168
BI1	36	0	4.257	2	0.686	1.032	-0.809
BI2	37	0	4.094	2	0.566	0.82	-0.635
BI3	38	0	4.147	2	0.486	0.607	0.177
AP1	39	0	4.104	2	0.573	4.433	-1.043
AP2	40	0	4.098	1	0.596	3.783	-0.87
AP3	41	0	4.14	2	0.628	0.458	-0.353
SS1	42	0	4.238	2	0.587	0.543	-0.3
SS2	43	0	4.358	2	0.627	1.108	-0.768
SS3	44	0	4.283	2	0.572	0.384	-0.618

All of the cases were used in the final data analysis without any exclusion. We perform exploratory factor analysis

TABLE 3. Item loading cross factor.

Construct	Item	Loading	Alpha	CR	(AVE)
Interactivity	IN1	0.635			
	IN2	0.791	0.772	0.727	0.571
	IN3	0.719			
Support Assessment	SA1	0.685			
	SA2	0.740	0.733	0.803	0.673
	SA3	0.876			
	SA4	0.894			
Teacher Subject Knowledge	TSK1	1.000	0.845	1.000	1.000
Academic Performance	AP1	1.000			
	AP2	0.580	1.000	1.000	1.000
	AP3	0.702			
Behavior Intention	BI1	0.937			
	BI2	0.707	0.814	0.813	0.689
	BI3	0.673			
Effectiveness	EF1	0.630			
	EF2	0.725	0.754	0.807	0.68
	EF3	0.913			
Perceived Ease of Use	PEOU3	0.832	0.709	0.826	0.704
	PEOU4	0.846			
Student Satisfaction	SS2	0.849	0.813	0.826	0.704
	SS3	0.828			
Perceived Usefulness	PU1	0.765			
	PU2	0.908	0.943	0.904	0.703
	PU3	0.823			
	PU4	0.851			
Technology Integration	IT1	0.930			
	IT2	0.891	0.946	0.925	0.804
	IT3	0.868			
Course Content	CC1	1.000			
	CC2	0.592	0.884	1.000	1.000
	CC3	0.627			
	CC4	0.638			
Continue Intention to Use	CI1	0.873			
	CI2	0.868	0.883	0.875	0.7
	CI3	0.765			

with rotated factor solution. The results show that the initial model factors have many negative results in Cronbach's alpha values. Therefore, the model was adjusted one more time by excluding low value loading from the items of factors measured (see Table 3). The new results show that (a) we did not find a single factor that emerged from the factor analysis; and (b) three factors with different values adjusted to 1 were extracted, which indicates that common method bias is likewise of no major concern in this paper. The reliability of the constructs was assessed by Cronbach's alpha. Values larger than 0.70indicate good reliability. The Cronbach's alpha values of the constructs of the adjusted model were as follows: course content (0.884), Perceived Usefulness (0.943), teacher subject knowledge (0.845), interactivity (0.772), Academic performance (1.00), Technology Integration (0.946), Behavior Intention (0.814), continue intention to use e-learning (0.883), Effectiveness (0.754), Perceived Ease of Use (0.709) and Support Assessment (0.733). All of the constructs thus had adequate reliability.

In testing validity, two dimensions must be considered: convergent validity and discriminant validity. Convergent validity is used to assess whether items within the same construct are highly correlated with each other. Discriminant validity is used to assess whether items load more on

their intended construct than on others. Construct validity was tested using factor analysis with principal component analysis and varimax rotation. The diagonal line of loading between 0.45and 0.54 is generally considered fair; loading between 0.55–0.62is good; loading between 0.63–0.70 is very good; loading is considered excellent if it is higher than 0.71 [72]. The modified factor loading analysis indicated that all the constructs in the model had both good convergent and discriminant validity, with each value greater than the AVE results (see Table 4). Meanwhile, we also performed the Fornall Larcker criterion correlations among all the variables (including the control variables) to make a robustness examination of discriminant validity [70]. As shown in the results of Table 4, we found that the square root of AVE is greater than the correlations for all constructs, indicating sound discriminant validity. Table 5 shows the cross loading between items themselves, and all their values are above 0.7, as shown in bold values in Table 5.

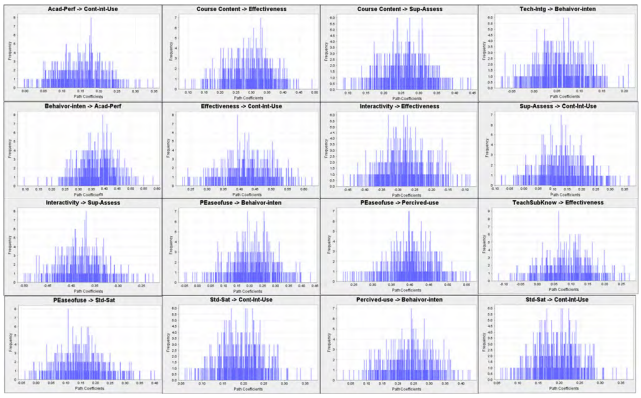

FIGURE 4. Path coefficient histogram.

In addition, see Figure 4 for a path coefficient histogram after bootstrapping the Fornell Larcker criterion results.

3) STRUCTURAL MODEL FOR HYPOTHESES TESTING

The 16 hypotheses explained above were examined collectively using structural equation modeling (SEM) with partial least squares (PLS) implementation. These techniques allow for the analysis of both relationships between constructs and the reliability and validity measures. The test of the structural model includes the R^2 values, which represent the amount of variance explained by the independent variables, and estimates of the path coefficients, which indicate the strengths of the relationships between the dependent and independent variables.

Table 6 illustrates the R^2 and the resulting path coefficients of the proposed research model. Perceived usefulness is found to be significantly determined by the direct effect of perceived ease of use, resulting in an R^2 of 0.155. Thus, the above mentioned variables explain 15.5% of variance in the perceived usefulness. Likewise, support assessment is found to be significantly determined by the two exogenous variables, i.e., interactivity and course content, resulting in an R^2 of 0.225. Thus, the above mentioned exogenous variables explain 22.5% of variance in the support assessment. Effectiveness is significantly determined by three variables of interactivity, teacher subject knowledge and course content, resulting in an R^2 of 0.201, that mentioned exogenous explain 20.1% of variance in effectiveness. The behaviour intention is significantly determined by three variables of technology integration, perceived usefulness, and perceived ease of use, results R^2 (0.162) that equal to (16.2%) of variance on behaviour intention. Academic performance used only one variable of behaviour intention, results R^2 (0.130) that exogenous to (13%). Student satisfaction used two variables of perceived usefulness and perceived ease of use, results to R^2 (0.271), that give (27.1%) of variance on student satisfaction. The dependent variable continuance intention to use is significantly determined by four variables of support assessment, effectiveness, academic performance and student satisfaction, resulting in an R^2 of 0.407. In other words, the combined effects of the four dependent variables explain 40.7% of the variance in continuance intention to use.

The Critical Ratio (CR) is calculated as depicted in Table 7; CR higher than 1.96 (or lower than_1.96) indicates two-sided significance at the customary 5% [73]. The CR criterion holds true for all model hypotheses with bootstrap of (1000 round of execution), except Perceived Ease of use to Student Satisfaction, Support Assessment to Continued Intention to Use, Teacher Subject Knowledge to Effectiveness and Technology Integration to Behavior-intention, hence these are not supported by the proposed model.

V. DISCUSSION

A. THEORETICAL EFFECT OF THE MODEL

The model proposed in this study not only contributes in several ways to the existing literature but also helps researchers and practitioners gain a better understanding of user behaviors in continued use of e-learning and the UCOM model. This research has value because it reveals multiple statistically significant relationships that explain why individuals choose UCOM and why they continue to use it as a complementary system with MOOC. We extend prior work on UCOM by highlighting the importance of achieving course content, teacher subject knowledge, interactivity and technology integration. Our results suggest that continued intention to use UCOM is indirectly affected by the perceived ease of use, perceived usefulness, technology integration, teacher subject knowledge, interactivity and course content. The proposed integrated model provides a better explanation and richer insights than the individual. It is worth noting that this study's results enhance the understanding of factors influencing students' continued intention to use UCOM.

1) THE EFFECT OF TAM

The hypotheses regarding perceived ease of use to perceived usefulness, perceived usefulness to behavioral intention, perceived ease of use to behavioral intention and perceived usefulness to student satisfaction(H1-H4) are supported, but

TABLE 4. Fornell Larcher criterion.

TI												0.897
TSK											1	0.143
SA										0.82	0.239	0.339
SS									0.839	0.367	0.413	0.205
PU								0.838	0.502	0.473	0.491	0.535
PEOU							0.839	0.393	0.326	0.261	0.331	0.353
IN						0.756	-0.085	-0.169	-0.186	-0.396	0.012	-0.032
EF					0.824	-0.305	0.314	0.475	0.293	0.605	0.171	0.369
CC				1	0.34	-0.075	0.482	0.435	0.327	0.289	0.309	0.084
CI			0.837	0.435	0.591	-0.111	0.419	0.669	0.343	0.455	0.362	0.384
BI		0.83	0.553	0.246	0.373	-0.019	0.32	0.348	0.107	0.302	0.188	0.252
AP	1	0.36	0.202	0.193	0.205	0.1	0.148	0.152	-0.15	-0.053	0.037	0.173
	Academic performance	Behavior Intention	Continue Intention use	Course Content	Effectiveness	Interactivity	Perceived ease of use	Perceived usefulness	Student satisfaction	Support assessment	Teacher subject know	Technology Integration

hypotheses is 5 is not, as shown in Table 7. TAM extended with this model, behavioral intention and student satisfaction should be considered a valuable tool for exploring behavior in UCOM contexts.

H5, perceived ease of use to student satisfaction, is not supported. H5 gives an unsupported response between perceived ease of use and the dependent variable of student satisfaction. The reason behind this is that some studies have reported students' dissatisfaction with MOOC learning experiences, due to reasons such as low-quality discussion, misunderstanding contents, missing feedback, ambiguity in guidance, and technical problems [74], [75].

For the first factor in this survey, student motivation in PEOU and PU test. The researchers find the student

TABLE 5. Discriminant cross loading factor.

	Academic Performance	Behavior intention	Continues intention	Course content	Tech-integrity	ffective	Inter-activity	PEOU	PU	Student satisfy	Support assess	Teacher sub-know
AP1	1	0.36	0.202	0.193	0.173	0.205	0.1	0.148	0.152	-0.15	-0.053	0.037
BI1	0.33	0.937	0.58	0.311	0.237	0.369	-0.078	0.37	0.396	0.209	0.376	0.238
BI2	0.271	0.707	0.266	0.009	0.175	0.226	0.109	0.085	0.104	-0.147	0.025	0.007
CI1	0.145	0.373	0.873	0.4	0.325	0.571	-0.089	0.407	0.537	0.37	0.451	0.252
CI2	0.239	0.449	0.868	0.336	0.402	0.473	-0.091	0.397	0.674	0.293	0.292	0.446
CI3	0.123	0.613	0.765	0.353	0.229	0.421	-0.103	0.223	0.468	0.167	0.392	0.211
CC1	0.193	0.246	0.435	1	0.084	0.34	-0.075	0.482	0.435	0.327	0.289	0.309
EF2	0.165	0.167	0.317	0.235	0.401	0.725	-0.168	0.396	0.347	0.354	0.452	0.223
EF3	0.177	0.402	0.605	0.317	0.258	0.913	-0.31	0.187	0.432	0.184	0.544	0.099
IN2	-0.118	-0.111	-0.187	-0.068	-0.047	-0.311	0.791	0.007	-0.22	-0.063	-0.267	0.04
IN3	0.295	0.096	0.032	-0.043	0.001	-0.14	0.719	-0.146	-0.024	-0.229	-0.338	-0.026
PEOU3	0.195	0.337	0.38	0.422	0.26	0.444	-0.27	0.832	0.27	0.259	0.332	0.225
PEOU4	0.056	0.203	0.324	0.387	0.332	0.09	0.119	0.846	0.388	0.286	0.111	0.328
PU1	-0.019	0.174	0.462	0.245	0.421	0.311	-0.118	0.307	0.765	0.48	0.47	0.412
PU2	0.183	0.394	0.617	0.4	0.625	0.44	-0.131	0.394	0.908	0.422	0.47	0.397
PU3	0.21	0.264	0.569	0.36	0.346	0.426	-0.188	0.337	0.823	0.318	0.348	0.368
PU4	0.134	0.313	0.589	0.446	0.368	0.413	-0.138	0.276	0.851	0.456	0.292	0.469
SS2	-0.149	0.078	0.275	0.195	0.271	0.302	-0.176	0.305	0.442	0.849	0.288	0.357
SS3	-0.1	0.101	0.301	0.358	0.067	0.186	-0.134	0.24	0.399	0.828	0.33	0.336
SA2	-0.037	0.28	0.464	0.301	0.294	0.574	-0.331	0.122	0.412	0.308	0.894	0.124
SA4	-0.054	0.208	0.25	0.149	0.265	0.396	-0.328	0.361	0.367	0.302	0.74	0.312
TSK1	0.037	0.188	0.362	0.309	0.143	0.171	0.012	0.331	0.491	0.413	0.239	1
IT1	0.091	0.283	0.511	0.235	0.93	0.482	-0.097	0.426	0.609	0.344	0.483	0.222
IT2	0.237	0.214	0.154	-0.073	0.891	0.16	0.045	0.25	0.37	0.027	0.129	0.049
IT3	0.17	0.095	0.301	-0.06	0.868	0.288	0.006	0.16	0.374	0.074	0.186	0.035

TABLE 6. R2of path coefficients.

Factor	R^2
Academic Performance	0.13
Behavior Intention	0.162
Continues Intention to Use	0.407
Effectiveness	0.201
Perceived usefulness	0.155
Student Satisfaction	0.271
Support Assessment	0.225

TABLE 7. Bootstrapping mean, Std, T-test, P-values, Bias, supporting.

Hypothesis		Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)
H1	Perceived Ease of use -> Pre- use	0.393	0.402	0.055
H2	Perceived-use -> Behaviour-inten	0.239	0.234	0.073
H3	Perceived Ease of use -> Beh-inten	0.209	0.201	0.084
H4	Perceived-use -> Std-Sat	0.442	0.441	0.064
H5	Perceived Ease of use -> Std-Sat	0.152	0.151	0.079
H6	Tech-Intg -> Behaviour-inten	0.05	0.062	0.053
H7	Course Content -> Effectiveness	0.293	0.288	0.066
H8	Course Content -> Sup-Assess	0.261	0.26	0.057
H9	TeachSubKnow -> Effectiveness	0.084	0.083	0.065
H10	Interactivity -> Sup-Assess	-0.377	-0.377	0.048
H11	Interactivity -> Effectiveness	-0.284	-0.293	0.066
H12	Behaviour-inten -> Acad-Perf	0.36	0.361	0.065
H13	Acad- Perf -> Cont-Int-Use	0.152	0.152	0.066
H14	Effectiveness -> Cont-Int-Use	0.42	0.42	0.074
H15	Sup-Assess -> Cont-Int-Use	0.138	0.139	0.072
H16	Std-Sat -> Cont-Int-Use	0.192	0.196	0.051

Hypothesis	T Statistics	P Values	Bias
H1	7.108	0	0.009
H2	3.268	0.001	-0.004
H3	2.484	0.013	-0.007
H4	6.929	0	-0.002
H5	1.91	0.057	0
H6	0.957	0.339	0.012
H7	4.443	0	-0.004
H8	4.575	0	0
H9	1.296	0.195	-0.001
H10	7.815	0	0
H11	4.287	0	-0.008
H12	5.575	0	0
H13	2.31	0.021	0
H14	5.699	0	0.001
H15	1.91	0.057	0
H16	3.761	0	0.005

motivation reliability are highly accepted and activated with using of UCOM model. While, in previous study presented by [17] the used self determination factor in the Moodle as E-learning factor and the results shows earn in student intention more than student motivation. Also a study by [14] they used motivation as main factor of E-learning use but the results shows the positive effects on student satisfaction and acceptance more than student motivation pass.

2) THE EFFECT OF TECHNOLOGY INTEGRATION, TEACHER, COURSE CONTENT AND EFFECTIVENESS

H6, technology integration to behavior intention, is not supported. The reason behind that has examined the technology integrity of student motivation and behavioral intention of use

of this technology in MOOC that are fundamentally different from traditional classroom-based instruction [76].

H7, course content to effectiveness, and H8, course content to support assessment, are supported by the results. Hypothesis H9 is not supported. H9, teacher subject knowledge to effectiveness, is not supported. If students use easy course content, and all electronic material is available, teacher subject knowledge is not highly required in this type of model. In other studies, the more complex a course is supposed by students, the less power it has on the course effect, while the effect of teacher subject knowledge on their intention to use increases. This may because teachers' knowledge and the way they present the subject matter can help students better understand the central thesis of even difficult course content. These findings reveal the underlying dynamic relationship between course content itself and teacher subject knowledge. Therefore, teachers' knowledge is further important to students' intention when the course is more complex [13].

Where academic staff rely heavily on communications that could give redesign to adopt courses. Another study presented by [1], [4], the researchers prove the positive effect of using TEL and different types of applications. But still this study has no light effect on the use of interactivity effect on SLO or performance.

Another factor proposed in UCOM model was the technology integration. The researchers found that technology integration effect are negatively affecting the target from using UCOM or any other E-learning system. A study in literature presented by [48] they used T3 technology and the found high level of effect on the critical thinking and in teaching development and improving learning skills. On the other side, a study by [63] used blended learning technology and the results give positive effect. But it's give negative feedback on the support assessment or developing the assessment method.

In addition, the factor in this study is the teacher performance. This research results shows a positive relationship and improvement on teacher performance after applying UCOM model. All the other studies in literature review show the positive affect of developing teacher performance using E-learning model [33]. But still these article did not include the factor of assessment development or how this type of performance and reflect on support assessment using E-learning systems.

At the last stage of testing and discussing results, it's related to support assessment factor. This study approves the high positive acceptance of reliability and average variance extracted (AVE) using UCOM model. Schmid *et al.* (2014) shows the acceptance of assessment method are high when it's used dataset of technology and self- evaluation only without testing the effect with other factors in large relationships of factors effectiveness.

3) THE EFFECT OF INTERACTIVITY AND BEHAVIOR INTENTION

H10-H11, the relations between interactivity and support assessment and between interactivity and effectiveness, are not supported by the model shown in Tables 7 and 8. The findings also show that interactivity does not make a significant difference in either relatively easy or complex courses of supporting assessment or with course effectiveness. Some studies find that the mixture of flip videos with practical experiences and immediate feedback help in support assessment, and this may prove to be much more effective than traditional learning approaches. In the current situation, the interactivity of many video tubes and random topics could reflect negatively on the interactivity level. Therefore, the interactivity factor explained in the literature does not strongly affect this model with two different factors of effectiveness or support assessment.

H12, behavior intention to academic performance, is supported, as shown in Table 7. This relation is newly suggested in this model, and the tested results show highly related between the two dependent factors. The learners of the model have high behavior intention to use coming from indirect connection by perceived usefulness and perceived ease of use, which is supported in the results, even with less support for the technology integration effect on behavior intention. All these factors generate supported results in the model.

4) CONTINUED INTENTION TO USE

H13-H16, academic performance to continued intention to use, effectiveness to continued intention to use, support assessment to continued intention to use, and student satisfaction to continued intention to use, are supported, as shown in Table 7.

H14, the outcomes of effectiveness with continued intention to use, gives high reliability and is supported. The course content has a significant effect on effectiveness. This effect is mediated by effectiveness of continued intention to use as a type of retention [12], [32].

H15 [13], the study proves there is a significant effect of course content and teacher subject knowledge on support assessment. This effect can be directly reflected in the significant result of continued intention to use the model.

H16, the study by [14] is, to the best of our knowledge, the only research that has examined the relationship among TAM, satisfaction and continued intention of using MOOCs. They found that perceived usefulness and satisfaction positively affect continued intention to use the application.

B. PATH VALUE DISCUSSION

In terms of path analysis, Table 8 demonstrates the path coefficients and p-values for each hypothesis. It can be noticed that 12 out of 16 hypotheses are supported, which in turn indicates that 12 paths are significant between the independent and dependent variables. **H1**($B = 0.393$, $p < 0.000$) describes the path between perceived ease of use and perceived usefulness, indicating that the perceived ease of use enhances the perceived usefulness of this UCOM model. **H2** ($B = 0.293$, $p < 0.001$) shows the path between perceived usefulness and behavior intention, representing that the perceived usefulness leverages the behavior intention

TABLE 8. Path coefficient and β results.

Relation	β	P value	Remarks
H1-Perceived ease of use → Perceived usefulness	0.393	0	Supported
H2-Perceived usefulness → behavior intention	0.293	0.001	Supported
H3-Perceived ease of use → behavior intention	0.209	0.013*	Supported
H4-Perceived usefulness → student satisfaction	0.442	0	Supported
H5-Perceived ease of use → student satisfaction	0.150	0.057*	Supported
H6-Technology integration → behavior intention	0.050	0.339	Not supported
H7-Course content → effectiveness	0.293	0	Supported
H8-Course content → support assessment	0.261	0	Supported
H9-Teacher subject knowledge → effectiveness	0.084	0.195	Not supported
H10-Interactivity → support assessment	-0.377	0	Not supported
H11-Interactivity → effectiveness	-0.284	0	Not supported
H12-Behavior intention → academic performance	0.360	0	Supported
H13-Academic performance → continuo intention to use	0.152	0.021*	Supported
H14-Effectiveness → continuo intention to use	0.420	0	Supported
H15-Support assessment → continuo intention to use	0.138	0.057*	Supported
H16-Student satisfaction → continuo intention to use	0.192	0	Supported

Note: * P<0.01

to use the UCOM model. **H3** ($B = 0.209$, $p < 0.013$) demonstrates the path between perceived ease of use and behavior intention, revealing that perceived ease of use positively influences the behavior intention to use UCOM. **H4** ($B = 0.442$, $p < 0.000$) describes the path between perceived usefulness and student satisfaction, indicating that perceived usefulness significantly affects the student satisfaction of UCOM model. **H5** ($B = 0.15$, $p < 0.057$) illustrates the path between perceived ease of use and student satisfaction, indicating that perceived ease of use significantly affects the student satisfaction. **H6** ($B = 0.05$, $p < 0.339$) describes the path between technology integration and behavior intention, indicating that technology integration does not significantly affect the behavior intention. **H7** ($B = 0.293$, $p < 0.000$) shows the path between course content and effectiveness, indicating that course content significantly affects the effectiveness. **H8** ($B = 0.261$, $p < 0.000$) demonstrates the path between course content and support assessment, revealing that course content significantly affects the support assessment. **H9** ($B = 0.084$, $p < 0.195$) describes the path of teacher subject knowledge and effectiveness, indicating that teacher subject knowledge does not significantly affect the effectiveness. **H10** ($B = -0.377$, $P < 0.000$) shows the path of interactivity and support assessment, indicating that interactivity does not significantly affect support assessment. **H11** ($B = -0.284$, $p < 0.000$) indicates the path between interactivity and effectiveness, representing that interactivity does not significantly affect effectiveness. **H12** ($B = 0.360$, $p < 0.000$) indicates the path between behavior intention and academic performance, indicating that behavior intention significantly affects academic performance. **H13** ($B = 0.152$, $p < 0.021$) illustrates the path between academic performance and continued intention to use, indicating that academic performance significantly affects continued intention to use. **H14** ($B = 0.420$, $P < 0.000$) reveals the path between effectiveness and continued intention to use, indicating that effectiveness significantly affects continued intention to use. **H15** ($B = 0.138$, $p < 0.057$) shows the path between support assessment and continued intention to use, indicating that support assessment significantly affects continued intention to use. **H16** ($B = 0.192$, $p < 0.000$) indicates the path between student satisfaction and continued intention to use, representing that student satisfaction significantly affects continued intention to use.

The results of this research study suggest that both PEOU and PU positively affect the behavior intention by undergraduate students, course content positively affects the effectiveness of those who perceive the use of the UCOM model as easy and useful, and they are highly motivated toward the incorporation of such pedagogical tools in their learning process. At the same time, it can positively increase the student satisfaction and support assessment with development in academic performance. Thus, it can be concluded that all of these factors enhance the continued intention to use UCOM. In addition, the decision-makers of the higher educational institutions should take these results into their consideration in their future attempt to construct e-learning infrastructure.

C. PRACTICAL EFFECT OF THE MODEL

First, UCOM practitioners must be aware that continued intention depends not only on one factor but also on perceived usefulness, perceived ease of use, technology integration, and interactivity. Because perceived usefulness and interactivity are the most important determinants of continued intention to use UCOM, the continued intention of students can be increased by improving their beliefs in the effectiveness of MOOCs and UCOM.

Second, this study provides evidence that the continued intention to use UCOM determines course content, interactivity and teacher subject knowledge, and support assessment is mediated by these three factors. Thus, UCOM should be organized to determine the requirements and challenges of courses, including the levels of prior knowledge needed and the availability of online and electronic resources necessary for students. UCOM practitioners should be particularly aware of the importance of technology integration, interactivity and teacher subject knowledge to better match the individual.

Finally, this means that they may distinguish their course offerings from others by ensuring that their courses are useful for students. However, they must attach importance to the effect of academic performance and support assessment, for which they can use behavior intention and student satisfaction to facilitate continued usage.

VI. LIMITATIONS AND FUTURE RESEARCH

The research attempts to add more assessment types of MOOC applied on UCOM as a new model that explains the

Table 9a. Questionnaire element measures details.

No	Measures	References
	Perceived Usefulness	
PU1	UCOM enhance my effectiveness	[65][39]
PU2	UCOM improves my academic learning performance	[65][39]
PU3	UCOM easily translates the learning material into specific Knowledge.	[38] [65]
PU4	Using UCOM would enable me to accomplish tasks more effectively	[42][17]
	Course Content	
CC1	UCOM model effectively challenged me to think	[32][12]
CC2	Course assignments were interesting and stimulating	
CC3	This course was up-to-date with developments in the field	
CC4	Student evaluation techniques such as projects, assignments, and exams were related to the learning objectives of this course	
CC5	UCOM course included applied learning and problem solving	
	Perceived Ease Of Use	
PEOU1	UCOM application is easy to use	[38],[65]
PEOU2	It's easy to get materials from UCOM application	
PEOU3	UCOM application is clear and understandable	
PEOU4	UCOM application allows me to submit my assignments	
	Interactivity	
IN1	I felt free to express and explain my own views throughout UCOM application	[32], [12]
IN2	I had sufficient opportunity to interact with other students using UCOM application	
IN3	The instructor provided timely feedback on assignments, exams or projects	
IN4	UCOM application facilitates the collaboration among the students	
	Teacher Subject Knowledge	
TSK1	UCOM application is trusted by faculty to enhance learning	[78]
TSK2	UCOM application can be used to improve 21st century skills.	
TSK3	UCOM application allows the student to enjoy privacy with the instructor	
TSK4	UCOM application guides curriculum updating courses	
TSK5	UCOM application increases the effectiveness of moderation	
	Technology Integration	
IT1	The interactive content of UCOM effectively communicated from same course	[32], [12]
IT2	The interactive content of UCOM included information not covered in printed material of the same course	
IT3	The interactive content of this course contributed towards learning	
	Support Assessment	
SA1	UCOM application guarantees trusted in assessment Timely and quality feedback	[66], [65]
SA2	Projects/assignments were clearly explained using UCOM	[65]
SA3	UCOM application guarantees support my learning motivation	[65]
SA4	UCOM application makes technology convenience to any time	[66]

Table 9b. *(Continued.)* Questionnaire element measures details.

	Academic Performance	
AP1	I anticipate good grades in courses where UCOM application is used heavily	[65]
AP2	I anticipate better grades in classes where UCOM application is used heavily compared to where they are not used	[65]
AP3	UCOM application efficiently allows faculty-student interaction	[66]
	Behavioral Intention	
BI1	I found myself considering the new information I have learned with UCOM when taking action related to the topic.	[79]
BI2	It is worth to recommend the UCOM for other students.	[77]
BI3	I'm interested to use the UCOM more frequently in the future	[77][38]
	Continuous Intention to use	
CI1	I intend to use UCOM in the future continuously	[17]
CI2	I intend to utilize UCOM for various purposes such as self-development as well as earning credit hours.	
CI3	If UCOM becomes diverse in the future, I intent to use it frequently even after graduation.	
	Student Satisfaction	
SS1	UOCM application is user friendly	[38]
SS2	I am really happy with UCOM after using it	[65]
SS3	Learning in UCOM is a very delighting experience.	[17]
	Effectiveness	
EF1	I would recommend UCOM to friends/colleagues	[32]
EF2	I have learned a lot in this UCOM	
EF3	I have enjoyed learning UCOM	

high need of variance in assessment and variety of assignment types on the same topic and project. These adopted quantitative data indicate that the nuance of the applied mechanism is not captured, and the findings do not fully capture the original MOOC features. The reasons behind the participant judgment are the basis of the model. To upgrade this work, participants were given the opportunity to respond to an open-ended question at the end to determine the reasons to complete or drop out of the system. This can support the analysis in positive comments related to the UCOM content and assessment details. The negative comments were related to the number of assessment surveys and the content difficulty with participant who did not join UCOM. Additionally, they highlight themes of flexibility regarding accessing material and working to complete achievements. In addition, they added value to increasing work with programming tools to be applied within MOOC and UCOM to clarify the assignment with attached videos and examples.

Additionally, we mainly conducted a cross-sectional study. However, user behavior is dynamic, and research may provide more insight into the development of user behavior. Thus, it is also necessary to gather evidence if we are to deepen our understanding of the interrelationships or causality among variables relevant to the technology acceptance measurement. In addition, the cross-sectional design of the study makes it difficult to determine causal effects among the constructs.

The aim of the questionnaire is to collect data from a random population based on different interests and to confirm that e-learning models are important for all the major programs and job requirements. This paper is a part of a

Doctorate degree program in computer science that is concerned with the improvement of academic performance and student satisfaction in HEI.

APPENDIX

See Tables 9a and 9b.

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