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An Empirical Investigation into Students' Actual Use of MOOCs in Saudi Arabia Higher Education

Uthman Alturki * and Ahmed Aldraiweesh

Educational Technology Department, College of Education, King Saud University, Riyadh 11451, Saudi Arabia
* Correspondence: ualturki@ksu.edu.sa

Abstract: Massive Open Online Courses, or MOOCs, are a type of educational innovation where enrollment in the courses given is free and available online. The MOOCs course selection is extensive and may accommodate hundreds or thousands of students at once. The current study, however, aims to look into how the academic self-efficacy of real MOOC users affects learning engagement and perseverance in higher education in Saudi Arabia. This study added the Technology Acceptance Model (TAM) to social cognitive theory. Therefore, the primary goal is to create a new model by examining the variables that affect the perceived utility and perceived service quality, as well as the students' general perceptions of MOOCs that are really used. Therefore, this research used a quantitative approach and distributed the questionnaire online through a Google Form. It collected data from 276 King Saud University students and used it to test the hypothesized correlations using structural equation modeling (SEM-PLS). The study's findings showed that perceptions of perceived benefits and service quality consistently had a significant influence on social interaction, influence, networks of support, and social identity. A further finding was that reported utility and perceived service quality have always been significantly influenced by academic self-efficacy in actual MOOC use. Because of this, learning engagement and perseverance in Saudi Arabian higher education are significantly impacted by the academic self-efficacy of real MOOC users. According to the findings, MOOC programs generally have a positive influence on the kingdom's higher education system. As a result, it is almost certain that this research model will assist university decision-makers in determining whether or not MOOC usage is prevalent at Saudi educational institutions.

Keywords: social cognitive theory; technology acceptance model (TAM); academic self-efficacy of actual users of MOOCs; structural equation modeling (SEM)

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1. Introduction

Massive open online courses (MOOCs) are used to sustain education, attract a large student base, and, in most cases, provide free courses with open access. MOOCs have altered the way higher education is delivered in Saudi Arabia [1]. Although MOOCs were created with the intention of being used for informal learning, traditional academic institutions have recently started to accept them [2]. The higher education industry's lack of readiness for the transition to online learning was made clear by the COVID-19 epidemic. There has been an upsurge in the adoption of ready-to-use MOOCs as a supplementary teaching and learning technique [3]. According to Tseng et al. [4], despite their popularity, MOOCs were not as frequently used by academics during the epidemic as other distance learning and educational technologies. In another study, Wang and colleagues [3] discovered that although the epidemic pushed more people to choose MOOCs as a method of education, there was a risk that online learning might exacerbate rather than lessen socioeconomic status gaps among students.

The hybrid learning paradigm will, however, continue to assist education after COVID-19, given the trend towards further integrating technology-mediated education into modern teaching and learning. The epidemic also brought to light the importance of student learning and wellbeing issues, which will probably continue to be covered in academic circles [5].

The acrimonious debate regarding MOOCs' potential to revolutionize higher education was highlighted by De Freitas et al. [6,7]. On the one hand, MOOCs differ from traditional online learning formats in that they allow open access to a sizable population [7,8]. In a similar vein, Daradoumis et al. [9] claimed that MOOCs built on free educational resources are one of the most adaptive methods to give access to high-quality education, especially for people living in distant or underdeveloped areas. Nonetheless, Ref. [10] stated that the teaching quality is still below average, even though the majority of MOOCs have been effectively structured. Low graduation rates were another issue that was brought up in the research [11]. To overcome these challenges, massive learning analytics are needed for administration, forecasts, and student aid in MOOCs [12,13].

However, learning analytics research focuses on more than just its practical application to increase student retention and promote their engagement [14]. Learning approaches, including stats, deep learning, and information visualization, are increasingly used in MOOC research. The challenges outlined above have mostly been researched from the perspective of students, whether it is senior executives in institutions [15] or institutional measures for implementing MOOCs [16,17]. The advantages of MOOCs for education and the factors that affect instructors' utilization of MOOCs are not well covered in the research. Academics may use MOOCs (or online courses) for a number of purposes, such as personal interest, publicity, raising the standard of instruction, or incentives and rewards [18].

Moreover, because it is not possible to accommodate and meet the needs of every student, the architecture of a program, the arrangement of its materials, and the rigor of its teaching methods are the key components of MOOC quality. In contrast with certain other open educational resources, MOOC materials must be structured with students in mind, employing instructional design concepts and taking into account best practices for creating online learning content [19]. Nonetheless, it was recognized that a staff member's lack of excitement for pedagogical changes was one of the major obstacles to the widespread use of MOOCs [20].

According to the 98% of Saudi Arabian teachers who replied, the post-pandemic age will see an increase in the digital revolution in education that began with the pandemic catastrophe [21]. Notwithstanding this outlook, teachers' views on MOOCs are very diverse. Different MOOCs-user profiles, including those who are interested in its possible benefits, those who only value specific MOOC features, as well as those who take a utilitarian perspective, seeing MOOCs as a temporary way to get around time and location barriers to education, were identified by Donitsa-Schmidt et al. [22]. The epidemic also brought to light the importance of schoolchildren and wellbeing issues, which are expected to be on the study agenda going forward [5].

Massive Open Online Courses, or MOOCs for short, are a type of educational innovation where enrollment in the courses given is free and available online. The MOOCs course selection is extensive and may accommodate tens of thousands of learners at once. The courses are also not time-bound, allowing any student to access instruction from any location at the same time [23–25].

The lack of preparation, unexpected overloading of all stakeholders, and higher risks of security breaches, which could result in a tarnished reputation and decreased enrollment, were noted as hazards for online learning in prior research [26]. Another difficulty in implementing online learning is the rapid shift of exams online, the lack of practical knowledge, poor attendance because of heavy Web traffic, the lack of student learning, the ambiguity of regulations, and rising cybercrime, but this is not an excuse for MOOCs learning methods [27]. Last but not least, the compelling need to adapt their existing skills to virtual classrooms exposed instructors' ignorance of the core ideas behind web-based teaching contexts and the requirements for high-quality online learning [11].

From doctoral programs to undergraduate settings, MOOCs have been used as campus-style classes [28]. They have become increasingly common in recent years as cutting-edge online learning resources accessible to a broad audience regardless of geography or availability [29,30]. Global users have access to a wide variety of MOOCs used for sustainable education from a variety of companies, colleges, and websites [31].

The use of MOOCs in higher education is recognized universally as a significant advancement in Saudi Arabia [1]. According to Alhazzani [32], the majority of Saudi Arabian university professors believe that MOOCs have a direct impact on raising educational standards and fostering student learning abilities. MOOCs can make it easier for university graduates to enroll in online classes taught by professionals and academics who lack the expertise or necessary job-market skills [33].

As a result, elite universities around the world have embraced MOOCs. For example, Stanford University offers Coursera and online courses, and academics from these institutions produce useful information [34]. The MOOCs are accessible to students all around the world. As an example, an Arab nation like Jordan offers the Edraak MOOC, which has roughly 12,203 students from outside the Arab nations. Nearly 120,868 students from Arab nations are enrolled in MITx or HarvardX in Western nations like the US [35].

In order to advance the global spread of MOOCs, it is crucial to examine MOOC adoption within different economic, social, or cultural contexts [36,37]. As a result, this study responds to the aforementioned need. The biggest issue for MOOC providers is the low acceptance rate, particularly in developing nations [36]. Universities in Saudi Arabia have adapted MOOCs in the meantime. King Khalid University (2012), for instance, offers MOOCs so that all of its lectures are accessible online. By providing high-skilled training programs, MOOCs have the potential to modernize the Saudi labor force and alter the educational system [33], but they can only achieve this if students are ready to adopt the MOOC methodology. Therefore, it would be ideal to pinpoint the key elements influencing learners' adoption of MOOCs [38].

The difficulties that Saudi students confront when enrolling in MOOCs courses are compared with the results of other studies. According to research, it can be challenging to evaluate students' work, teachers feel like they are speaking into a void because there is not any immediate student reaction, there are high time and financial demands, and students do not engage in online communities [39].

Additionally, when MOOCs are brought into the Saudi university system, learning and teaching may encounter difficulties and limitations [32]. Despite the fact that this study was initiated during the COVID-19 pandemic, it is important to note how all Saudi Arabian and global educational institutions have suddenly shifted to relying on eLearning to sustain the student learning process from their homes. Many KSA universities have undergone successful transformations. There are obstacles to be overcome, including a lack of well-designed academic courses.

The new 2030 Agenda for Sustainable Development of the United Nations recognizes the importance of an appropriate education response in transformation towards sustainability. Education is explicitly formulated as a stand-alone goal, one of 17 Sustainable Development Goals (SDGs) in the agenda. As education can contribute to all of the objectives, many targets connected to education are also included in other SDGs [18,39]. Education for Sustainable Development (ESD) should promote the transition to sustainability at all educational levels, from preschool through higher education and lifelong learning. Massive Open Online Courses (MOOCs), which are gaining in popularity and are providing a variety of new teaching and learning options, are opening up new opportunities in this regard. We think that little research focuses on the problems of the inclusion of sustainable development goals to the education content, particularly within the framework of MOOC-based learning, despite the fact that researchers frequently study sustainable development and emphasize the role of education in achieving sustainable development goals. In our opinion, there is a research gap concerning the problems of the transition of sustainable development objectives into formal and non-formal educational practice.

Many teachers use MOOCs to bolster their academic courses. Therefore, the focus of this study is on the opinions of the professors regarding MOOCs. The Alharthi Study [40] looked at faculty and student views regarding MOOCs as well as the conditions that Saudi universities have to meet in order to use them. This leads us to the conclusion that academics are open to MOOCs and understand their importance. This study closes the knowledge gap left by earlier local investigations on the topic. No previous studies have examined how students perceive social contact, social interaction, social power, support networks, social identity, perceived service quality, and their own self-perception of actual MOOCs use, which in turn affects learning engagement and retention persistence. As a result, a new model must be created to examine how social cognition with having to learn input factors (TAM) affects perceived usefulness and service quality perceptions, as well as the indirect effects of academic self-efficacy on the use of MOOCs themselves, which, in turn, enhances students' learning and persistence.

2. Research Hypotheses and Theoretical Model

This research used social cognitive theory with the TAM model and two moderating factors: Perceived satisfaction and perceived service quality. Humans use their perception, motor, and cognitive processes as tools to carry out tasks and accomplish the goals that give their lives direction and significance [41]. The social cognitive theory supports the concept of growing interactive agency [42,43]. Humans are neither autonomous performers nor mechanical carriers of energizing environmental stimuli. Mental events are caused by brain activity, not by immaterial objects that exist outside of neural systems. Nevertheless, materialism does not necessarily entail reductionism. In non-dualistic mysticism, thought processes emerge as brain activity that is not ontologically traceable [44].

Human adaptation and change are both influenced by social support and perceived social efficacy. Social assistance does not just materialize, waiting to shield overworked people from stress. Instead, people need to look for and maintain meaningful relationships for themselves. Those with high perceived social efficacy create situations that are more favorable to themselves as compared to those who are self-conscious about their social abilities [45]. According to [46,47], they explored intelligent learning systems and MOOCs' uses for educational purposes. Moreover, Refs. [48,49] investigated trends in behavioral intention across general e-learning platforms and MOOCs and discovered that learners' behavioral intentions across both platforms are influenced by their feelings about society and their perceived value. Academic self-efficacy influences learning engagement and perseverance in MOOC usage in higher education, according to Alamri [50], and computer self-efficacy influences MOOC use intention, according to Fianu et al. [51]. Users will learn from their experiences and form opinions on the effectiveness and quality of MOOCs. According to Liao et al. [52], actual use confirmation will have an impact on post-consumption expectations, including perceived utility and service quality.

2.1. Social Engagement (SE)

Social engagement is defined as taking part in official (like joining a club or association) and informal (like hanging out with a group of friends) shared social activities [53,54]. Participating in community activities and feeling a sense of belonging to a society are crucial factors to take into account because a young adult's sense of community may affect their general behaviors, self-efficacy, and socialization [55,56]. By engaging in social activities, young adults can build social networks and obtain social support [53]. The foundation for a more in-depth assessment of the benefits of social networks for engagement can be laid by looking at how social media is used in daily life [57]. Because of digital media, particularly social media, people can now participate in social activities in remote locations [54]. Scholars have studied the integration of offline and online social interaction spaces in digital media [58]. People's communication patterns have been found to change as a result of the interactive and practical qualities of a communication environment in which many others from various backgrounds are connected [59]. Because social media platforms are based on interpersonal relationships, it stands to reason that people could be keener on finding out about social events that their friends share and may be encouraged to interact through social networking sites, which in turn may push them to engage in social activities. On the basis of the discussion above, the following hypotheses were put forward:

H1. *SE is positively correlated with PU.*

H2. *SE is positively correlated with PSQ.*

2.2. Social Interaction (SI)

The contact between pupils and educators is known as "social interaction", which occurs when instructors use strategies to encourage interpersonal assistance as well as inclusion [60]. Lonn et al. [61] classified social interactions into three categories: Learner–learner, student–student, and learner–instructor. Learner-to-learner exchanges take place in a virtual setting, whether or not teachers are present [62]. When students have access to knowledge via a number of channels, such as the internet and social media courses, their perceptions of their academic accomplishments and involvement will rise [63]. The expression "learner–instructor interaction" describes the sharing of knowledge, the giving of useful assistance, the clearing up of student misconceptions, and the escalating of pupil elation [64].

These three different types of social interaction are crucial in determining student satisfaction. When different types of interaction are used in the educational setting, learning becomes more enjoyable [65]. Even if student–student connection is essential for online students' satisfaction, the frequency, quality, and promptness of student–instructor engagement are the most significant factors in determining student satisfaction [66]. In a study of 120 online nursing degree students, Thurmond et al. [67] discovered that receiving timely feedback from their instructor, choosing the evaluation method, and having a positive relationship with the instructor all increased student satisfaction. These results are consistent with those from [68].

The researcher found that those respondents who were most excited to say they knew their professors acknowledged taking part in online discussions more actively and frequently. These findings highlight how important it is to encourage student–teacher interaction in order to promote active learning. In a quantitative analysis of 186 online graduates, Espasa and Meneses [69] also discovered a statistically significant association between teacher comments on finished projects and learning goals, as assessed by student satisfaction and overall grades. These findings highlight the role of enjoyment in online learning as well as the value of student engagement in enhancing student performance. On the basis of the discussion above, the following hypotheses were put forward:

H3. *SI is positively correlated with PU.*

H4. *SI is positively correlated with PSQ.*

2.3. Social Influence (SIN)

The process by which a person's views, attitudes, or behavior are influenced by the presence or activity of other people is known as "social influence". The four facets of social influence are obedience, compliance, conformity, and minority influence. The Fishbein and Ajzen-developed reasoned action theory (TRA) includes examining how social standards of identification and conformity may influence behavior. They demonstrated how, when conjoined with an individual's personal beliefs, these social influences—which they referred to as "subjective norms" could be utilized to predict behavior. Normative beliefs are the pressures that professors, students, or other important figures in the educational environment put on students to comply with the rules. The subjective norm concept states that other people have an influence on how students use and take ownership of the virtual learning system [70,71]. Based on past research on how peers and teachers might support effective interactive reality, the study in [72] found that subjective norms had an impact on how frequently students utilized ICT in the classroom. It has been proven that subjective norms set by superiors (like parents or employers) have an impact on a person's decision to enroll in an online school [73]. According to a study from [74], the participation of the instructor or social power among students has an effect on course attendance, student engagement, academic success, and attitudes towards virtual learning platforms. Peers have a significant impact on how people adopt technology and how they use it for e-learning, according to a number of studies. Peer pressure's effects on academic achievement and attitudes towards online learning were examined in the study by [75]. According to Shin [76], there is no proof that peer pressure affects performance. However, according to recent research, students who have a strong sense of community with their classmates are happier and much more likely to stick with online courses. On the basis of the discussion above, the following hypotheses were put forward:

H5. *SIN is positively correlated with PU.*

H6. *SIN is positively correlated with PSQ.*

2.4. Social Support (SSP)

Social support is a three-part concept with several different parts. It is defined as a behavior in which individuals interact with one another while experiencing, perceiving, and communicating emotional concern, helpful support, or information [77]. In the study of [78], it was described as "interaction with others that gives children insight and exceptional learning experiences". According to Demaray et al. [79], "social support" refers to "information, assessment, and psychological support, which come from a variety of sources, including instructors, parents, colleagues, and coworkers, that enhance student satisfaction". Social support is one of the most critical and significant parts of intermediate education. It is an important component that's regularly used in socioeducative materials and has educational potential [80].

Close acquaintances and coworkers aid children in establishing themselves at their schools, in line with Bean's findings [81]. Social support strengthens intragroup and intergroup ties, per the study of [82]. Student satisfaction is positively connected with social support from peers or family members [83]. According to [84], pupils who are involved in their social lives show higher levels of satisfaction. Their quality of life improves when they are a part of the college social scene. Participating in a wide range of social activities with other students helps them establish a good mindset and encourages academic performance, claims a study by [85].

When there is a lack of social support, it may be more difficult to speak up for oneself, maintain autonomy, and develop and sustain relationships, all of which have a substantial impact on a person's life and learning. Interactions between students and between students and instructors can be used to give online learners social support [86]. As students learn and grow, institutions must play a critical role in assisting them in practicing social inclusion and developing their interpersonal skills. On the basis of the discussion above, the following hypotheses were put forward:

H7. *SSP is positively correlated with PU.*

H8. *SSP is positively correlated with PSQ.*

2.5. Social Identity (SID)

Identity theory and self-categorization theory are both components of social identity [87,88]. A person's social identity can be defined as their self-concept regarding their participation in a social group [88]. Self-identified members of various socioeconomic classes or groups can be found [89,90]. Individuals organize and locate themselves in their social environments by using categories [91,92]. According to the research of [93], which experimentally investigated the relationship between students' group identities and their achievement in online courses, social identities were influenced by how well they engaged in online learning environments. In order to increase the efficiency and pleasure of online learning, their research also emphasizes the necessity of fostering students' social identities. Social identification, which increases in-group uniformity [94] and fortifies social ties within a group, improves a student's commitment to learning, educational success, and satisfaction with the curriculum and structure. Success in achieving academic goals increases the likelihood that students will be satisfied with the academic program and institution [95]. Since education is an identity experience that affects a person's potential, schooling, and societal identity are strongly intertwined [96]. When students initially enroll in college, they have an academic self-concept or a belief in their own academic abilities. As a result, high-achieving pupils had positive academic self-concepts that are linked to extraordinary goal achievement. On the basis of the discussion above, the following hypotheses were put forward:

H9. *SID is positively correlated with PU.*

H10. *SID is positively correlated with PSQ.*

2.6. Perceived Usefulness (PU)

Perceived utility in this study refers to how much people believe a MOOC has helped them learn, develop personally, or perform better at work. According to earlier studies [8,97], perceived and actual user happiness seem to be positively correlated. Users will be pleased if MOOC learning can enhance their performance in their job or otherwise meet their needs. Numerous empirical studies on MOOCs have shown that perceived usefulness not only influences behavior, such as the intention to use or continue using MOOCs, but also indirectly influences user happiness [8,98,99]. When using MOOCs significantly improves users' performance, they feel good about themselves and are more likely to continue using them. On the basis of the discussion above, the following hypotheses were put forward:

H11. *PU is positively correlated with LE.*

H12. *PU is positively correlated with ASE.*

2.7. Perceived Service Quality (PSQ)

According to this study, "perceived quality of service" refers to how well-rounded and high-caliber the MOOC platforms' offers are considered by their consumers. As part of many evaluation methods, tangibles, dependability, reactivity, empathy, ease of use, accuracy, safety, contents, and timeliness are all key factors to consider [100]. System quality, quality of information, and service quality can be used to group these dimensions [101]. Therefore, in this study, PSQ is measured using these three forms of quality. Quality and satisfaction are inextricably linked [102], a finding that was confirmed by Roca et al.'s study [103]. According to Mohammadi [104], service quality and e-learning satisfaction are positively correlated. The overall level of quality seems to have a substantial impact on the intention to continue [105]. On the basis of the discussion above, the following hypotheses were put forward:

H13. *PSQ is positively correlated with PU.*

H14. *PSQ is positively correlated with ASE.*

H15. *PSQ is positively correlated with LP.*

2.8. Academic Self-Efficacy (ASE)

ASE is defined as the self-reported confidence that students have in their MOOC achievement. It is a crucial predictor of self-control and performance in online learning [106], as well as a mediator that connects students' motivation and behavior [107]. A number of settings, including e-learning, have demonstrated how ASE impacts LE and success. Numerous studies [108] have revealed that ASE significantly affects students' engagement [109] and learning outcomes [LP]. Learners' ASE is anticipated to have a key influence on their involvement and perseverance in MOOCs, given the extended course lengths and the high level of autonomy required [110]. The premise put forth for this concept is that LE and LP during the COVID-19 pandemic have a favorable influence on students' ASE when they use MOOC systems. On the basis of the discussion above, the following hypotheses were put forward:

H16. *ASE is positively correlated with LE.*

H17. *ASE is positively correlated with LP.*

2.9. Learning Engagement (LE)

The most popular metric for measuring educational objectives in MOOCs is LE, which stands for continuous effort that a learner puts forth in the learning plan to reach learning goals [111]. Additionally, LE typically consists of multidimensional variables like motivation, knowledge, and attitude rather than a single dimension like actions [112]. Although several models for MOOC engagement have been created and tested, the majority concentrate on the behavioral rather than the complex components of LE. However, an improvement in the social, intellectual, and behavioral aspects of LE is required in order to build a strategy for promoting LE in MOOCs as a whole [113,114]. The premise put forth for this concept is that LP during the COVID-19 epidemic positively influenced students' LE in the use of MOOC systems. On the basis of the discussion above, the following hypothesis was put forward:

H18. *LE is positively correlated with LP.*

2.10. Learning Persistence (LP)

LP is divided into two categories: The desire to complete the present path and the desire to enroll in a different course at a later time [115]. Since LP is a holistic assessment of a learner's motives, attitudes, intelligence, and behaviors, it has drawn a lot of interest. Addressing issues and temptations that arise during the learning process is critical for learning retention [116]. According to MOOC outcomes, LP refers to a learner's capacity to finish learning activities they begin, such as completing courses they began or getting degrees [117]. Studies of MOOC graduation rates in the past few years have mostly concentrated on how tenacious students are in MOOC learning environments. According to Reich et al. [118,119], during the COVID-19 pandemic, students used MOOCs for learning. As a result, this study combined the social learning theory and academic self-efficacy concept to examine how learning engagement and perseverance affected higher education students' intentions to use MOOCs.

3. Research Methodology

In this research, we distributed the questionnaire online through a Google Form on 20 September 2022 (Semester II), and the objectives of the study were explained to the respondents. Moreover, the respondents were asked to respond to a questionnaire that was primarily for all factors focused on in the research model described in Figure 1. The research model factors are as follows: Social engagement, social interaction, social influence, social support, social identity, and perceived usefulness, perceived service quality, academic self-efficacy, learning engagement, and learning persistence. The questionnaire was written in Arabic because that is the language of instruction for undergraduate and graduate students at the majority of Saudi colleges and universities, including King Saud University. The TAM model and Bandura's theory of social cognition were both included in the questionnaire (see Supplementary Materials). The questionnaire was adapted from previous research on learning-related research, and each item was assessed on a Likert scale of 1 to 5, with the note that (1) represents "strongly disagree", (2) "disagree", (3) "neutral", (4) agree," and (5) "strongly agree" [43,120].

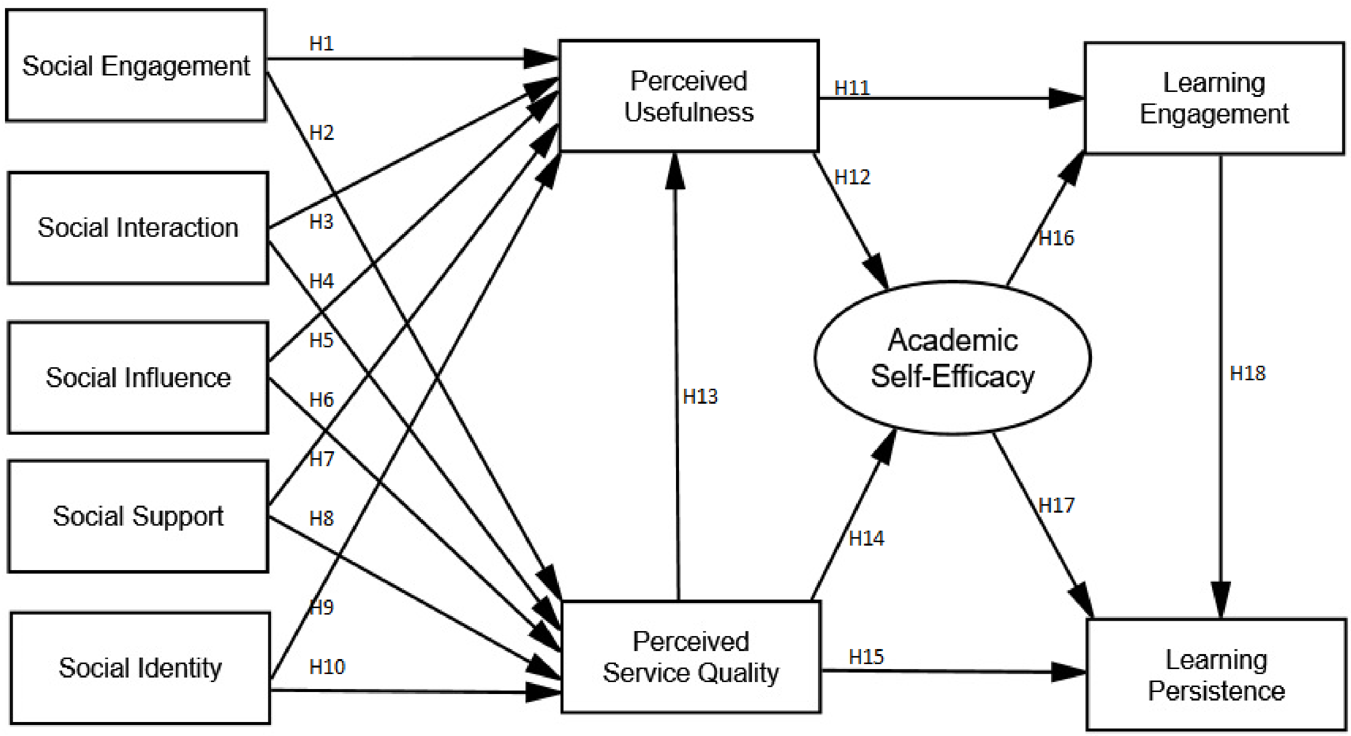

Figure 1. Research model.

Nearly 300 questionnaires were distributed, and 284 of those were answered by respondents, representing a 92% return rate. Following a manual evaluation of these questionnaires, 8 of them were incomplete and had to be disregarded. Therefore, the remaining 276 questionnaires were entered into SPSS for analysis. Therefore, this research used a quantitative approach and distributed the questionnaire online through a Google Form. This approach was also supported by [121], who stated that outliers should be ignored because they have a tendency to provide false statistical results. This study employed structural equation modeling (SEM) using partial least squares to test the given hypotheses (PLS).

PLS enables the analysis of relationships between theoretical constructs and evaluates the model's validity and reliability [121]. In this sense, handling the formative measurements and moderating effects can be done with ease and dependability using Smart-PLS software [122]. In order to analyze the linkages in the structural model, particularly for the confirmatory factor, Smart-PLS 3.3.3 was utilized (CFA). SPSS 26 was used to produce the initial descriptive and inferential statistics and correlations.

The following items, with factor loading, make up the study questionnaire: Academic self-efficacy (5 items) was adjusted from [77], learning engagement (5 items) was adjusted from [87,88], perceived usefulness (4 items) was adapted from [120], perceived service quality (6 items) was adjusted from [100], social engagement (4 items) was adjusted from [106,107], learning persistence (5 items) was adapted from [53,54], social identity and social interaction (4 items) was adjusted from [60], and social influence and social support (5 items) was adjusted from [70]. A categorical assessment of whether the MOOC had been completed was combined with a self-reported measure of student retention (4 and 5 items) in order to grant a certification denoting success (this was subsequently also used as the end point of the learner retention scale measuring the proportion of the MOOC completed). Age, gender, level of study, specialization, length of use of MOOCs, were the demographic variables that were gathered (See questionnaire in Supplementary Materials).

4. Result and Data Analysis

4.1. Demographic Data

The total data composition is shown in Table 1. Out of 276 topic samples, 94 (34.1%) of the respondents were men and 182 (64.9%) were women. Within this demographic, 37 (13.4%) respondents were between the ages of 18 and 21, 166 (60.1%) were between the ages of 22 and 25, 17 (6.2%) were between the ages of 25 and 29, 28 (10.1%) were between the ages of 30 and 33, and 28 (10.1%) were over the age of 33. Regarding respondents' levels of study, 111 (40.2%) were postgraduate students, and 165 (59.8%) were undergraduate students. 92 respondents from the scientific colleges responded (33.3%), 117 from humanities colleges responded (42.4%), and 67 from medical colleges responded (24.3%), as shown in Table 1. Finally, 299 (83%) of the participants had taken MOOCs for more than four years.

Table 1. Demographic Characteristics of MOOCs users.

Demographic	Description	N	%	Cumulative Percent
Gender	Male	94	34.1	34.1
	Female	182	65.9	100.0
Age	18–21	37	13.4	13.4
	22–25	166	60.1	73.6
	26–29	17	6.2	79.7
	30–33	28	10.1	89.9
	>34	28	10.1	100.0
Level of study	Undergraduate	165	59.8	59.8
	Postgraduate	111	40.2	100.0
Specialization	Scientific Colleges	92	33.3	33.3
	Humanities Colleges	117	42.4	75.7
	Medical Colleges	67	24.3	100.0
Length of use of MOOCS	1 year	9	3.3	3.3
	1–2 years	5	1.8	5.1
	2–3 years	33	12.0	17.0
	more than 4 years	229	83.0	100.0

4.2. Measurement Model

Partial least squares (PLS) analysis of source data was used to validate the conceptual framework. The capacity to evaluate the structural equation model and the measurement model simultaneously was provided by PLS [121]. In comparison to covariance-based structural equation modeling (CB-SEM), PLS-SEM was chosen for data analysis because it is effective with both small and large sample sizes and does not impose any limitations on the normal distribution [121]. PLSSEM is recognized as suitable and accurate for analyzing complex models and validating their explanatory power [121]. The analysis by PLS was permitted for the aforementioned reasons. SmartPLS 3.3.3 [121] is the software version used for analysis. The reliability and validity of the constructs were calculated using the measurement model. Variance and standard deviation, composite reliability (CR), and Cronbach's alpha extracted were used to assess each construct's internal coherence and item dependability (AVE).

See Table 2. According to reliability measurements, the significance level for AVE, Cronbach's alpha, and composite reliability (CR) should all be higher than 0.7 [123]. Because Cronbach's alpha value was greater than 0.7 [124], all of the constructs had excellent levels of validity and internal reliability, as seen in Table 2. All of the constructions are considered to be reliable and internally consistent if their CR values are greater than 0.7. Convergent validity was assessed by the factor loading of each component. The composite reliability of all notions was validated because AVE values were found to be higher than the cutoff value of 0.5 [121]. Two well-known methods of evaluating discriminant validity (DV), which measures how distinct one notion is from another, and the HTMT (heterotrait–monotrait ratio) [123,125], see Table 3.

Table 2. Reflective indicator loadings, internal consistency reliability, and convergent validity.

Factors	Items	Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Academic Self-Efficacy	ASE1 ASE2 ASE3 ASE4 ASE5	0.757 0.924 0.893 0.858 0.711	0.887	0.918	0.693
Learning Engagement	LEN1 LEN2 LEN3 LEN4 LEN5	0.869 0.860 0.896 0.792 0.758	0.891	0.921	0.700
Learning Persistence	LPE1 LPE2 LPE3 LPE4 LPE5	0.748 0.744 0.789 0.745 0.773	0.817	0.872	0.578
Perceived Service Quality	PSQ1 PSQ2 PSQ3 PSQ4 PSQ5 PSQ6	0.777 0.863 0.737 0.784 0.862 0.814	0.892	0.918	0.652
Perceived Usefulness	PU1 PU2 PU3 PU4	0.843 0.813 0.806 0.831	0.842	0.894	0.678
Social Engagement	SEN1 SEN2 SEN3 SEN4	0.880 0.928 0.929 0.874	0.924	0.946	0.816
Social Influence	SINF1 SINF2 SINF3 SINF4 SINF5	0.804 0.843 0.866 0.855 0.871	0.883	0.915	0.683
Social Interaction	SINT1 SINT2 SINT3 SINT4	0.910 0.897 0.904 0.871	0.918	0.942	0.802
Social Identity	SLD1 SLD2 SLD3 SLD4	0.861 0.891 0.718 0.788	0.832	0.889	0.668
Social Support	SSU1 SSU2 SSU3 SSU4 SSU5	0.845 0.809 0.748 0.780 0.703	0.837	0.885	0.606

Table 3. Fornell–Larcker criterion.

Factors	ASE	LEN	LPE	PSQ	PU	SEN	SLD	SINF	SINT	SSU
Academic Self-Efficacy	0.832									
Learning Engagement	0.766	0.836								
Learning Persistence	0.653	0.780	0.760							
Perceived Service Quality	0.731	0.786	0.750	0.807						
Perceived Usefulness	0.664	0.745	0.729	0.810	0.823					
Social Engagement	0.566	0.624	0.706	0.713	0.646	0.903				
Social Identity	0.653	0.679	0.714	0.847	0.793	0.666	0.817			
Social Influence	0.639	0.685	0.737	0.795	0.671	0.770	0.811	0.826		
Social Interaction	0.645	0.704	0.669	0.854	0.783	0.610	0.782	0.725	0.896	
Social Support	0.725	0.719	0.702	0.820	0.777	0.646	0.853	0.762	0.750	0.779

According to the concept of convergent validity, a topic related to measuring the construct, studies using the same or similar constructs should be closely related [121]. The computation of the AVE value resulting from this inquiry (AVE) provides composite reliability. The AVE was calculated using Smart PLS 3.3.3 [121]. According to the algorithm, AVE values must be at least 0.500 and account for at least 50% of a fluctuation (Table 2). As a consequence of the computation, all constructs had an early AVE that was greater than 0.500 or accounted for more than 50% of the variance. The AVE for academic self-efficacy, for instance, was 0.693.

Discriminant validity was reached [123] when the square root of each construct's AVE was greater than any linkages with other constructs. The DV conditions were met, as shown in Table 3. The HTMT gauges how comparable the predictor variables are. DV is regarded as established if the HTMT is smaller than one [6]. The HTMT readings are all clearly inside the cut-off threshold, as shown in Table 4. As a result, the outcomes of these tests confirm their validity.

Table 4. Heterotrait–monotrait ratio for discriminant validity (HTMT < 0.900).

Factors/Code	ASE	LEN	LPE	PSQ	PU	SEN	SLD	SINF	SINT	SSU
Academic Self-Efficacy										
Learning Engagement	0.845									
Learning Persistence	0.748	0.809								
Perceived Service Quality	0.785	0.880	0.878							
Perceived Usefulness	0.739	0.862	0.874	0.829						
Social Engagement	0.600	0.688	0.813	0.785	0.731					
Social Identity	0.730	0.789	0.866	0.883	0.644	0.761				
Social Influence	0.691	0.771	0.869	0.894	0.769	0.850	0.844			
Social Interaction	0.686	0.780	0.768	0.736	0.890	0.662	0.891	0.800		
Social Support	0.821	0.831	0.747	0.848	0.820	0.734	0.721	0.875	0.848	

According to Hair et al. [121], the absence of concept validity is indicated by an HTMT value larger than 0.900, although validity will also be evident when the HTMT is below 0.900. Because all of the HTMTs in Table 4 were assessed and found to be significantly distinct from one another and below 0.900, the HTMT evaluation backed up the discriminant validity. The association between social power and academic self-efficacy has the lowest HTMT value, while the connection between social effect and reported quality of service has the highest HTMT value (0.894). A more thorough justification of the HTMT values is shown in Table 4.

For determining the value of R2 in PLS path analysis, squared correlations of 0.75, 0.50, and 0.25 are regarded as large, moderate, and weak, respectively [121]. R2 statistics demonstrate how the independent variable affects the dependent variable (s). The latent dependent construct's R2 value, which is 0.69, as seen in Figure 2 and Table 5, is larger than 0.50 and near 0.75, making it a moderate to high value.

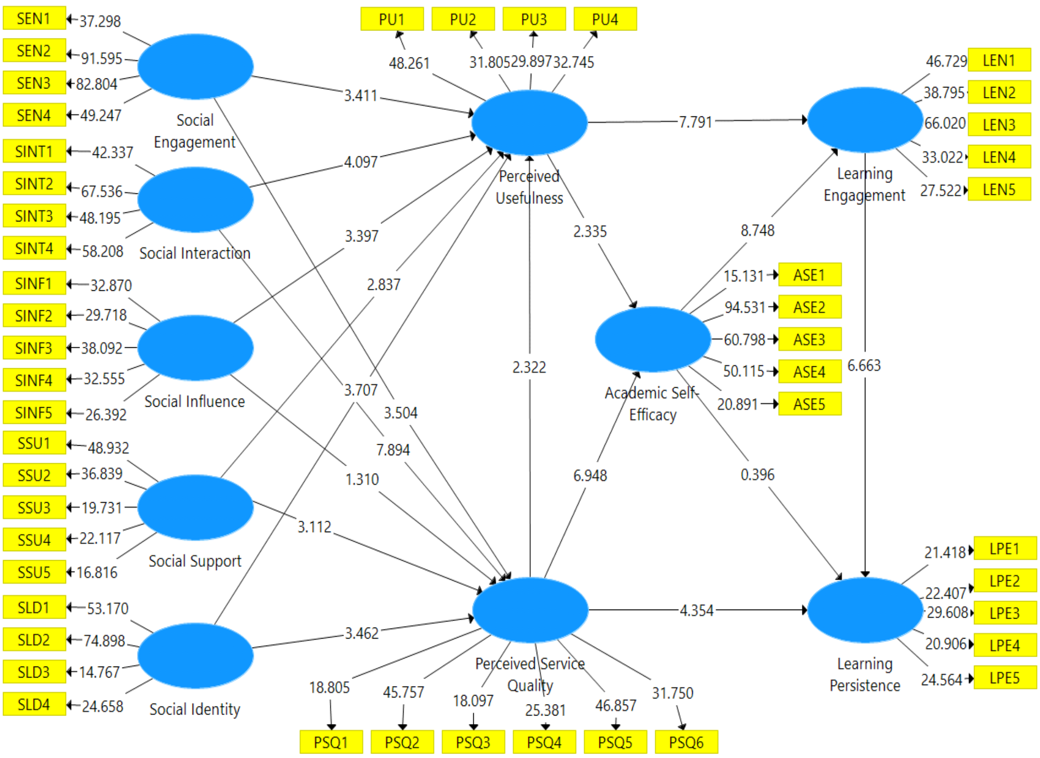

Figure 2. Path (T-Values).

Table 5. The value of R2.

Factors	R Square	R Square Adjusted	Results
Academic Self-Efficacy	0.550	0.546	substantial
Learning Engagement	0.687	0.685	substantial
Learning Persistence	0.658	0.654	substantial
Perceived Service Quality	0.842	0.839	substantial
Perceived Usefulness	0.740	0.734	substantial

The measure of each independent variable's impact on the dependent variable is called the effect size (f2). When regression analysis is taken from the PLS path model, it assesses whether the predictor variables have a significant impact on the dependent variable's value by measuring the variance in square correlation values [121], as shown in Table 6.

Table 6. Effect size f2.

Factors	ASE	LEN	LPE	PSQ	PU
Academic Self-Efficacy		0.423	0.382		
Learning Engagement			0.266		
Learning Persistence					
Perceived Service Quality	0.245		0.320		0.230
Perceived Usefulness	0.232	0.320			
Social Engagement				0.225	0.342
Social Identity				0.265	0.199
Social Influence				0.218	0.234
Social Interaction				0.360	0.270
Social Support				0.315	0.287

4.3. Structural Model (Collinearity)

The evaluation of the structural equation model included consideration of the model's capacity for prediction. However, before providing the structural model, the collinearity value must be acknowledged by supplying the values for the variance of the inflation factor (VIF). Interestingly, collinearity between the predictor sets was explored [121], perceived utility and service quality were found to be predicted by social presence. Perceived service quality predicts learner engagement and perceived utility (Table 7). VIF values should be below 3, those above 3 are frequently seen as having multicollinearity problems. The results of the data analysis show that all VIFs are under 3. As an example, the VIF score for socializing as a determinant of perceived quality of service and usefulness was 1.320 (1.657). Learning engagement and persistence were predicted by academic self-efficacy, which had VIF values of 1.787 and 1.707, respectively (Table 7 and Figure 2). Thus, counteraction is not a problem for the study's model.

Table 7. Variance inflation factor.

Factors	ASE	LEN	LPE	PSQ	PU	SEN	SLD	SINF	SINT	SSU
Academic Self-Efficacy		1.787	1.707							
Learning Engagement			2.292							
Learning Persistence										
Perceived Service Quality	2.920		1.923		2.317					
Perceived Usefulness	1.908	1.787								
Social Engagement				1.320	1.657					
Social Identity				2.204	1.517					
Social Influence				2.242	2.276					
Social Interaction				1.881	1.914					
Social Support				2.079	2.273					

4.4. Structural Model—Testing of Hypotheses

By evaluating the determination coefficient, t-statistics, and *p*-values, the structural model's validity for all real impacts and assumptions was determined. The results of the bootstrapping computation are displayed in Table 8 and Figure 3. The study's results, encompassing all collaborations are summarized in Table 6 and Figure 2. Additionally, social engagements (p = 0.168, t = 3.411), interpersonal contact (p = 0.274, t = 4.097), social power (p = −0.220, t = 3.397), peer aid (p = 0.212, t = 2.837), social identity (p = 0.273, t = 3.707), and perceived quality of service (p = 0.225, t = 2.322).

Table 8. Testing of hypotheses.

Relationship	β	T Values	*p* Values
Social Engagement —> Perceived Usefulness (H1)	0.168	3.411	0.001
Social Engagement —> Perceived Service Quality (H2)	0.147	3.504	0.001
Social Interaction —> Perceived Usefulness (H3)	0.274	4.097	0.000
Social Interaction —> Perceived Service Quality (H4)	0.404	7.894	0.000
Social Influence —> Perceived Usefulness (H5)	0.220	3.397	0.001
Social Influence —> Perceived Service Quality (H6)	0.074	1.310	0.191
Social Support —> Perceived Usefulness (H7)	0.212	2.837	0.005
Social Support —> Perceived Service Quality (H8)	0.175	3.112	0.002
Social Identity —> Perceived Usefulness (H9)	0.273	3.707	0.000
Social Identity —> Perceived Service Quality (H10)	0.223	3.462	0.001
Perceived Service Quality —> Perceived Usefulness (H11)	0.225	2.322	0.021
Perceived Service Quality —> Academic Self-Efficacy (H12)	0.563	6.948	0.000
Perceived Service Quality —> Learning Persistence (H13)	0.350	4.354	0.000
Perceived Usefulness —> Learning Engagement (H14)	0.423	7.791	0.000
Perceived Usefulness —> Academic Self-Efficacy (H15)	0.207	2.335	0.020
Academic Self-Efficacy —> Learning Engagement (H16)	0.485	8.748	0.000
Academic Self-Efficacy —> Learning Persistence (H17)	0.025	0.396	0.692
Learning Engagement —> Learning Persistence (H18)	0.485	6.663	0.000

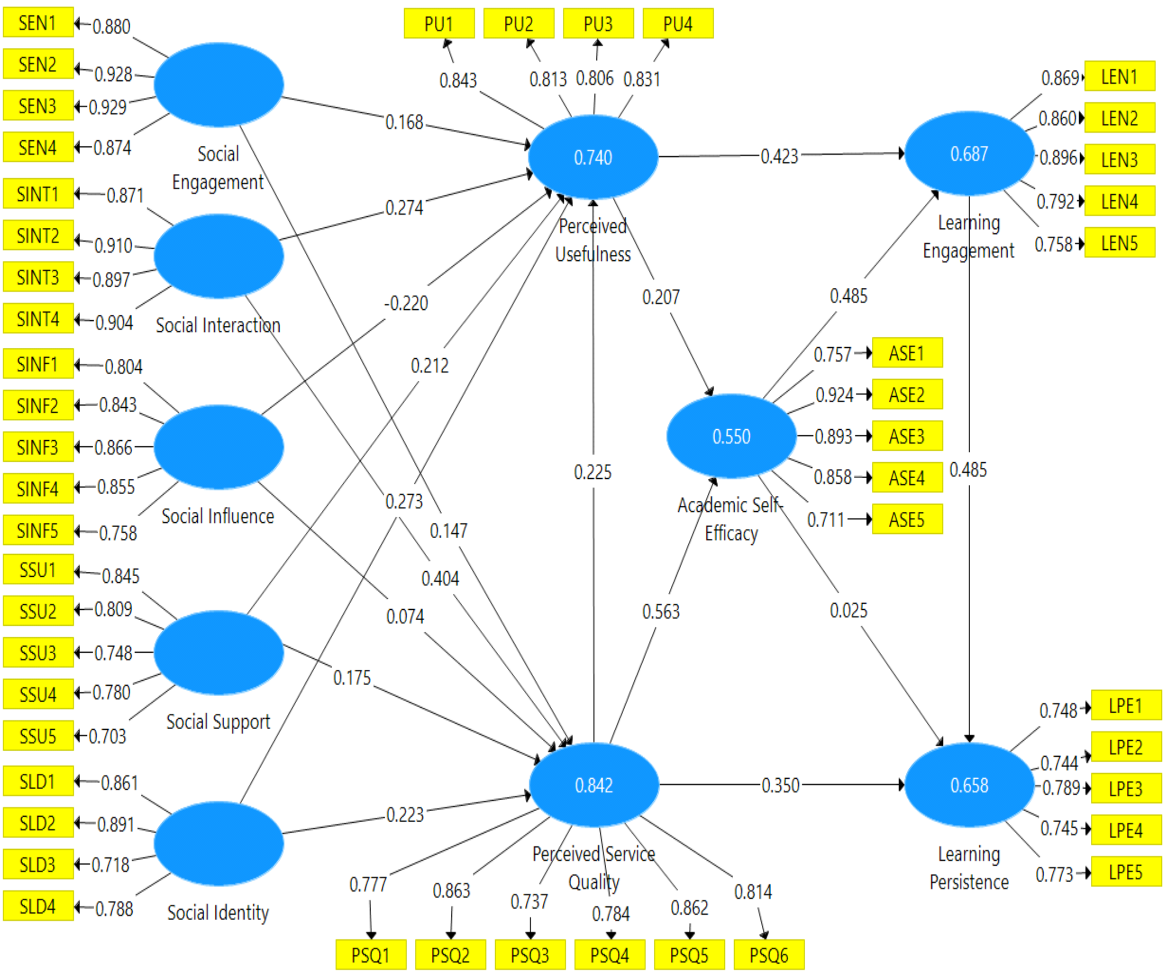

Figure 3. Path coefficient findings.

Additionally, social engagement (H2: = 0.147, t = 3.504), human engagement (p = 0.404, t = 7.894), peer benefits (p = 0.175, t = 3.112), and social identity (p = 0.223, t = 3.462) all had a favorable impact on perceived quality of service, confirming H2, H4, and H10. H6 is not supported by social influence (p = 0.074, t = 1.310) because it has no beneficial effect on perceived service quality. Similarly, perceived service quality plays a substantial role in positively influencing academic self-efficacy (p = 0.563; t = 6.948) and learning persistence (p = 0.350; t = 4.354). As a result, the H12 and H13 hypotheses were confirmed. In terms of the relationships, perceived usefulness has no impact on academic self-efficacy (p = 0.207; t = 2.335) or learning engagement (p = 0.423; t = 7.791).

The theories were, therefore, accepted. Additionally, the findings support H16 and H17 by demonstrating a substantial, favorable relationship between academic self-efficacy (H17) and learning engagement (p = 0.485, t = 8.748). H17 is not supported since academic self-efficacy (p = 0.025, t = 0.396) has no beneficial effect on learning persistence. The findings support H18 because they show that learning involvement (p = 0.485, t = 6.663) significantly affects learning persistence. See Table 8.

5. Discussion and Implications

This study sought to determine the effects of actual MOOCs use on student engagement and perseverance. It did this by combining social cognition theories with the TAM model and two moderating factors: Perceived satisfaction and perceived service quality. This research aims to create a new model as well as expand the social cognitive theory and TAM model in order to look into students' actual use of MOOCs in Saudi Arabian higher education. It also validated the positive relationships between social cognitive theory and academic self-efficacy, learning engagement, and learning persistence. In accordance with Bandura [42,43], the social cognitive theory postulates that a student's social cognitive theory, such as self-efficacy, influences positive feelings as a personal component and also has an impact on academic accomplishment and learning immersion through a cerebral path (metacognitive strategies). The correlations between academic self-efficacy, learning engagement, and learning persistence were highly supported by our findings.

As described in Section 2, research hypotheses and theoretical model, Bandura's theoretical framework for this study is thought to have a substantial impact on how useful people perceive the TAM model to be [42,43]. Therefore, this study's results first showed how social engagement, social interaction, social influence, social support, and social identity affect perceived usefulness, perceived service quality, and academic self-efficacy. This is in line with some research that found a link between perceived usefulness and social cognitive factors [54,60,70,77,87,120].

Second, the study's results showed how social support, social identity, social contact, and social engagement can affect how well a service is regarded. As previously indicated, cognition theory is founded on Bandura and is thought to be significant in the perception of service quality [42,43]. Additionally, service quality is composed of three main characteristics in the models of Rust and Oliver [126] and Dabholkar et al. [127]: Interaction quality, engagement quality, and outcome quality. As a result, this is in line with our study model, and certain studies [53,66,72,75,87,100,101] found a link between social cognitive characteristics and perceived service quality.

Third, the study's findings also showed how perceived service quality can affect how beneficial something is regarded as being, in addition to academic self-efficacy and learning persistence. As indicated above, according to Rust and Oliver [126] and Dabholkar et al. [127], perceived usefulness, academic self-efficacy, and learning persistence are all important components of service quality. This is in line with research that found a link between perceived service quality and perceived usefulness, academic self-efficacy, and learning perseverance [101,106,107,115].

Fourth, the study's findings showed how academic self-efficacy and learner engagement are impacted by perceived usefulness. The fact that, in accordance with Bandura [42] and Davis' TAM model [120], perceived usefulness is seen to be a significant influence in academic self-efficacy or learning engagement is consistent with previous studies [108,112,120] that discovered a connection between perceived usefulness and learner engagement. Fifth, the results of the study demonstrated how academic self-efficacy influences learning persistence and engagement.

According to Artino et al. [128], academic self-efficacy plays a crucial role in learning participation and educational perseverance, as was previously mentioned. This is consistent with some research that discovered a connection between active learning, persistence, and academic self-efficacy [114,117]. The study's findings also demonstrated how learning engagement impacts learning persistence. This is consistent with Alamri model [51], which asserts that learning engagement is a crucial element of learning persistence and is in line with earlier research that found a connection between student engagement and perseverance [57,73,108].

5.1. Structural Model—Testing of Hypotheses

Some study findings (see Figure 3 and Table 8) have to do with social contact, social influence, support networks, social identification, perceived utility, perceived service quality, and academic self-efficacy in relation to using MOOCs to enhance learning engagement and perseverance. This study demonstrates how proficient Saudi Arabian students are in utilizing MOOCs in higher education. A validated method that integrates social cognition theory and the TAM model has also been developed as a result of this research to analyze the academic self-efficacy of MOOCs users in real-world contexts in order to improve student engagement and persistence in Saudi Arabia's higher education system. The theoretical implications of this research are the following:

- With relation to the independent components, it was discovered that the engagement, interpersonal interaction, social power, support systems, and social identity hypotheses had a direct impact on perceptions of benefits and service quality.
- According to the mediators' assumptions, perceived value and perceived quality of service influenced students' academic self-efficacy, study motivation, and persistence.
- Regarding the mediators' hypothesis, it was discovered that current learning perseverance was directly impacted by academic self-efficacy.
- Regarding the dependent factor hypothesis, it was shown that implementing MOOCs in Saudi Arabia's higher education has a direct impact on students' ability to persist in their studies.

5.2. Practical Implications

The results of this study give us a clearer understanding of the key elements influencing the use of MOOCs in higher education. Due to these factors, MOOC creators, educational managers, and lecturers can benefit from a number of practical contributions, which are as follows:

- First, this study's findings indicate that learning engagement and academic self-efficacy were directly and significantly impacted by perceptions of the utility of MOOCs in real-world use. This suggests that actual MOOC use is more effective than perceived, as evidenced by heightened levels of academic self-efficacy. As a result, education managers should promote and highlight these advantages for academic performance, and professors should urge students to enroll in MOOCs that offer useful courses that boost students' academic performance.
- Second, the research findings indicate that three variables—perceived usefulness, academic self-efficacy, and learning persistence—were directly and significantly impacted by the perceived service quality of MOOCs that were actually used. This suggests that actual MOOC usage, as experienced by users, exhibits higher levels of utility, academic self-efficacy, and learning persistence. As a result, this conclusion directs MOOC designers and developers to prioritize service quality and students' needs, lowering the amount of work required from students to utilize them, guaranteeing that MOOCs provide quality services, and offering a user-friendly system.
- Thirdly, the results of this study showed that the academic self-efficacy of real MOOC users affected both learning and current learning perseverance in a direct and significant manner. This suggests that students who believe they can successfully use MOOCs exhibit greater levels of participation and perseverance in their use of MOOCs. As a result, in terms of MOOC utilization, education managers should focus on qualities that promote good academic self-efficacy. Universities could also plan tutorials and other events to help students become more proficient MOOC users.
- Lastly, this study's findings demonstrated that learning involvement through real MOOC use had a significant and immediate effect on knowledge persistence. This suggests that learners who participate in positive learning behaviors while using MOOCs have higher levels of learning perseverance. Therefore, by providing learners with necessities like computer laboratories, free internet access, and technical help, colleges could effectively encourage student use of MOOCs. This promotes learning engagement and persistence.

5.3. Limitations and Future Work

To generalize these findings, a number of issues need to be resolved, and further research has to be done.

- First, the model accounts for 84% of the variables influencing the real use of MOOCs, leaving 16% unaccounted for because some other components were not included in the research model. Future model expansion should include new constructs, including system quality, quality of information, learning and teaching performance, ego education, intent to use, and student happiness.

- In order to evaluate the impacts of the variables on the model, including age, gender, experience, and level of education, future studies should choose diverse samples from other institutions. Participants in this study were chosen at random from a single university.
- A bigger sample size should be used in future research to analyze the models drawn from Saudi Arabia as well as other nations, even if the sample size was adequate for studying the model and performing the model's structural equation analysis.

6. Conclusions and Future Work

This study presents the characteristics that influence students' use of MOOCs and offers 18 hypotheses based on models that incorporate TAM variables to further the social cognitive theory. Two of these 18 hypotheses have been ruled out. Perceived value and service quality explain 55% of academic self-efficacy in real-world MOOCs. The proposed model accounts for 69% of the factors that influence academic self-efficacy of real-world MOOC users by student engagement and 69% of the factors that influence academic self-efficacy of real-world MOOC users by having to learn persistence. As a result, this paper develops a research framework based on the determinant factors and TAM variables of the social cognitive theory that influence academic self-efficacy of using MOOCs to actually impact learning engagement and persistence in Saudi Arabia's higher education. The factors used to build the study model include social engagement, human engagement, social influence, support networks, social identity, perceived utility, service quality, academic self-efficacy, learner engagement, and learning persistence. A thorough study of the literature was done to identify the 10 elements that influence how well MOOCs can affect learning, learner engagement, and learner persistence. The suggested framework would, therefore, contribute to the existing literature on the real-world application of MOOCs for long-term educational sustainability.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15086918/s1.

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