Influence of Massive Open Online Courses Implementation on Satisfaction and Continuance Intention of Students

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Abstract:

Purpose: The engineering courses offered in Somali universities attract many students, ranging between 300 and 500 every semester, making management and delivery of the course challenging. The increasing popularity of massive open online courses (MOOC) has led to rapid growth in enrollment, posing difficulties in effectively managing and delivering content to large volumes of learners. To this end, this study aimed to explore the influence of MOOC implementation factors on learners' continuance intention and satisfaction to provide insights that can enhance the learning experience and ensure long-term engagement.

Design/methodology/approach: The study utilized a survey approach based on an extensive literature review to collect data on the challenges faced by Somali universities in managing and delivering engineering courses. The survey included a series of questions, and 148 responses were collected from students enrolled in different programs. The data collected was analyzed using partial least squares-structural equation modeling and deep neural network approaches.

Findings: The result demonstrated that MOOC implementation factors, including course design quality, instructor reputation, self-paced flexibility, information relevance, platform usability, and student support services significantly affect students' continuance intention and satisfaction. Therefore, the study recommends universities should enhance MOOC implementation factors to improve the quality of teaching and increase students' continuance intention to study in a MOOC environment.

Originality/value: The study provides empirical evidence on how MOOC implementation factors affect the level of satisfaction and continuance intention of engineering students. It suggests that the findings could be useful for university management and lecturers to increase teaching and learning quality in the course and develop new strategies and approaches that suit modern-day learners. The

study also aims to enhance the efficiency and effectiveness of class delivery and improve student engagement in the learning process.

Keywords: Massive online open courses (MOOC), continuation intention, PLS-SEM, deep neural network

1. Introduction

Institutions of higher learning, particularly in developing nations, play a vital role in promoting sustainable education. To achieve this, they need to propose effective solutions for addressing issues such as improving the quality of instruction, reducing costs, and bridging educational inequalities [1]. Massive online open courses (MOOCs) have emerged as a viable solution to address the educational, strategic, and financial difficulties that higher education establishments are presently encountering. MOOCs are regarded as a paradigm of large knowledge delivery that may aid in overcoming these obstacles [2].

Numerous studies indicated MOOCs may have a negative effect on the higher-education system [3-6]; yet, there is increasing agreement that MOOCs will be included in the existing system of higher education [3]. As an innovative form of online education, MOOCs have been utilized alongside traditional face-to-face university courses [4, 5].

Incorporating technology into the educational process necessitates determining whether students are willing to remain utilizing it. The technological lenience model was constructed for this specific purpose by Davis [6]. MOOC researchers have extensively employed this approach [7-10]. Current studies show a correlation between the purpose to continue utilizing information technology and the possibility of repurchasing it [11]. Furthermore, Studies in higher education have shown that overall quality, perceived value, and continued use are all linked [12]. Concerns exist over the quality of MOOCs, supported by research indicating a high intention to use them but relatively low completion and motivation rates [13]. Evaluating the intention to continue using MOOCs can help identify why users are not completing or staying motivated in the courses. Therefore, it is crucial to evaluate users' viewpoints, perceived value, and intent to continue utilizing them.

Engineering is a required course for all students enrolled in engineering faculties, with a semester enrollment of 300 to 500 students. The course is instructed by four or five lecturers from various engineering departments. However, other problems have emerged, needing immediate action to ensure the course's viability. Handling such a large number of students is particularly difficult, especially in terms of scheduling lectures, assignments, and exams as well as the availability of enthusiastic expert lecturers [14]. Since students from various engineering disciplines are enrolled in the course, it is also challenging to locate convenient class times and locations for all students. Moreover, due to the large number of pupils, appraising them became a serious concern. The lessons are delivered in traditional lecture halls, which provide a minimal opportunity for student-instructor interaction [15]. In addition, tracking class attendance is challenging because it is completed manually, and students may register attendance for absent classmates [16]. Due to the various challenges faced by the engineering course, the study suggests incorporating the MOOC concept to enhance the learning system and address the issues. MOOCs have been effectively implemented worldwide and have attracted a large number of participants [17, 18]. The assessment procedure for MOOCs is often carried out online via a variety of available programmes, and the structure of MOOCs involves instructor-student interaction. This method is suitable for modern students who are proficient with social media and other online communication tools [19]. In this study, we leverage an open learning online platform to conduct the MOOC. This platform is widely employed among multiple Malaysian universities, offering insights into its application and benefits across various educational institutions [20].

The main objective of this research is to create a model that integrates the elements influencing the implementation of MOOCs and the students' intention to continue learning using this system. The study aims to determine the correlations between these elements not only the students' intention to continue but also their overall satisfaction. The research findings will be valuable to other researchers interested in understanding elements influencing students intending to continue utilizing MOOCs. The study also aims to determine the most effective strategies to combine MOOCs with traditional classrooms to improve instructional efficacy, efficiency, and student engagement. This approach can help to develop online education based on MOOCs. Lastly, this study could help identify which MOOC methods learners perceive as the most effective in terms of quality.

2. Background

MOOCs are online courses that do not require traditional prerequisites and provide free of charge content delivery exclusively through the Internet [21]. Students are not bound by any university affiliation, enrollment timelines, or negative consequences for not meeting specific criteria [22, 23]. MOOCs are considered useful resources for enhanced access to high-quality education [24], expanding access to knowledge and facilitating learning for a broader audience [25]. Despite the various positive impacts attributed to MOOCs, some concerns raised about their inadequate quality of instruction and educational methods as they lack support for personalized and adaptable education [26]. They are unable to provide tailored responses and engagement to students [21, 27]. The assessment models used in MOOCs, which heavily rely on multiple-choice questions, do not allow for the assessment of a wide range of capabilities and qualifications [24-26]. Consequently, MOOCs do not fulfill the standards of instructional design [28]. Although MOOCs have been criticized for not meeting certain instructional design standards, their unique ability to democratize education, increase access to knowledge, and offer learning opportunities to a diverse global audience is what has led to their continued application and significance. The versatility, scalability, and capacity to reach learners globally continue to be strong arguments for MOOCs' continued relevance and application in modern educational environments.

In higher education, the expression "intend to continue using" refers to a positive attitude towards the educational institution, which leads to favorable recommendations or a desire to pursue further studies in the same institution [12]. In the context of this research, "intention to continue to use" can be defined as having a favorable attitude towards MOOC-based online learning and advocating for its implementation in future courses. The perceived quality of an option is a gauge of its superiority or excellence [29], and effective integration of resources into courses can affect the quality of online education. [30]. Thus, in this study, perceived quality is assessed in two aspects: the online learning course, including activity management, MOOC integration, and communicating procedure, and activity evaluation; and the quality of the MOOC itself, which considers collaboration, teamwork, communication, and course design.

System quality is the efficacy of the interaction between hardware and software, demonstrating how effectively system data is processed, whereas information quality is a system's capacity to generate high-quality data [31]. In contrast, the level of service pertains to how service providers or the information system industry provide their services, encompassing both the scope and how they are delivered [32]. Samarasinghe [33] DeLone and McLean's [34] approach to measuring system efficacy lacked significant components for online learning success, including crucial aspects connected to both students and courses. Therefore, it is recommended to include additional relevant components into the model, as suggested by Albelbisi [34, 35]. The research gives a model with six variables: attitude, course quality, information quality, service quality, system quality, and continuance intention. The potential relationships between these six model variables are depicted in Figure 1.

The model consists of the following variables: student attitude, course quality, information quality, service quality, system quality, and intention to continue. The student attitude is the learner's perspective on whether MOOCs are advantageous or detrimental. Course quality refers to the learner's impression of the MOOC content's quality. Information quality refers to the precision and applicability of the MOOC structures' delivered information. System quality refers to the learner's perception of the MOOC system's usability, learnability, reliability, and integrity. The objective of this study is to investigate the following hypothesis:

H1: MOOC implementation variables have a significant impact on the intention to continue.

H2: MOOC implementation factors have a significant influence on student satisfaction.

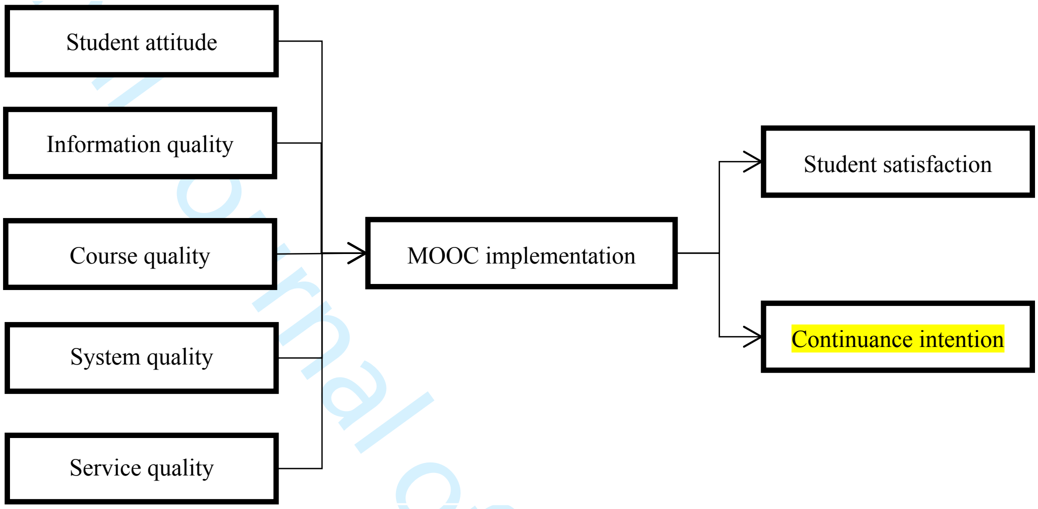


Figure 1. Conceptual model

3. Research Methodology

The study employs a positive analysis approach to conduct an empirical analysis, using a questionnaire survey to collect primary data. This method is widely used in the current literature on construction management [36-40]. Positivism was utilized in this study to review previous research, identify relevant MOOC implementation elements that affect continuance intention, and establish a conceptual model. Consequently, the relationships between constructs have been established using structural equation modeling (SEM) and artificial neural network (ANN) approaches. Figure 2 illustrates the overall epistemological research design.

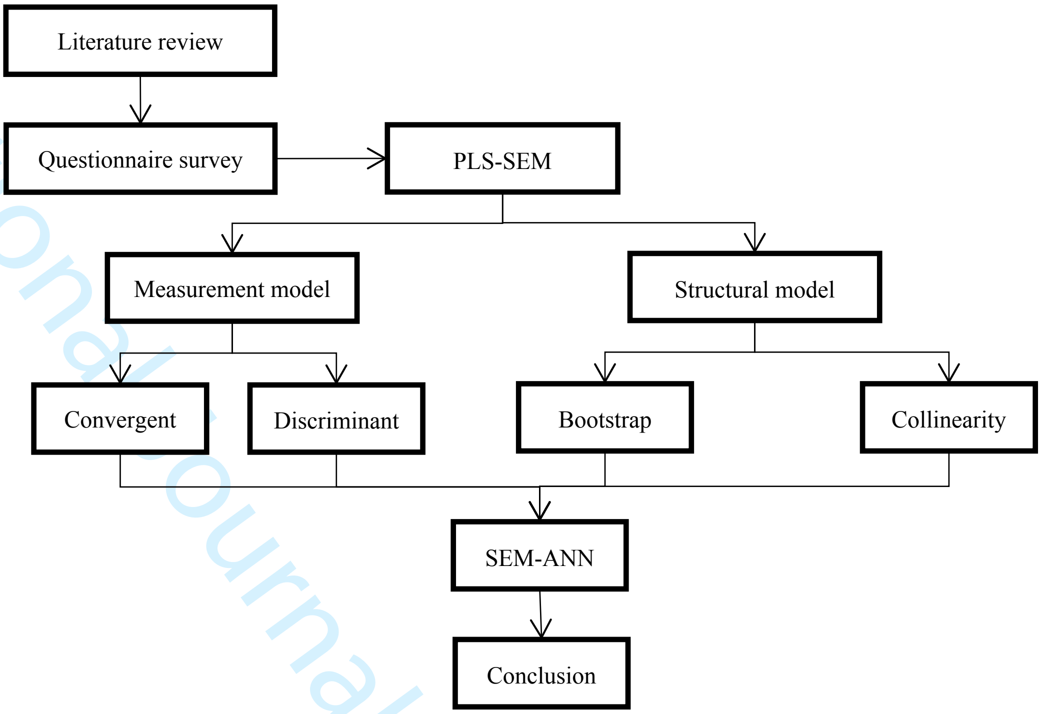


Figure 2. Research design

3.1 Administration of the Survey

The measurement items of the constructs outlined in Table 1 were assessed using a 5-point Likert scale, where 5 denoted a very high score, 4 indicated a high score, 3 represented an average score, 2 corresponded to a low score, and 1 indicated an extremely low score, which has been commonly used in prior research studies [41-48]. A closed-ended questionnaire was selected for its ability to obtain pertinent responses from a vast survey sample and its cost-effective administration costs [49]. The survey collected a total of 148 responses from the 200 students enrolled in the online course, with 128 of these responses deemed reliable for subsequent analysis [50, 51]. According to Yin [52] recommended that for SEM, the sample size should be at least 100 or more to achieve reliable results.

Table 1. Questionnaire items

Construct	Items	References
Continuance intention	If allowed to enroll in this course again, I would prefer the instructor to incorporate MOOCs into the curriculum. I would advise that more course topics consider incorporating MOOCs into their curriculum.	[10]

Construct	Items	References
	I am confident that I made the correct decision in selecting a school that integrates MOOCs into its curriculum.	
Attitude	I am confident in utilizing MOOCs. I find it enjoyable to use MOOCs for my studies. I think that MOOCs provide me with an opportunity to gain new knowledge. I believe that MOOCs enhance my overall learning experience I think that accessibility is a crucial aspect of MOOCs I think that MOOCs improve the quality of learning because they integrate various forms of media. I believe that incorporating MOOCs leads to higher student satisfaction. I find it interesting to study courses that incorporate MOOCs. The courses I have taken in MOOC have current and updated content.	[34, 35]
Course quality	In the MOOC courses I have taken, the learning objectives are presented in concise and easily understandable statements. In my experience with MOOCs, courses are structured in a way that promotes problem-solving activities as a means of developing a deeper understanding of the topics covered. I have discovered that the course material is efficiently presented to me in my MOOC learning experiences.	[34, 35]
Information quality	I think that the MOOC system delivers the results that are necessary for me I think that the MOOC system provides easily accessible and usable learning materials. I believe that the information provided by the MOOC system, including learning materials, is presented clearly and understandably. I think that the learning resources provided by the MOOC system are succinct.	[34, 35]
System quality	I find the MOOC system user-friendly I find it easy to manage the MOOC system. The MOOC system meets my expectations In my opinion, the MOOC system has all the essential features and functions needed for my studies. In my opinion, all the data within the MOOC system is properly integrated and coherent.	[34, 35]
Service quality.	Instructors are supportive of students in my experience with MOOC education. In my experience with MOOC learning, instructors are personable and kind to students. In my experience with MOOC education, the course teachers have adequate expertise in the material covered. In my experience with MOOC learning, teachers are accessible by email or phone.	[34, 35]

3.2 Data Analysis

The questionnaire's internal consistency was assessed using Cronbach's alpha reliability test [53, 54], indicating a high level of dependability (Cronbach's alpha coefficient = 0.750). Furthermore, SEM was employed to analyze multivariate regression, evaluating structural relationships between constructs [55-57]. In this study, statistical analysis was performed using SmartPLS3.2.7 software, which employs measurement and structural model evaluation techniques elaborated on in the following sub-sections.

- Measurement model comprises convergent and discriminant validity assessments to establish connections between indicators or measures and the underlying constructs [58], ensuring distinctiveness and correlation within and between constructs [59-62].
- Structural model is constructed using path analysis to examine all complex interrelationships between constructs simultaneously [63, 64].

Finally, the ANN algorithm was employed to investigate a wide range of variables and their complicated relationships to pinpoint the important elements.

4. Results

4.1 Measurement Model (First-Order Construct)

This study employed a SEM, as shown in Figure 3, to replicate the conceptual model previously mentioned. To assess the measurement aspects of the proposed model, several techniques, including Cronbach alpha analysis, composite reliability, average variance extracted (AVE), and discriminant validity, were utilized as stated in reference [65]. Items with external loadings between 0.40 and 0.65 were evaluated for potential removal from the scale, but only if their exclusion resulted in a significant improvement in composite reliability and AVE [65-67]. An improvement in composite reliability and AVE occurs when the construct accounts for at least half of the variation in an item, and the reported variance exceeds the error variance. The external loadings for the measurement models are depicted in Figures 3 and 4.

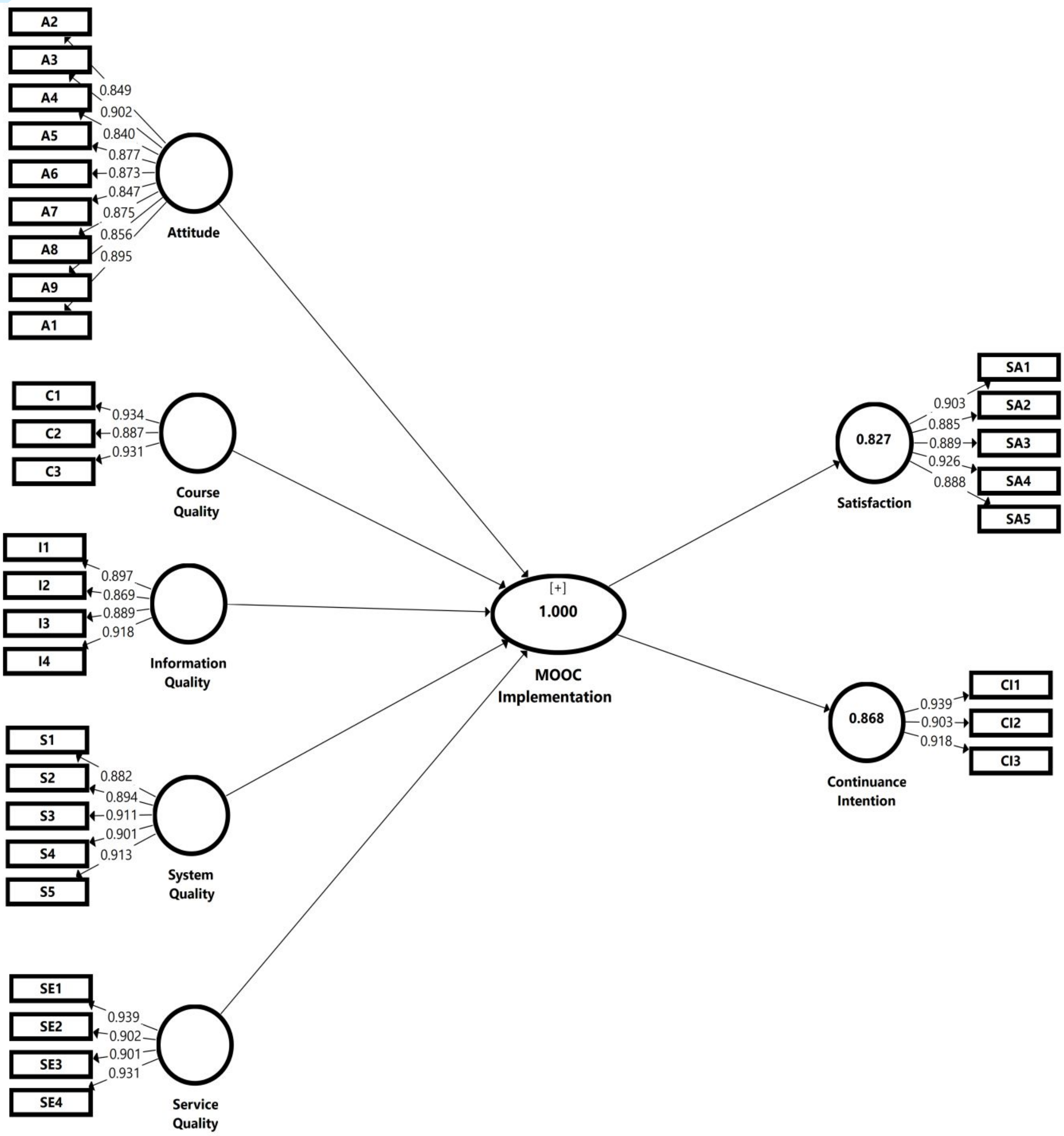


Figure 3. Initial PLS model with outer loading and R^2

Thus, all external loadings were deemed acceptable, and composite reliability (cr) was examined to account for the potential limitations of Cronbach's alpha, which can be influenced by the number of items included [65, 67]. Based on the results of both analyses, all constructs met the standards of having a Cronbach's alpha greater than 0.60 and a cr greater than 0.60, indicating their appropriateness for use [68-70]. The AVE test results in Table 2 indicate that all constructs demonstrated convergent validity, with values greater than 0.50 [68, 71].

Table 2. Construct reliability and validity tests

Constructs	Cronbach's alpha	Composite reliability	Average variance extracted
Attitude	0.959	0.965	0.754
Continuance intention	0.909	0.943	0.847
Course quality	0.906	0.941	0.842
Information quality	0.916	0.941	0.798
MOOC implementation	0.983	0.984	0.716
Satisfaction	0.94	0.954	0.807
Service quality	0.938	0.956	0.843
System quality	0.942	0.955	0.811

To ensure that each construct in the proposed model represents distinct phenomena that are not captured by other constructs, a discriminant validity analysis is necessary, as mentioned in reference [72, 73]. In this study, Fornell and Larcker [74] criteria and cross-loading criteria are used to evaluate discriminant validity. According to these criteria, Table 3 shows that the measurement model demonstrates discriminant validity, as the square root of the AVE for each construct exceeds the correlation between the latent variables [75, 76].

Table 3. Discriminant validity

Constructs	Attitude	Continuance intention	Course quality	Information quality	Satisfaction	Service quality	System quality
Attitude	**0.868**						
Continuance intention	0.819	**0.92**					
Course quality	0.8	0.872	**0.918**				
Information quality	0.853	0.83	0.789	**0.893**			
Satisfaction	0.892	0.861	0.812	0.797	**0.898**		
Service quality	0.828	0.922	0.887	0.855	0.888	**0.918**	
System quality	0.874	0.833	0.837	0.784	0.868	0.879	**0.9**

Despite the consistency of the Fornell and Larcker [74] criterion for assessing discriminant validity, some studies have reported different results. Hence, in this study, the cross-loading criteria were also utilized to confirm discriminant validity. This approach examines whether the indicators of a construct have higher loadings on their construct than on other constructs. Table 4 demonstrates that the loading of all indicators for each construct is greater on their construct than on other constructs, supporting the cross-loading criteria and confirming discriminant validity (as shown by the rows).

Table 4. Cross loading test

Items	Attitude	Course quality	Continuance intention	Information quality	System quality	Satisfaction	Service quality
A1	**0.895**	0.767	0.806	0.743	0.75	0.788	0.832
A2	**0.849**	0.777	0.777	0.729	0.737	0.797	0.778
A3	**0.902**	0.823	0.813	0.806	0.775	0.79	0.841
A4	**0.84**	0.769	0.768	0.725	0.758	0.773	0.803
A5	**0.877**	0.79	0.793	0.748	0.751	0.765	0.775
A6	**0.873**	0.753	0.813	0.719	0.781	0.797	0.818
A7	**0.847**	0.764	0.764	0.711	0.744	0.715	0.755
A8	**0.875**	0.825	0.83	0.777	0.777	0.78	0.836
A9	**0.856**	0.765	0.816	0.704	0.754	0.767	0.808
C1	0.865	**0.934**	0.835	0.754	0.794	0.752	0.864
C2	0.786	**0.887**	0.774	0.676	0.734	0.735	0.747
C3	0.824	**0.931**	0.792	0.738	0.773	0.749	0.828
CI1	0.889	0.822	**0.939**	0.82	0.802	0.807	0.894
CI2	0.818	0.775	**0.903**	0.718	0.744	0.78	0.809
CI3	0.827	0.81	**0.918**	0.751	0.752	0.79	0.84
I1	0.737	0.68	0.731	**0.897**	0.694	0.656	0.726
I2	0.725	0.667	0.694	**0.869**	0.654	0.691	0.73
I3	0.785	0.748	0.755	**0.889**	0.717	0.736	0.8
I4	0.798	0.72	0.783	**0.918**	0.734	0.76	0.797
S1	0.779	0.766	0.737	0.713	**0.882**	0.752	0.791
S2	0.771	0.744	0.706	0.691	**0.894**	0.792	0.771
S3	0.796	0.776	0.781	0.671	**0.911**	0.767	0.791
S4	0.801	0.762	0.785	0.772	**0.901**	0.803	0.82
S5	0.785	0.718	0.74	0.681	**0.913**	0.795	0.785
SA1	0.751	0.65	0.761	0.693	0.726	**0.903**	0.763
SA2	0.811	0.749	0.757	0.73	0.775	**0.885**	0.783
SA3	0.81	0.736	0.788	0.703	0.8	**0.889**	0.787
SA4	0.857	0.779	0.815	0.746	0.813	**0.926**	0.836

Items	Attitude	Course quality	Continuance intention	Information quality	System quality	Satisfaction	Service quality
SA5	0.774	0.726	0.744	0.703	0.781	**0.888**	0.816
SE1	0.89	0.857	0.87	0.797	0.819	0.829	**0.939**
SE2	0.825	0.807	0.845	0.782	0.78	0.801	**0.902**
SE3	0.854	0.791	0.852	0.755	0.82	0.837	**0.901**
SE4	0.838	0.803	0.82	0.809	0.811	0.796	**0.931**

4.2 Measurement (Second-Order Construct)

The significant standard path coefficients β (outer weights) for the attitude, course quality, information quality, service quality, and system quality first-order subscales of MOOC implementation are displayed in Table 5.

Table 5. Bootstrapping analysis for formative constructs.

Paths	*β*	SE	*T* values	P values
Attitude ➔ MOOC implementation	0.373	0.009	43.817	0
Course quality ➔ MOOC implementation	0.13	0.004	33.12	0
Information quality ➔ MOOC implementation	0.158	0.005	34.404	0
Service quality ➔ MOOC implementation	0.184	0.005	35.959	0
System quality ➔ MOOC implementation	0.21	0.005	42.499	0

4.3 Structural Model (Path Analysis)

Once the measurement model has been fitted, evaluation of the structure model can begin. The structural design explains the relations between variables in-depth, including both the external and endogenous constructs [77]. The hypothesized parameter values are then evaluated to evaluate the magnitude, direction, and significance of the model's variables [77]. In this study, SEM was used to test the research hypotheses. Specifically, the influence of MOOC implementation on continuance intention and student satisfaction was examined using partial least squares-structural equation modeling (PLS-SEM), as shown in Figure 4.

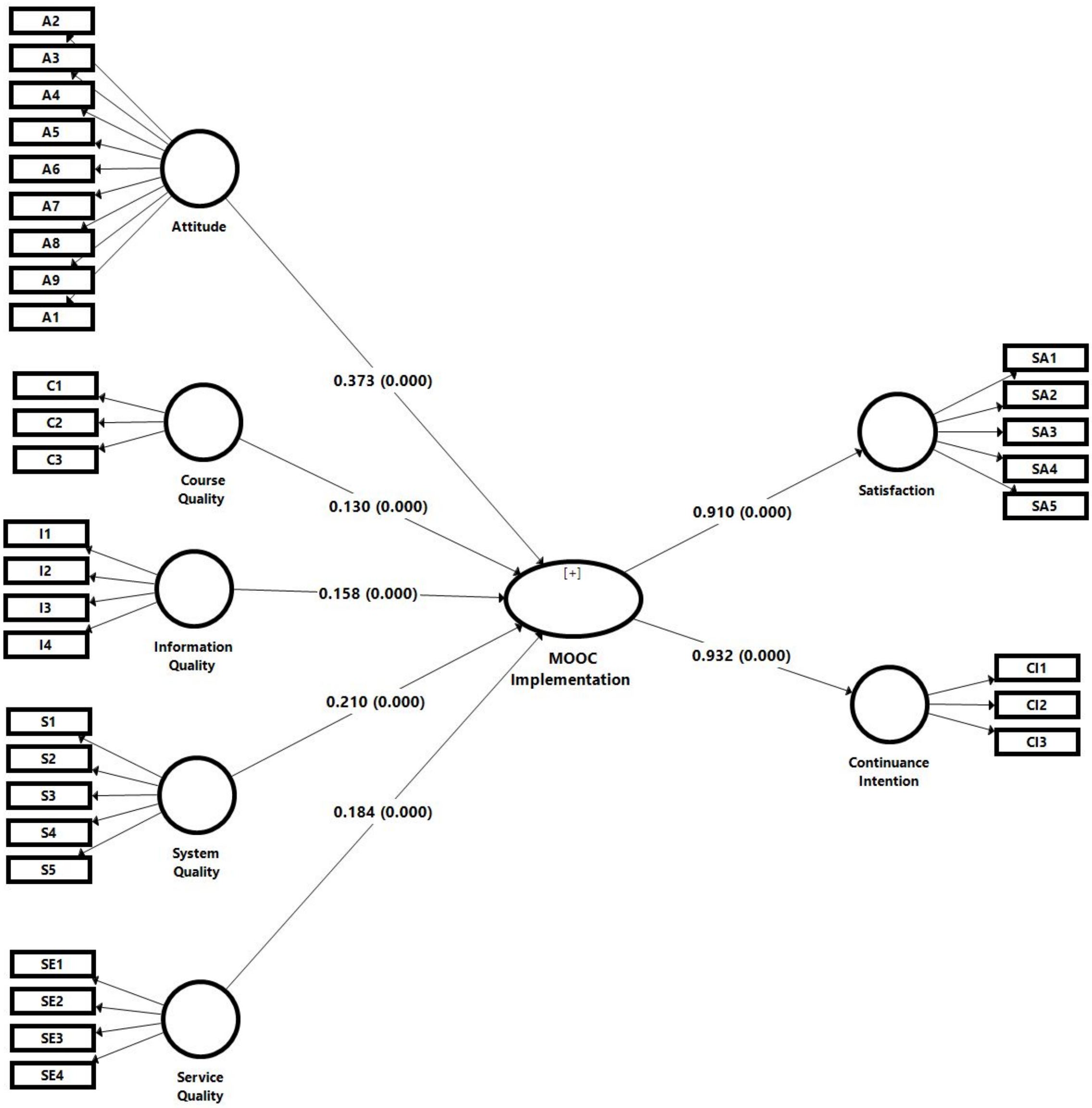


Figure 4. Bootstrapping analysis

To evaluate the significance of the model hypotheses, the reliability of data, and the accuracy of the computed path coefficients, the bootstrapping technique was utilized [78]. The findings demonstrate that the impact of MOOC acceptance on both continuing education intention and student satisfaction was statistically significant, as depicted in Figure 4 and Table 6.

Table 6. List of hypotheses and relative paths for the model

Paths	β	SE	T values	P values
MOOC implementation ➔ Continuance intention	0.932	0.016	57.49	0
MOOC implementation ➔ Satisfaction	0.91	0.027	33.443	0

4.4 Prediction Analysis (R^2)

R^2 represents the entire variation explained by the model. A greater R^2 value indicates that the structural model's predictive robustness is stronger. R^2 values greater than 0.70 are considered outstanding, with values ranging from -1 to 1 [79]. Moreover, Ringle, et al. [80] suggest that values between 0.02 and 0.12 indicate weak effects, values between 0.13 and 0.25 indicate moderate effects, while values greater than 0.26 indicate strong effects. In this study, the PLS algorithm was used to determine the R^2 values, which are comparable to those obtained using conventional regression analysis. The corrected R^2 values for continuing education intention and student satisfaction were 0.868 and 0.827, respectively, as shown in Table 7. These results suggest, Chin [81], guidelines, that the impact of MOOC implementation is substantial.

Table 7. Results of prediction analysis (R^2)

Endogenous latent variable	R-square	R-square adjusted	Explained size
Continuance intention	0.868	0.868	High
Student satisfaction	0.827	0.827	High

4.5 Predictive Relevance of the Structural Model

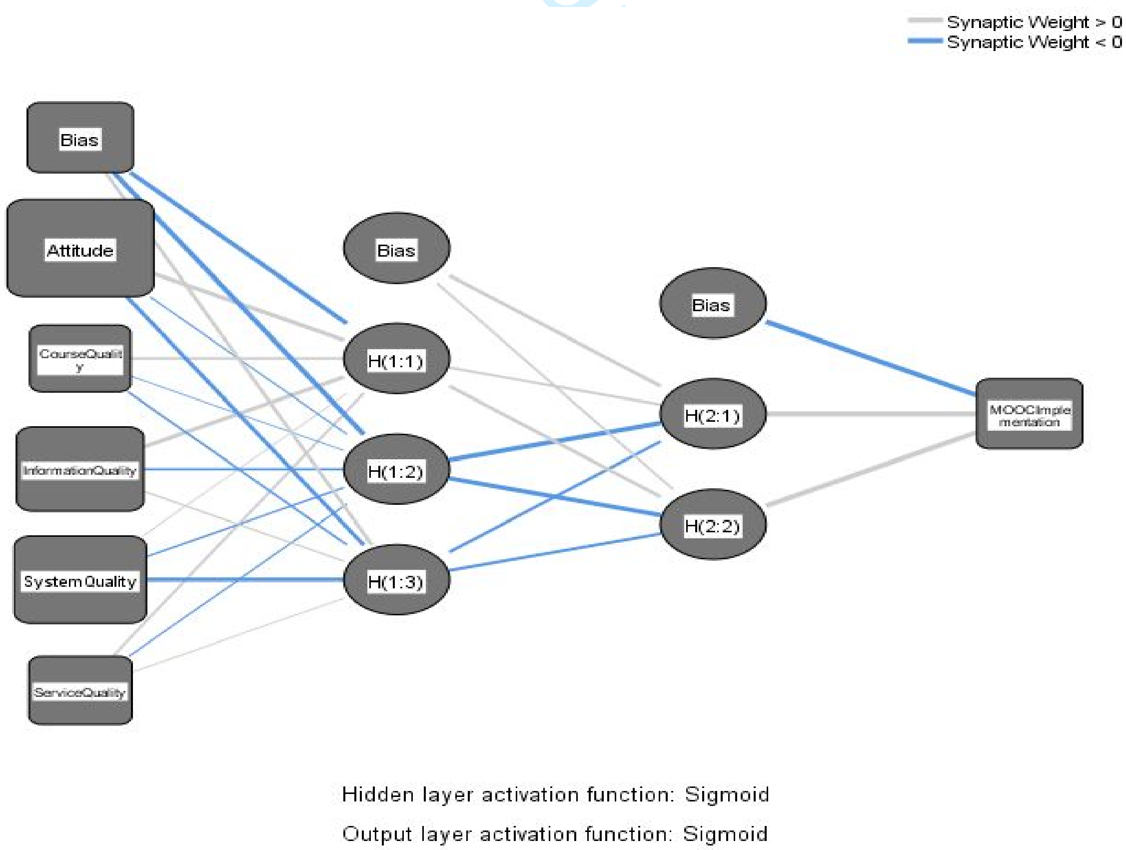
Assessing the predictive relevance of a structural model is a crucial task. To accomplish this, the study utilized the blindfolding procedure to evaluate the important measures of each dependent variable. The results revealed that the Q^2 values for continuance intention (0.727) and student satisfaction (0.656) were above zero, suggesting that the independent variable (MOOC implementation) has predictive significance for the dependent variables (as demonstrated in Table 8). [82].

Table 8. Results of predictive relevance (Q^2)

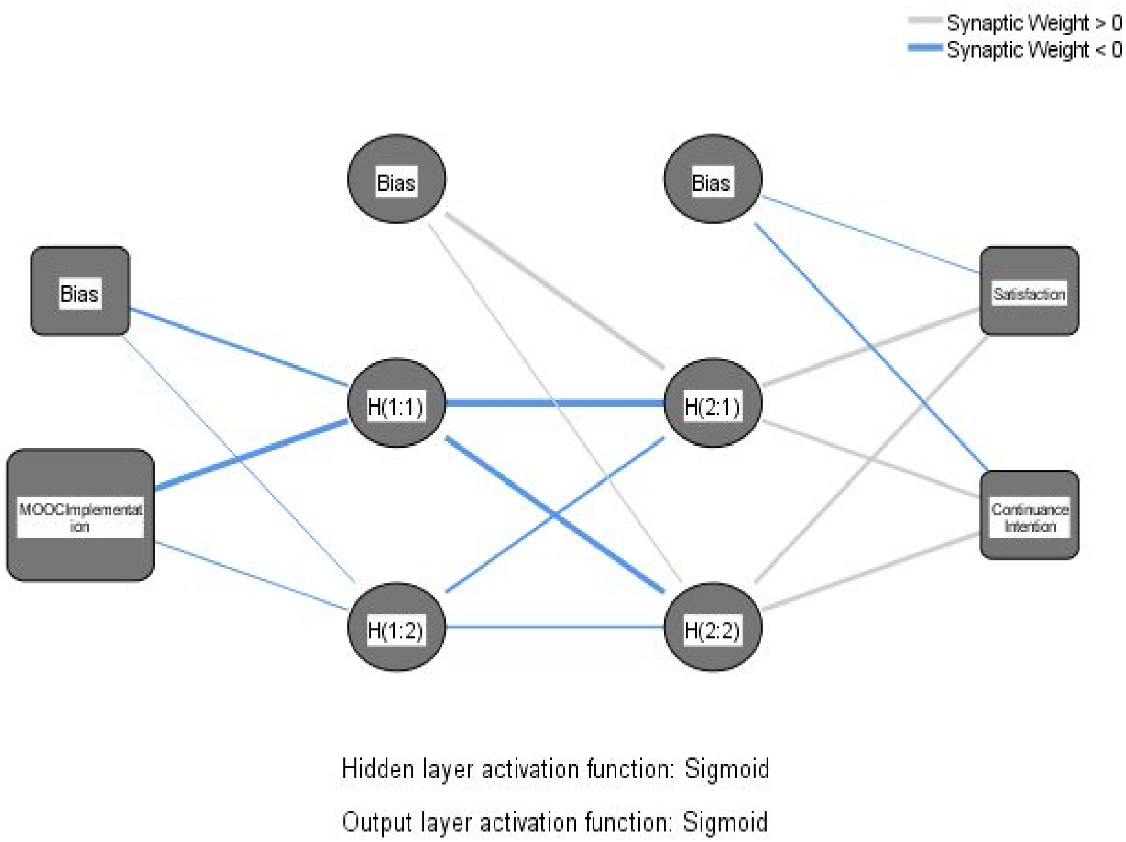
Endogenous latent variable	Sum of squares of observations (SSO)	Sum of squares of prediction error (SSE)	Q^2 (=1-SSE/SSO)
Continuance intention	384	104.89	0.727
Student satisfaction	640	220.3	0.656

4.6 Artificial Neural Network Analysis

The PLS-SEM results are supplemented by ANN, which is used to emphasize each predictor's factor important importance. SEM is less capable at predicting linear or non-linear connections than ANN. Two models are developed, such that in Model A, attitude, course quality, information quality, system quality, and service quality served as the input neurons; while MOOC implementation served as the output neuron. In Model B, the MOOC implementation functioned as the input neuron, while the output neurons were satisfaction and continuation intention. While a shallow ANN architecture only provides shallow learning, a deep ANN design allows for deeper learning. The deep learning ANN models are depicted in Figure 5. The deep learning models employed in this study have an input layer, two hidden layers, and an output layer. The model used the sigmoid function as the activation function for both the hidden and output neurons, and it automatically generates the number of hidden neuron nodes. A ten-fold cross-validation process is employed to solve the over-fitting issue, in which 90% of the data are used for training and the remaining 10% are utilized for testing.



(a)



(b)

Figure 5. ANN models

Table 9 displays the outcomes of the study, including the sum of square error (SSE) and root mean square error (RMSE) values for the training and testing datasets. In general, a decrease in the values of SSE and RMSE is indicative of an improvement in the accuracy of predictions. Upon analysis of the outcomes, it is evident that diverse networks attained distinct degrees of precision. In Model A, networks 1, 8, and 5 demonstrated comparatively lower error values in both training and testing, and these networks indicate superior predictive performance with respect to the dependent variable. Conversely, networks 3 and 4 exhibited elevated error values, signifying a relatively reduced level of forecasting precision. In model B, networks 9 and 6 displayed relatively lower error values in both training and testing, in contrast to networks 10 and 5, which exhibited the poorest predictive performances. The results suggest that specific architectures of the ANN model are more efficient in comprehending the intricate connections among the variables that influence the execution of MOOC.

Table 9. Sample size of testing and training analysis

Neural network	Model A						Model B					
	Training			Testing			Training			Testing		
	Sample size	SSE	RMSE	Sample size	SSE	RMSE	Sample size	SSE	RMSE	Sample size	SSE	RMSE
ANN 1	118	0.027	0.015	10	0.001	0.010	115	1.57	0.117	13	0.091	0.084
ANN 2	115	0.067	0.024	13	0.003	0.015	114	1.325	0.108	14	0.12	0.093
ANN 3	111	0.137	0.035	17	0.031	0.043	108	1.398	0.114	20	0.193	0.098
ANN 4	116	0.174	0.039	12	0.014	0.034	116	1.347	0.108	12	0.048	0.063
ANN 5	115	0.031	0.016	13	0.002	0.012	111	1.681	0.123	17	0.07	0.064
ANN 6	114	0.056	0.022	14	0.004	0.017	110	1.164	0.103	18	0.288	0.126
ANN 7	115	0.108	0.031	13	0.014	0.033	119	1.443	0.110	9	0.059	0.081
ANN 8	113	0.027	0.015	15	0.002	0.012	109	1.372	0.112	19	0.226	0.109
ANN 9	115	0.058	0.022	13	0.003	0.015	115	1.08	0.097	13	0.298	0.151
ANN 10	113	0.063	0.024	15	0.004	0.016	110	1.78	0.127	18	0.183	0.101
Mean		0.0748	0.0244		0.0078	0.0207		1.416	0.1119		0.1576	0.0971
Standard deviation		0.050	0.008		0.009	0.011		0.216	0.009		0.093	0.027

The order of numerous constructs related to the impact of MOOC implementation on students' satisfaction and intention is shown in Table 10. Aspects of attitude, course quality, information quality, system quality, and service quality are included in the aforementioned constructs. The normalized importance scores, a gauge of each construct's relative relevance, are used to determine the significance rankings such that high scores suggest a greater level of relevance. The statistics show that the attitude has achieved the highest normalized significance score of 1.0. Information quality, system quality, service quality, and course quality are in the following places. The results indicate that, in descending order of significance, attitude, information quality, system quality, service quality, and course quality are the factors that have the greatest impact on the implementation of MOOCs. The importance ranks are significant since they can clarify how these constructs were prioritized. The aforementioned conclusions have the ability to direct resource allocation toward addressing the most important factors that support the successful integration of MOOC inside Somali universities.

Table 10. Importance rank of construct

Neural network	Model A					Model B
	Attitude	Course quality	Information quality	System quality	Service quality	MOOC implementation
1	0.286	0.127	0.218	0.236	0.133	1
2	0.41	0.09	0.16	0.13	0.21	1
3	0.572	0.051	0.098	0.166	0.113	1
4	0.45	0.09	0.21	0.15	0.11	1
5	0.386	0.162	0.153	0.16	0.14	1
6	0.377	0.068	0.187	0.149	0.219	1
7	0.415	0.013	0.187	0.236	0.149	1
8	0.403	0.095	0.215	0.163	0.124	1
9	0.251	0.185	0.249	0.18	0.136	1
10	0.384	0.096	0.186	0.207	0.127	1
Average importance	0.393	0.097	0.186	0.178	0.146	1.000
Normalized importance (%)	405.573	100.000	192.260	183.798	150.568	100.000
Rank	1	5	2	3	4	1

5. Discussion

This study sought to investigate the integration of MOOCs into online education and examine students' perceptions of the value and quality of this methodology. The results emphasized several critical elements for creating MOOC-based online learning experiences. Notably, elements such as collaboration and teamwork, diverse assessment strategies, student feedback sessions, and clear teaching materials were shown to be essential in promoting engagement and resolving issues with instructional design, collaboration, and technology integration [83-85].

Regarding the influence of attitudes on continuance intention, our findings supported a strong correlation between student retention in digital learning and a favorable attitude toward MOOCs. This is consistent with other studies that showed the importance of student attitudes to the success of online learning [86, 87]. It implies that encouraging positive attitudes might enhance students' desire for online learning, including attitudes of interest and confidence in using MOOCs [88, 89].

The study also found a significant correlation between students' intention to continue using MOOCs and the caliber of the courses. In alignment with other studies highlighting the influence of course materials on online learning outcomes, elements such as course design, content relevance, and material clarity were crucial in promoting ongoing engagement [90-92].

Ultimately, our results highlight the importance of high-quality services, system functioning, and information quality to maintaining students' interest in MOOC-based learning. These results are consistent with other research highlighting the significance of accessible and comprehensible material and trustworthy support systems in online learning [93, 94].

However, it is crucial to recognize the study's limitations. The results were derived from a particular sample and context, which might limit their generalizability. Furthermore, even though the study investigated a variety of topics, there might be additional important aspects influencing students' interaction with MOOCs, warranting further investigation.

6. Conclusion

This study examined how the implementation of MOOCs influences the intention of engineering students in Somalia to continue their online education. Improving student attitudes, the quality of information, the system, the service, and the course were found to be critical for enhancing MOOC online learning environments. The study suggests that MOOC designers prioritize the development of interactive learning environments that satisfy these six requirements. The findings of this study can aid institutions of higher education in their adoption of MOOCs and guide MOOC designers in the development of effective MOOC environments. This investigation contributes to existing knowledge concerning MOOC-based online education. There is a need for additional research into students' satisfaction with MOOC-based continuing education.

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Reviewer(s) Comments

<u>Reviewer 1:</u>

Comment: The revision has further improved this paper. Overall, the paper exhibits a strong blend of theoretical depth and practical relevance, making it a valuable addition to scholarly discourse.

Response: Thanks for your positive feedback and recommending the paper for publication.

Reviewer 2:

Comment: The authors have addressed the comments given in the previous review. However, I feel that the following concerns should also be addressed:

1) The authors should use “continuance intention” instead of “continuous intention” throughout the paper, including figures, tables etc.

2) The references for the measurement items should be specified for all the constructs.

Response: Thank you for your feedback and for acknowledging the revisions made in response to the previous review.

1) Regarding your concern about the terminology used in the paper, we appreciate your suggestion to use “continuance intention” instead of “continuous intention”. We carefully reviewed the manuscript to ensure consistency in the terminology used throughout the paper, including figures, tables, and other sections.
2) We updated Table 1 in the revised manuscript to include clear references for all measurement items.

Comment: 1) Table 1 does not indicate the measurement items of all the constructs.

2) The following statement in section 3.1 does not match with the description of Table 1: “Table 1 illustrates that the survey comprised of two parts: 1) gathering respondent demographics, and 2) rating the constructs on a 5-point Likert scale.”

Response: Thanks for your constructive feedback, which has helped to improve our study.

1) We revised Table 1 to ensure that all measurement items of the constructs are clearly indicated.
2) In the revised manuscript, we clarified in Section 3.1 that Table 1 presents questionnaire items measured on a 5-point Likert scale, with no demographic data collected. All participants were male due to low female enrollment in Somali engineering education, which was a limitation of the study.
