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Research Paper

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ABSTRACT

This study aimed to apply the meta-analysis methodology to systematically synthesize results of primary studies to discover the main significant factors influencing student acceptance of massive open online courses (MOOCs) for open distance learning (ODL). An abundance of studies on MOOCs exists, but there is a lack of meta-analysis research on student acceptance of MOOCs, which is a novel contribution of the current study. The meta-analysis methodology was applied to investigate effect sizes, statistical heterogeneity, and publication bias across 36 primary studies involving 14233 participating students. The study findings show satisfaction to be the main significant factor influencing student acceptance of MOOCs. The findings can enlighten stakeholders in the decision-making process of implementing MOOCs for ODL and advance technology acceptance models. Moreover, this study has the potential to theoretically contribute to technology acceptance research by situating the widely known technology acceptance models in the context of education.

Keywords

Distance learning, influencing factor, meta-analysis study, MOOC acceptance, online courses, technology acceptance.

INTRODUCTION

The discovery of factors influencing student acceptance of teaching and learning technologies is generally important for educational institutions and educational software companies to surmount the intrinsic challenges of open distance learning (ODL). Surmounting ODL challenges is promising for achieving the global sustainable development goal of accessibility to inclusive, equitable, and quality education. ODL is a flexible technology platform for fostering activities associated with teaching and learning that focus on increased access to quality education without the hindrances of time and space (Dea Lerra, 2014). It has grown globally to contribute to the transformation of the higher education system by delivering quality education at the doorsteps of students, encouraging them to share innovative ideas, knowledge, and skills through collaboration (Bordoloi, 2018). It is a holistic strategy that is rapidly becoming an important integrator of the mainstream educational system worldwide. It removes the need for students and a teacher to be confined to the same physical classroom for learning to seamlessly occur (Musingafi et al., 2015). Its impact on the heterogeneity of educational conveyance systems for fostering distance learning has received huge support globally (Ghosh et al., 2012). It improves the quality of education, creates a unified educational environment, reduces training cost, and travel time to seamlessly access education (Beketova et al., 2020). However, despite the increasing growth of ODL and its benefits, it is fraught with challenges (Simpson, 2013; Sánchez-Elvira & Simpson, 2018), unconfirmed judgments, and clichés that some authors have disproved (Beketova et al., 2020).

The challenges of ODL can be appositely classified as institutional, individual, and instructional. The institutional challenges are related to the unavailability of suitable resources and lack of physical interactions (Arasaratnam-Smith & Northcote, 2017; Kara et al., 2019; Li & Wong, 2019; Sadeghi, 2019). In addition, they are related to the attitude of students and instructors toward distance learning interventions (Malangu, 2018). The individual challenges originate from the characteristics of students and socio-economic exigencies. They include financial constraints (Musingafi et al., 2015; Budiman, 2018; Kara et al., 2019), lack of technological skill (Ferreira et al., 2011), lack of time to study (Ferreira et al., 2011; Dea Lerra, 2014; Kebritchi et al., 2017; Kara et al., 2019), and inability to create a balance between education and social life (Budiman, 2018; Kara et al., 2019). Moreover, there is a lack of interest in a course (Kara et al., 2019), low concentration (Kara et al., 2019), low self-confidence (Sánchez-Elvira & Simpson, 2018; Kara et al., 2019), work overload (Dea Lerra, 2014; Kara et al., 2019), unconducive study conditions (Kara et al., 2019), lack of family support (Kara et al., 2019), lack of motivation (Kebritchi et al., 2017; Au et al., 2018; Budiman, 2018; Sánchez-Elvira & Simpson, 2018), and lack of satisfaction (Au et al., 2018; Sánchez-Elvira & Simpson, 2018). The instructional challenges are related to instructors and content development (Au et al., 2018). The issues related to instructors include passive resistance (Mahlangu, 2018), inability to facilitate interaction with students, and time management (Kebritchi et al., 2017). In most cases, instructors lack the basic skills to fully participate in distance education (Ferreira et al., 2011); they are unable to reflect on their works, adjust to enhance the learning experiences of students, and provide timely feedback (Ferreira et al., 2011; Brown et al., 2015; Kebritchi et al., 2017; Makhaya & Ogange, 2019; Sadeghi, 2019). The issues related to content development include the quality of the course content (Au et al., 2018) and course assessment (Makhaya & Ogange, 2019).

Literature has suggested that innovation through the application of technology is an appropriate intervention for curtailing the intrinsic challenges of ODL (Albelbisi, 2019). Technology offers intrinsic benefits of affordability of quality education, accessibility to learning resources, and supports the development of digitally resilient youths in marginalized communities (Ochieng et al., 2017). Different technology initiatives were recently employed by ODL institutions to mitigate the challenges of distance education (Musingafi et al., 2015; Mtebe & Raphael, 2017; Budiman, 2018). They include applications of virtual reality, augmented reality, smart classrooms, artificial intelligence, learning analytics, language immersion technology, Labster virtual laboratories, synchronous teaching platforms, and asynchronous video tutoring systems. The open educational resources (OERs) such as the massive open online courses (MOOCs) are interactive web courses for making the education system more vivacious and sustainable (McAndrew & Scanlon, 2013; Bordoloi, 2018). MOOCs are a modern evolution of distance education that promises to support unrestricted participation in flexible learning in a free or low-cost modality (Liu et al., 2021). It promises to improve the quality of education, boost the effectiveness of classroom activities, facilitate collaborative learning, foster collaborative creation of knowledge, ensure social cohesion, and promote sustainable development goals of quality education (Nisha & Senthil, 2015). It is attracting a great deal of curiosity in contemporary education and providing a long string of learning opportunities (Emanuel, 2013; Parkinson, 2014; Kononowicz et al., 2015; Liyanagunawardena et al., 2015; Preston et al., 2020).

MOOCs can expand a learning gamut for students. For instance, MOOCs are effective for remedial courses in terms of student achievement within a formal education context (Agasisti et al., 2021). Moreover, the functionality of video-clickstream data was used to analyze and visualize the watching behavior of students in a MOOC environment (Mubarak et al., 2021). However, the universal acceptance of MOOCs by students has remained low (Altalhi, 2021).- Furthermore, there is a lack of studies on meta-analysis to understand the significant factors that can help to improve the universal acceptance of MOOCs for ODL. A narrative type of literature review of papers published in the Web of Science database from 2014 to 2020 on the challenges of students and instructors for student engagement in MOOCs was performed by Alemayehu & Chen (2021). In addition, a systematic type of literature review of a nationwide initiative based on MOOCs in the Malaysian higher education system was performed by Albelbisi & Yusop (2020). This current study is unique in its focus and methodological approach because it uses meta-analysis (Crocetti, 2016) to unveil the significant factors influencing student acceptance of MOOCs. It is desirable to uncover the significant factors influencing student acceptance of MOOCs using a gold standard methodology of meta-analysis to understand what is required for universal acceptance of the technology for ODL. The necessity for meta-analysis is to enable a reliable synthesis of the available literature findings to discover novel insights. Moreover, meta-analysis will generally increase precision and provide confidence about the previous research findings. The distinctive contributions of this paper to theory and practice are the following:

1. The discovery of the significant factors influencing student acceptance of MOOCs to assist practitioners and stakeholders in the decision process of implementing MOOCs for open distance learning.
2. The determination of the sources of variation among studies on significant factors influencing student acceptance of MOOCs to support an improved decision-making process.
3. The investigation of publication bias in determining the validity of core findings of studies on significant factors influencing student acceptance of MOOCs.

The remainder of this paper is succinctly summarized as follows. The next section describes the study methodology. The section is followed by the presentation of the study findings. The discussion of findings is presented thereafter, followed by a concluding remark.

METHODOLOGY

The methodology of this study is rigidly based on the guideline of preferred reporting items for systematic reviews and meta-analyses (PRISMA) (Crocetti, 2016; Moher et al., 2009; Moher et al., 2015). Meta-analysis is an assemblage of statistical procedures for agglutinating and comparing results from multiple independent studies in a systematic way. The PRISMA protocol presents the essential steps of defining the research questions, specifying inclusion and exclusion criteria, searching the literature, selecting primary studies, coding primary studies, computing effect size of each primary study and pooled effect size of all primary studies, detecting statistical heterogeneity, conducting moderator analysis, examining publication bias, and publishing a meta-analysis (Crocetti, 2016). These steps have been compactly applied in this section of the paper.

Defining the Research Questions

Factors influencing student acceptance of MOOCs can be discovered based on technology acceptance models. In the past decades, several theoretical models have been developed in the discipline of information systems for explaining or predicting factors of technology acceptance by users. These factors have been explored in diverse application domains, for instance, to understand changes in belief and attitude toward the use of information systems (Bhattacherjee & Premkumar, 2004), explore factors influencing student readiness for online learning (Yu & Richardson, 2015), examine factors predicting e-learning integration by preservice teachers (Olugbara & Letseka, 2020) and investigate factors that moderate the relationship between intention and integration of e-learning (Olugbara et al., 2020). The current study aimed to apply the meta-analysis methodology to systematically synthesize results of primary studies to discover the main significant factors influencing student acceptance of MOOCs for ODL. The following research questions were posed to achieve this aim:

1. What are the main significant factors influencing student acceptance of MOOCs based on technology acceptance models?
2. What are the sources of variations, if any, among studies on the main significant factors influencing student acceptance of MOOCs based on technology acceptance models?
3. Are there significant biases in studies on the main significant factors influencing student acceptance of MOOCs based on technology acceptance models?

Specifying Inclusion and Exclusion Criteria

The specification of inclusion and exclusion criteria often defines the primary studies that will be eligible for selection in a systematic review with meta-analysis. In this study, we have established the following set of inclusion and exclusion criteria to address the defined research questions.

1. Duplicate records that signify the same primary studies retrieved by multiple search strategies were excluded to avoid biases and strengthen the validity of the meta-analysis.

2. Primary studies must be published in English language peer-reviewed journals from 2010 to 2020 after the invention of MOOCs in 2008. Grey literature, conference papers, and journal articles outside the study regime were excluded to strengthen the replicability of the meta-analysis. Moreover, it is a common practice to exclude such articles for studies with statistically significant results and to enhance the methodological rigor of a study (Crocetti, 2016).

3. Duplicate results published by the same authors in different articles were excluded to avoid biases and strengthen the validity of the meta-analysis.

4. Primary studies must focus on the overall broader connotation of technology acceptance models to expound significant factors influencing student acceptance of MOOCs. Published articles that did not apply a technology acceptance model to explain factors influencing student acceptance of MOOCs were excluded to conform to the study aim.

5. Primary studies that did not report on a complete set of data were excluded to strengthen the study findings. The articles with incomplete data are those that did not report on all the following

parameters: Factor reliability, factor validity, path coefficient, and coefficient of determination. Factor reliability was based on composite reliability or Cronbach alpha while factor validity was based on average variance expected or convergent validity (Joseph & Olugbara, 2018; Olugbara et al., 2020; Olugbara & Letseka, 2020). The authors have attempted to solicit for the missing data from certain previous authors through email correspondences without success. There was one primary author who responded to us that the software tool they used for data analysis did not report on the requested missing data.

6. Primary studies must apply the structural equation modeling technique (Hoyle, 1995) to analyze structural relationships amongst model factors. Published articles that did not apply the structural equation modeling technique for data analysis were excluded from the meta-analysis to ensure methodological rigor, reliability, and validity of research findings.
7. Primary studies must be conducted with student populations of varying education levels, including primary, secondary, or university education to inject population diversity into the research. Published articles with study populations other than students were excluded to fully take advantage of diversity in the meta-analysis.

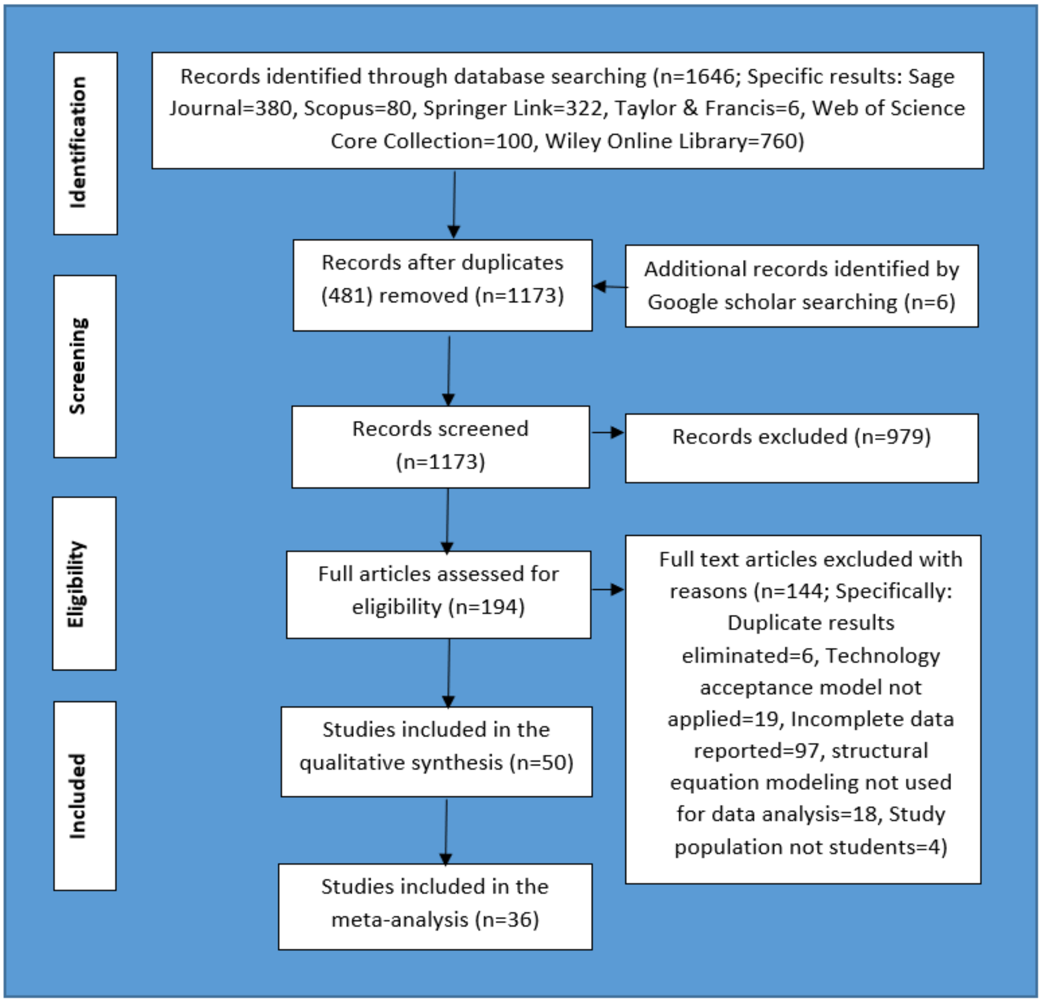
Searching the Literature

The relevant primary studies for this meta-analysis were retrieved through a series of search efforts to comprehensively identify the articles that meet our inclusion and exclusion criteria. First, a literature search was conducted with the widely used scholastic databases of Sage Journal, Scopus, Springer Link, Taylor & Francis, Web of Science Core Collection, and Wiley Online Library to expand the throng of related articles. Simple keywords of the form “MOOC acceptance” and “Factors of MOOC acceptance” were used as search parameters to focus the searching within each database. Second, a Google Scholar search was conducted to retrieve the specific articles discovered from the reference lists of other articles that were not necessarily included in the meta-analysis. This search strategy has increased the pool of the included studies by delivering further related articles.

The study duration spans about three years starting with the fourth author in January 2018. This was before the launching of ODL at the Durban University of Technology in partnership with higher education partners South Africa (HEPSA). The first author is an expert in e-learning technology acceptance, and the third author is a statistician. The second author is the ODL chair of the United Nations educational, scientific, and cultural organization (UNESCO) at the University of South Africa. The harvesting of research articles started in May 2019 and was completed in October 2020 when data became saturated. The detailed information regarding the search results is reported in this paper following the PRISMA protocol shown in Figure 1.

Figure 1

A PRISMA Protocol for Factors Influencing Student Acceptance of MOOCs



Note. Adapted from Crocetti, 2016; PRISMA = preferred reporting items for systematic reviews and meta-analyses; MOOCs = massive open online courses; n = number of articles.

Selecting Primary Studies

The inclusion and exclusion criteria were applied to a large chunk of the identified primary studies to select those eligible for meta-analysis. The study selection process was implemented independently by two authors in an unblinded standardized way. The purpose was to exclude duplicate records and primary studies that completely failed the test of eligibility criteria. The remaining references after removing duplicate records were taken through the screening exercise, during which titles, abstracts, and contents of articles were screened. During title screening, we searched for articles that contained important concepts such as “MOOC”, “massive open online course”, and at least one of the words, “acceptance”,” adoption”,” intention”,” readiness”,” continuance”,” use”, and” usage”. During the abstract screening, abstracts of articles that passed the title screening test were perused looking for important information such as sample size, country of study, factors of acceptance, and structural equation modeling. During the content screening, retained articles that partially passed the abstract screening test were assessed in full text looking for the missing information not contained in the abstracts. If an article matched the eligibility criteria, it was included in the qualitative synthesis, otherwise it was excluded with the appropriate reasons given. The articles included in the qualitative synthesis were further included in the meta-analysis provided they fully passed the eligibility test. In total, 50 primary studies out of 194 studies investigated for eligibility criteria were included in the qualitative synthesis, and 36 of them that fully satisfied the eligibility requirements were included in the meta-analysis. The number of articles that were finally included in the meta-analysis translates to 18.56% of those investigated for eligibility. The study selection process conformed rigidly to the PRISMA protocol shown in Figure 1.

The selection process was focused on research articles that applied technology acceptance models to explore significant factors influencing student acceptance of MOOCs. The models reported as theories include uses and gratification theory (UGT) (Katz et al., 1973), self-efficacy theory (SET) (Bandura, 1977), social cognitive theory (SCT) (Bandura, 1986), theory of planned behavior (TPB) (Ajzen, 1991), social support theory (SST) (Wills, 1991), task-technology fit (TTF) theory (Goodhue & Thompson, 1995), self-regulation theory (SRT) (Zimmerman, 1995), innovation diffusion theory (IDT) (Dillon & Morris, 1996), self-determination theory (SDT) (Deci et al., 1999; Ryan & Deci, 2000), unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and distance learning theory (DLT) (Anderson & Dron, 2011). In addition, the models include stimulus organism response model (SORM) (Mehrabian & Russell, 1974), Triandis model (TMO) (Triandis & Values, 1979), technology acceptance model (TAM) (Davis et al., 1989), expectation-confirmation model (ECM) (Bhattacherjee, 2001), information systems success (ISS) model (DeLone & McLean, 2003), student online learning readiness (SOLR) model (Yu & Richardson, 2015) and technology user environment (TUE) model (Ma & Lee, 2019).

Researchers have recently agglutinated or extended the existing models by integrating additional factors to realize novel models. Several researchers have extended the TAM by incorporating the factors of perceived quality, perceived enjoyment, and usability (Tao et al., 2019); perception of time (Teo & Dai, 2019); computer self-efficacy, perceived convenience, learning tradition, and self-regulated learning (Al-Adwan, 2020); knowledge access, knowledge storage, knowledge application, and knowledge sharing (Arpaci et al., 2020); social influence, course quality, collaboration, and perceived enjoyment (Razami & Ibrahim, 2020); perceived learner control, e-learning self-efficacy, and personal innovativeness in information technology (Zhang et al., 2017). The UTAUT as a progeny of TAM was extended by factors of perceived value (Mulik, et al., 2018); attitude and computer self-efficacy (Altalhi, 2020); instructional quality, computer self-efficacy and service quality (Fianu et al., 2020); motivation, course design, interest, course delivery, assessment, media, and interactivity (Haron, et al., 2020). The ECM was extended by factors of perceived reputation, perceived openness, and perceived enjoyment (Alraimi et al., 2015); knowledge outcome, performance proficiency, and social influence (Zhou, 2017). The amalgam of ECM and TAM was extended to incorporate factors of MOOC performance, and student habit (Dai et al., 2020) while the blend of TTF with SDT was extended by introducing the factor of social motivation (Khan et al., 2018).

Coding Primary Studies

Coding is a procedure used to extract relevant data from the included studies for the computation of effect sizes. In this study, we developed a codebook to extract relevant data from the included studies. The first author extracted the coded data, the second author guided the first author, the fourth author checked the extracted data, and the third author performed the statistical analysis using the Strata software data analytics tool. The only disagreement among authors who managed the coded data pertained to the articles that did not report on the coefficient of determination (R^2) of a structural model employed in an included study. The disagreement was resolved by a consensus that such articles be included in the meta-analysis because the contentious parameter did not constitute an eligibility criterion. The coded data are the name of an author (author), the year an article was published (year), the sample size of participating students (size), path coefficient (path), country of study (country), the theoretical model applied for factor identification (model), the most significant factor of student acceptance of MOOCs (factor), and type of technology acceptance behavior (type). The type of acceptance behavior could be an intention to use (intention), readiness to use (ready), continuous intention to use (continual), or the actual usage of MOOCs (usage). The influencing factors are the exogenous variables while the type of technology acceptance behavior is the endogenous variable in a structural model. Previous authors have reported numerous influencing factors based on technology acceptance models earlier explicated, but the most significant one with the highest path coefficient statistic was selected per the included article. The inherent limitation of a technology acceptance model to give a low R^2 provides the impetus to select an acceptance factor with the strongest path coefficient per article.

Computing Effect Sizes

The data extracted during the coding phase were used to compute the effect size of each included primary study and the pooled effect size of all primary studies. The fundamental assumption of our analysis is based on the random-effects model. The randomization assumption is plausible because data were extracted from published articles written by numerous authors who operated independently on different factors, theories, models, and students from diverse countries of the world. A random-effects model assumes different underlying effect sizes of the included studies (Kavvoura & Ioannidis, 2008). The forest plot (Moher et al., 2009) was used to compute effect sizes as a prelude for examining heterogeneity and biases in the outcomes of included studies. Forest plot is an orthodox device for visualizing how the estimates of effect sizes of primary studies are distributed around zero or pooled effect size. The effect size of a study is represented in a forest plot as a square box with the square location indicating the effect size (Crocetti, 2016). The area of the box represents the weight of a study contributing to the pooled effect size estimate while the center of a diamond equals the pooled effect size. The ends of the diamond indicate the limits of 95% confidence interval and the global estimate is the diamond whose width is the associated 95% confidence interval. The studies with significant results are those for which the confidence intervals do not include the vertical dotted line corresponding to the zero lines (Crocetti, 2016). The effect size, confidence interval, standard error, and weight were calculated for each primary study. The standard error of an effect size reflects the amount of statistical information available in a primary study and the percentage weight indicates the amount that each primary study has contributed.

Detecting Statistical Heterogeneity

The random-effects model was applied to estimate and detect the sources of statistical heterogeneity that may arise for different reasons (Borenstein et al., 2010; Melsen et al., 2014). The test for statistical heterogeneity, which is a measure of variations in true effect sizes was conducted to establish whether all the included studies are consistent. The Cochran’s Q statistic, between-study variance $\tau^{2,}$ and I^2 statistic are among the widely used metrics for estimating statistical heterogeneity (Kavvoura & Ioannidis, 2008). The Cochran's Q statistic reflects the weighted sum of squared deviations of the study-specific effect sizes and pooled effect size. However, this metric is weedy in detecting true statistical heterogeneity because it is affected by the number of the included studies. The τ^2 reflects how much the estimates of true effect sizes in the included studies differ. It depends on the respective effect size metric and is not comparable among meta-analyses using different effect size metrics. The I^2 statistic quantifies the degree of inconsistency as a percentage of variation attributed to statistical heterogeneity rather than chance (Higgins & Thompson, 2002). It is independent of the number of studies, and it provides the advantage of determining consistency over the other heterogeneity metrics.

Conducting Moderator Analysis

The main void of statistical heterogeneity metrics is that they only provide global measures of variations without supplementary information about the sources of variations. The inherent void demands that moderator analysis be performed to unveil the sources of heterogeneity. Moderator analysis is often used to test the factors that can explain the statistical heterogeneity of study findings and to clarify inconsistent results in the literature (Crocetti, 2016). Moderators are variables that have been assumed to affect the magnitude of effect sizes across the primary studies that contain those variables. Subgroup analysis and meta-regression are widely used for conducting moderator analysis in a systematic review with meta-analysis (Borenstein et al., 2010). Subgroup analysis is the splitting of participant data into subgroups to establish comparisons among a subset of data. The interpretation of subgroup meta-analysis can lead to informative insights into the proper implication that is not obtainable from the non-subgroup analysis. Meta-regression is conceptually synonymous with regression analysis (Crocetti, 2016). In this study, subgroup and meta-regression analyses were used to test whether there are subsets of the included studies that capture the pooled effect size (Borenstein et al., 2010; Melsen et al., 2014). Meta-regression was performed for each level of a moderator to regress the observed effect sizes on one or multiple study characteristics. The results of the analyses were tested for statistically significant differences. The year of publication, acceptance model applied, type of technology acceptance, country of study, and the sample size was examined as moderators in the meta-regression model.

Examining Publication Bias

Literature has recommended the examination of publication bias in meta-analysis research to draw a reasonable conclusion about the generalizability of the cumulative findings that can be affected by biases (Borenstein et al., 2010; Nakagawa et al., 2017). The purpose of the examination was to identify the degree to which publication bias influences a study outcome in determining the validity of core findings. The funnel plot is a standard visual method for identifying publication bias (Light & Pillemer, 1984). It is a scatterplot of standard errors of log odd ratio against the effect size computed by log odd ratio. The central idea is that studies should be symmetrically spread to the left and right of a vertical line marking the pooled effect size if no relevant findings are missing. The vertical and diagonal dashed lines represent the pooled effect size estimate and 95% confidence interval respectively with each point in the plot representing a separate study. The vertical axis represents the standard error, the horizontal axis represents the logit transformed of the effect size estimate and asymmetry of the plot signals the presence of publication bias (Nakagawa et al., 2017). The funnel plot and Egger statistical test were used in this study to examine publication bias that may occur for different reasons (Borenstein et al., 2010; Lin & Chu, 2018). The visual examination of publication bias was conducted using the funnel plot while the statistical examination was done with the aid of the Egger test to complement the funnel plot with a more objective assessment. The asymmetry of a funnel plot is an indicator of publication bias and $p < .05$ was used to declare the statistical significance of publication bias.

FINDINGS

The findings of this study will be presented in three specimens of factors influencing student acceptance of MOOCs, sources of variations in studies on student acceptance of MOOCs, and significant biases in studies on student acceptance of MOOCs in providing responses to the research questions of this study.

Factors Influencing Student Acceptance of MOOCs

Table 1 presents the list of the most significant factors influencing student acceptance of MOOCs by their codes (code), generic names (factor), and definitions (definition). According to the table, 18 unique factors were discovered from the included studies to be the strongest influential forces of student acceptance of MOOCs for ODL.

Table 1

Definitions of the Most Significant Factors Influencing Student Acceptance of MOOCs

Code	Factor	Definition
Bint	Behavioral intention	The subjective probability of an individual to perform a certain behavior (Yang & Su, 2017).
Csef	Computer self-efficacy	A subjective assessment of the skill level of a person to effectively use MOOCs to perform learning tasks (Fianu et al., 2020).
Cqua	Course quality	Knowledgeability, the authority of course content, and attitude of lecturers toward teaching with MOOCs (Yang et al., 2017).
Enjo	Perceived enjoyment	Positive affection for interactive functions is provided within a MOOC environment (Mohamad & Abdul Rahim, 2018).
Eotp	Engagement on platform	The affective involvement of an individual with the learning process that results from his/her interactions with other learners and professors in a MOOC environment (Shao & Chen, 2020).
Fcon	Facilitating conditions	The degree to which an individual believes that an institution's technical and non-technical infrastructure exists to support the use of MOOCs (Altalhi, 2020).
Flow	Flow experience	The state of deep absorption in an intrinsically enjoyable activity while engaging within a MOOC environment (Zhao et al., 2020).
Icap	Intellectual capital	The degree to which an individual perceived he/she can know about knowledge from resources shared by MOOC teachers through exchanging and combining the knowledge (Lu & Dzikria, 2020).
Imot	Intrinsic motivation	The performance of an activity is for the good of an individual without receiving any reward, but mainly for the satisfaction and enjoyment of MOOCs (Pozón-López et al., 2020).
Kout	Knowledge outcome	Perception of students on the subject matter that will be provided to make them feel satisfied with learning using MOOCs (Zhou, 2017).
Pexp	Performance expectancy	The perception of students that using MOOCs will improve their learning performance (Mulik et al., 2018).
Prep	Perceived reputation	MOOC platforms are associated with highly regarded, influential, and trustworthy institutions of higher education (Alraimi et al., 2015).
Puse	Perceived usefulness	The degree to which students consider that MOOCs can be an effective device for enhancing academic performance (Al-Adwan, 2020).
Satt	Student attitude	The degree to which a student perceives a positive or negative feeling related to the use of MOOCs (Wu & Chen, 2017).

Code	Factor	Definition
Scom	Social competence	Represent skills, capacities, and a sense of control that is necessary for managing social situations, developing, and sustaining relationships through MOOCs (Al-Adwan & Khdour, 2020).
Shab	Student habit	The habitual use of MOOCs to lessen cognitive effort in activating the preceding actions in performing a complicated behavior and continuing participation in a MOOC environment (Dai et al., 2020).
Ssat	Student satisfaction	Perception of students about enjoyment and accomplishment in learning in a MOOC environment (Yu & Richardson, 2015).
Tskn	Teacher subject knowledge	MOOC courses can be evaluated with higher quality that can lead to further revisit intention of students (Huang et al. 2017).

Note. MOOC = massive open online course; Bint = behavioral intention; Csef = computer self-efficacy; Cqua = course quality; Enjo = perceived enjoyment; Eotp = engagement on platform; Fcon = facilitating conditions; Flow = flow experience; Icap = intellectual capital; Imot = intrinsic motivation; Kout = knowledge outcome; Pexp = performance expectancy; Prep = perceived reputation; Puse = perceived usefulness; Satt = student attitude; Scom = social competence; Shab = student habit; Ssat = student satisfaction; Tskn = teacher subject knowledge.

Table 2 shows the data characterizing a total sample size of 14233 students who participated in the studies included in the meta-analysis. The set of the most significant factors influencing student acceptance of MOOCs was constituted from the factor with the highest path coefficient per included study as shown in Table 2. It can be observed from the table that all the included articles were published within six years from 2015 to 2020. Most of the included articles were published in 2020 (44.44%), followed by 2018 (19.44%), both 2019 and 2017 experienced the same article publication rate of 16.67%, one article was published in 2015 (2.78%), while no article was published in 2016 and before 2015 (0.00%). This result signals the recency, interest, relevance, and trend in technology acceptance research in the education domain. In addition, this result delineates the novelty of the current study in the discipline of information systems. Student attitude recorded the minimum validity score of 0.518 and it was rated by 111 students, which is the minimum number of students across studies. Student satisfaction recorded the maximum reliability score of 0.964 and maximum validity score of 0.901. Student habit was rated by 1344 students, which is the maximum number of students across studies. Behavioral intention recorded the lowest path coefficient of 0.222, and the highest path coefficient of 0.823, and facilitating conditions recorded the lowest reliability score of 0.642. Most of the previous researchers (33.33%) applied the extended models of TAM, UTAUT, or ECM, 30.56% of them applied a blend of two existing models, 30.56% of them applied a solo model and 5.56% of them applied an extended combination of two existing models to discover significant factors influencing student acceptance of MOOCs.

Table 2

Characteristics of the Included Primary Studies

SID	Author	Year	Size	Rel	Val	Path [a]	Country	Model	Factor	Type
S01	Abdulatif & Velazyuez-Iturbide	2020	212	0.900	0.700	0.435	Spain	(SDT, SRT) [b]	Imot	Continual
S02	Al-Adwan	2020	403	0.940	0.810	0.394	Jordan	(TAM) [b]	Puse	Intention

SID	Author	Year	Size	Rel	Val	Path [a]	Country	Model	Factor	Type
S03	Al-Adwan & Khdour	2020	468	0.950	0.820	0.340	Jordan	SOLR	Scom	Ready
S04	Al-Rahmi et al.	2019	1148	0.930	0.605	0.709	Malaysia	(IDT, TAM) [b]	Satt	Intention
S05	Alraimi et al.	2015	316	0.949	0.862	0.239	Korea	(ECM) [c]	Prep	Continual
S06	Altalhi	2020	169	0.642	0.877	0.334	Saudi Arabia	(UTAUT) [c]	Fcon	Usage
S07	Arpaci et al.	2020	540	0.875	0.701	0.823	Turkey	(TAM) [c]	Bint	Usage
S08	Chen et al.	2018	854	0.964	0.901	0.561	Taiwan	UGT	Ssat	Continual
S09	Dai et al.	2020	1344	0.865	0.563	0.571	Australia	(ECM, TAM) [c]	Shab	Continual
S10	Daneji et al.	2019	368	0.897	0.688	0.600	Malaysia	ECM	Ssat	Continual
S11	Fianu et al.	2020	204	0.903	0.757	0.378	Ghana	(UTAUT) [c]	Fcon	Usage
S12	Gupta	2020	798	0.914	0.780	0.582	India	(TUE, SDT) [b]	Imot	Intention
S13	Haron, et al.	2020	400	0.940	0.850	0.543	Malaysia	(UTAUT) [c]	Bint	Usage
S14	Hsu et al.	2018	357	0.898	0.746	0.498	Taiwan	(TAM, SST) [b]	Satt	Intention
S15	Huang et al.	2017	246	0.912	0.727	0.323	China	TTF	Tskn	Intention
S16	Jo	2018	237	0.949	0.608	0.311	Korea	(ECM, TTF) [b]	Puse	Continual
S17	Khan et al.	2018	414	0.918	0.780	0.222	Pakistan	(TTF, SDT) [c]	Bint	Usage
S18	Lu & Dzikria	2020	203	0.935	0.828	0.531	Taiwan	DLT	Icap	Intention
S19	Lu et al.	2019	300	0.941	0.842	0.662	China	ECM	Ssat	Continual
S20	Mohamad & AbdulRahim	2018	251	0.940	0.797	0.465	Malaysia	SET	Enjo	Continual
S21	Mulik et al.	2018	310	0.814	0.523	0.273	India	(UTAUT) [c]	Pexp	Intention
S22	Pozón-López et al.	2020	210	0.940	0.770	0.540	Spain	(TAM, SDT) [b]	Ssat	Intention
S23	Razami & Ibrahim	2020	111	0.842	0.518	0.576	Malaysia	(TAM) [c]	Satt	Intention
S24	Shao	2018	247	0.940	0.840	0.739	China	(SCT, TAM) [b]	Puse	Continual
S25	Shao & Chen	2020	294	0.901	0.752	0.662	China	SORM	Eotp	Continual
S26	Subramaniam et al.	2019	413	0.925	0.713	0.314	Malaysia	SOLR	Csef	Ready
S27	Tamjidyamcholo et al.	2020	234	0.863	0.677	0.309	Iran	TMO	Fcon	Usage
S28	Tao et al.	2019	668	0.870	0.640	0.290	China	(TAM) [c]	Puse	Usage
S29	Teo & Dai	2019	209	0.916	0.687	0.363	Australia	(TAM) [c]	Satt	Intention
S30	Wan et al.	2020	464	0.909	0.666	0.481	China	(UTAUT, TTF) [b]	Ssat	Continual
S31	Wu & Chen	2017	252	0.916	0.730	0.509	China	(TAM, TTF) [b]	Satt	Continual
S32	Yang & Su	2017	272	0.890	0.680	0.455	Taiwan	(TAM, TPB) [b]	Bint	Usage
S33	Yang et al.	2017	294	0.866	0.619	0.392	China	(ISS, TAM) [b]	Cqua	Continual

SID	Author	Year	Size	Rel	Val	Path [a]	Country	Model	Factor	Type
S34	Zhang et al.	2017	214	0.940	0.839	0.440	China	(TAM) [c]	Puse	Intention
S35	Zhao et al.	2020	374	0.930	0.820	0.610	China	SORM	Flow	Continual
S36	Zhou	2017	435	0.925	0.806	0.495	China	(ECM) [c]	Kout	Continual

Note. SID = study identity; Rel = factor reliability; Val = factor validity; DLT = distance learning theory; ECM = expectation-confirmation model; IDT = innovation diffusion theory; ISS = information systems success; SCT = social cognitive theory; SDT = self-determination theory; SET = self-efficacy theory; SOLR = student online learning readiness; SORM = stimulus organism response model; SRT = self-regulation theory; SST = social support theory; TAM = technology acceptance model; TMO = Triandis model; TPB = theory of planned behavior; TTF = task-technology fit; TUE = technology user environment; UGT = uses and gratification theory; UTAUT = unified theory of acceptance and use of technology; Bint = behavioral intention; Csef = computer self-efficacy; Cqua = course quality; Enjo = perceived enjoyment; Eotp = engagement on platform; Fcon = facilitating conditions; Flow = flow experience; Icap = intellectual capital; Imot = intrinsic motivation; Kout = knowledge outcome; Pexp = performance expectancy; Prep = perceived reputation; Puse = perceived usefulness; Satt = student attitude; Scom = social competence; Shab = student habit; Ssat = student satisfaction; Tskn = teacher subject knowledge.

[a] All path coefficients were significant at $p <= .05$. [b] A blend of models. [c] An extension of one or more models.

Most of the included studies (41.67%) investigated factors influencing the continuous intention of students to use MOOCs, 30.56% investigated their usage intention, 22.22% investigated the actual usage and 5.56% investigated their readiness to use MOOCs. Figure 2 shows the distribution of the included studies across 13 different countries worldwide. Most of the studies came from Asia with 30.56% of the articles from China, 16.67% from Malaysia, 11.11% from Taiwan, and 2.78% from Africa represented by Ghana.

Figure 2

Distribution of the Included Studies per Study Country

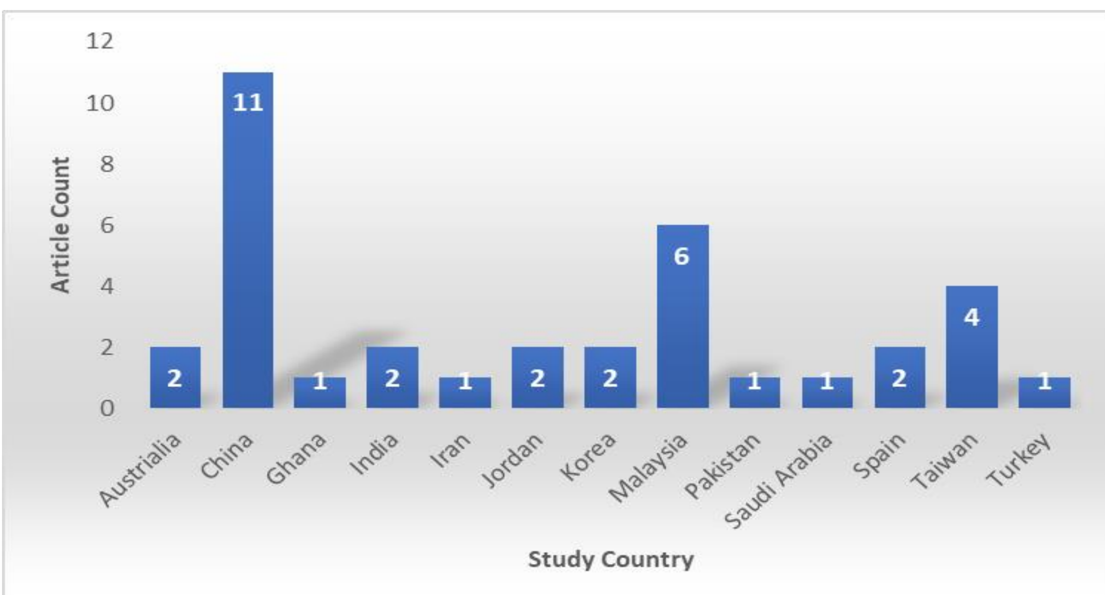
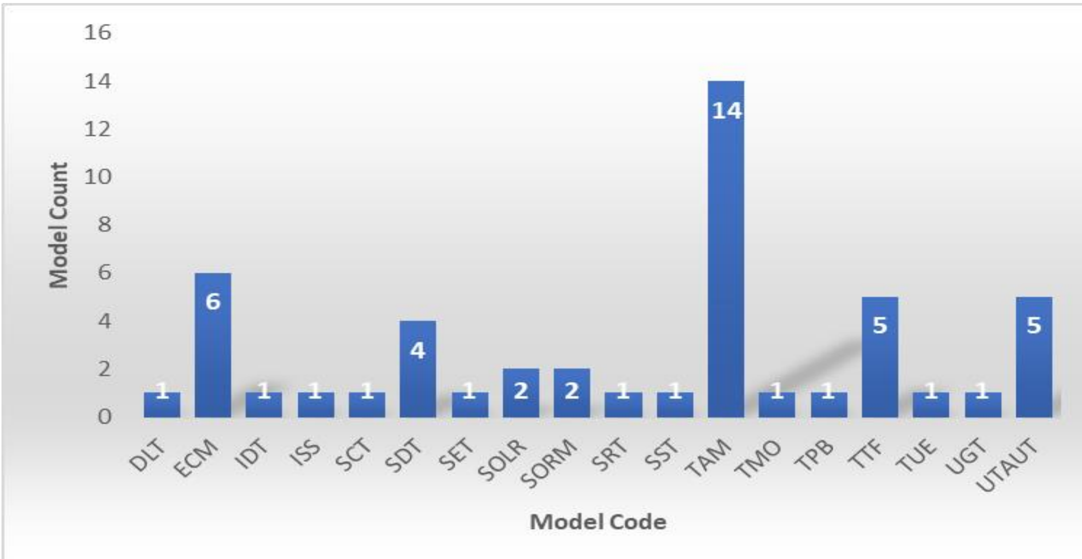


Figure 3 shows the distribution of 18 technology acceptance models that have been applied by the previous researchers for factor exploration. The famous TAM, ECM, UTAUT, and TTF models are most favored with application probabilities of 28.57%, 12.24%, 10.20%, and 10.20% respectively. It is not surprising that TAM recorded the highest probability of application because of its popularity in the field of information systems to predict decisions associated with technology adoption of users.

Figure 3

Distribution of Technology Acceptance Models Applied in the Included Primary Studies



Note. DLT = distance learning theory; ECM = expectation-confirmation model; IDT = innovation diffusion theory; ISS = information systems success; SCT = social cognitive theory; SDT = self-determination theory; SET = self-efficacy theory; SOLR = student online learning readiness; SORM = stimulus organism response model; SRT = self-regulation theory; SST = social support theory; TAM = technology acceptance model; TMO = Triandis model; TPB = theory of planned behavior; TTF = task-technology fit; TUE = technology user environment; UGT = uses and gratification theory; UTAUT = unified theory of acceptance and use of technology.

The distribution of data extracted from the 36 included studies has revealed 18 unique most significant factors influencing student acceptance of MOOCs. Most of the past authors found perceived usefulness (13.89%), student attitude (13.89%), and student satisfaction (13.89%) to be the strongest factors influencing student acceptance of MOOCs. These factors were followed by behavioral intention (11.11%), facilitating conditions (8.33%), intrinsic motivation (5.56%), and the remaining factors were found by fewer authors (2.78%) to be the strongest influencing factors as shown in Figure 4.

Figure 4

Distribution of the Most Significant Factors Influencing Student Acceptance of MOOCs

Note. MOOCs = massive open online courses; Bint = behavioral intention; Csef = computer self-efficacy; Cqua = Course quality; Enjo = perceived enjoyment; Eotp = engagement on platform; Fcon = facilitating conditions; Flow = flow experience; Icap = intellectual capital; Imot = intrinsic motivation; Kout = knowledge outcome; Pexp = performance expectancy; Prep = perceived reputation; Puse = perceived usefulness; Satt = student attitude; Scom = social competence; Shab = student habit; Ssat = student satisfaction; Tskn = teacher subject knowledge.

Table 3 shows the result of descriptive analysis of the included studies based on study identity (SID), name of the journal where an article was published (journal), database where an article was retrieved (database), name of the publisher (publisher), region of publication (region), and R-squared statistic in percentage unit (R^2). There are 13.88% of the included studies that did not report on R-squared statistics (Huang et al., 2017; Hsu et al., 2018; Jo, 2018; Al-Rahmi et al., 2019; Daneji et al., 2019). The article by Wu & Chen (2017) recorded the highest R-squared of 95.7% while the lowest R-squared of 28.0% was recorded by Tao et al. (2019) among those studies that specified R-squared statistics. The study by Tao et al. (2019) was conducted in China where they applied an extended TAM to discover perceived usefulness to be the most significant factor that predicted the usage of 668 MOOC students. The results of their study were published in the *Journal of Interactive Learning Environment* in 2019 by Taylor & Francis in the United Kingdom as indexed by Web of Science, Scopus, and Taylor & Francis. Similarly, the study by Wu & Chen (2017) was conducted in China where they used the amalgam of TAM and TTF to discover student attitude to be the most significant factor that predicted the continuous intention of 252 students to use MOOCs. The results of their study were published in the *Journal of Computers in Human Behavior* in 2017 by Pergamon-Elsevier Science in the United Kingdom and the United States as indexed by Web of Science and Scopus. Most of the articles were published in United Kingdom (50.00%), while the publication rates for other regions are United States (28.95%), Canada (5.26%), Australia (5.26%), Hong Kong (2.63%), India (2.63%), South Korea (2.63%), and Malaysia (2.63%). All the included articles (48.00%) were retrieved from the Scopus database, while the rates for other databases are Web of Science Core Collection (37.33%), Springer Link (6.67%), Taylor & Francis (6.67%), Sage Journal (1.33%) and none of the included articles were retrieved from Wiley Online Library database.

Table 3

Descriptive Analysis of the Included Studies

SID	Journal	Database	Publisher	Region	R^2
S01	Education and Information Technologies	Web of Science, Scopus, Springer Link	Springer New York LLC	United States	34.7
S02	Education and Information Technologies	Web of Science, Scopus, Springer Link	Springer New York LLC	United States	50.7
S03	Journal of Information Technology Education: Research	Web of Science, Scopus	Informing Science Institute	United States	65.4
S04	Interactive Learning Environments	Web of Science, Scopus, Taylor & Francis	Taylor & Francis Ltd.	United Kingdom	**
S05	Computers and Education	Scopus	Elsevier Ltd	United Kingdom	64.4
S06	Education and Information Technologies	Web of Science, Scopus, Springer Link	Springer New York LLC	United States	66.1
S07	Telematics and Informatics	Web of Science, Scopus	Elsevier Ltd	United Kingdom	68.0
S08	Library Hi-Tech	Scopus	Emerald Group Publishing Ltd.	United Kingdom	77.4
S09	Computers in Human Behavior	Web of Science, Scopus	Pergamon-Elsevier Science Ltd.	United States, United Kingdom	53.0
S10	Knowledge Management & E-Learning	Scopus	The University of Hong Kong	Hong Kong	**
S11	Education and Training	Web of Science, Scopus	Emerald Group Publishing Ltd	United Kingdom	75.8
S12	Interactive Technology and Smart Education	Scopus	Emerald Group Publishing Ltd	United Kingdom	72.6
S13	International Journal of Psychosocial Rehabilitation	Scopus	Hampstead Psychological Associates	United Kingdom	77.4
S14	Interactive Learning Environment	Web of Science, Scopus, Taylor & Francis	Taylor & Francis Ltd	United Kingdom	**
S15	International Journal of Information Management	Web of Science, Scopus	Elsevier Ltd	United Kingdom	**
S16	KSII Transactions on Internet and Information Systems	Web of Science, Scopus	Korea Society of Internet Information	South Korea	**

SID	Journal	Database	Publisher	Region	R^2
S17	Telematics and Informatics	Web of Science, Scopus	Elsevier Ltd	United Kingdom	64.3
S18	Knowledge Management Research & Practice	Web of Science, Scopus, Taylor & Francis	Taylor & Francis Ltd	United Kingdom	50.4
S19	Journal of Electronic Commerce Research	Web of Science, Scopus	California State University Press	United States	43.8
S20	International Journal of Supply Chain Management	Scopus	Excelling Tech Publishers	United Kingdom	71.0
S21	NMIMS Management Review	Web of Science, Scopus,	Narsee Monjee Institute of Management Studies	Mumbai	49.2
S22	Journal of Computing in Higher Education	Web of Science, Scopus, Springer Link	Springer Nature, New York LLC	United States	71.0
S23	Journal of Advanced Research in Dynamical & Control Systems	Scopus	Institute of Advanced Scientific Research	United States	55.0
S24	Internet Research	Web of Science, Scopus	Emerald Group Publishing Ltd	United Kingdom	63.2
S25	Internet Research	Web of Science, Scopus	Emerald Group Publishing Ltd	United Kingdom	49.1
S26	International Review of Research in Open and Distributed Learning	Web of Science, Scopus	Athabasca University Press	Canada	36.0
S27	Iranian Journal of Management Studies (IJMS)	Web of Science, Scopus	University of Tehran	Malaysia	17.4
S28	Interactive Learning Environment	Web of Science, Scopus, Taylor & Francis	Taylor & Francis Ltd	United Kingdom	28.0
S29	Interactive Learning Environments	Web of Science, Scopus, Taylor & Francis	Taylor & Francis Ltd	United Kingdom	45.0
S30	Sage Open	Web of Science, Scopus, Sage Journal	Sage Publications Inc.	United States	64.4
S31	Computers in Human Behavior	Web of Science, Scopus	Pergamon-Elsevier Science Ltd	United States, United Kingdom	95.7
S32	International Review of Research in Open and Distributed Learning	Web of Science, Scopus	Athabasca University Press	Canada	53.8
S33	Education Technology Research and Development	Web of Science, Scopus, Springer Link	Springer New York LLC	United States	47.2
S34	Australasian Journal of Educational Technology	Web of Science, Scopus	Australasian Society for Computers in Learning in Tertiary Education	Australia	62.2
S35	Computers and Education	Scopus	Elsevier Ltd	United Kingdom	37.0
S36	Australasian Journal of	Web of Science,	Australasian Society for	Australia	79.4

SID	Journal	Database	Publisher	Region	R^2
	Educational Technology	Scopus	Computers in Learning in Tertiary Education		

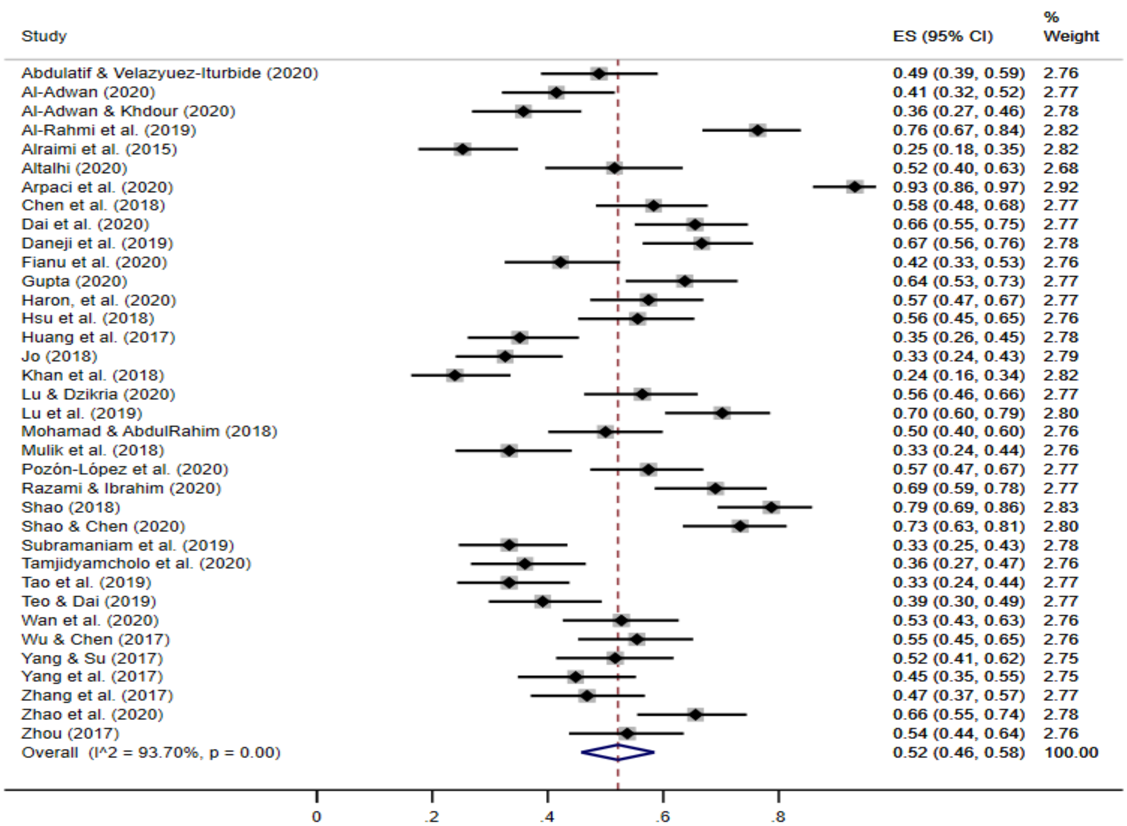
Note. SID = study identity.
** means the R-squared statistic was not specified in a study.

Sources of Variations in Studies on Student Acceptance of MOOCs

The statistical heterogeneity of effect sizes has been used to examine the sources of variations in the included studies. The result given in Figure 5 indicates that the proportion of student acceptance of factors influencing MOOCs was approximately 46 to 58 times the proportion of the increase in the acceptance. The high pooled effect size given by I^2=93.70% shows a very large statistical heterogeneity (Kavvoura & Ioannidis, 2008) across the included studies. Since the 95% confidence interval for the overall effect size estimate did not include zero, the decrement of about 6% in student acceptance of MOOCs was statistically significant at a 5% level of significance. The model fit gave a pooled effect size estimate of 0.52 within a 95% CI [.46, .58] with standard error fluctuating from 0.026 to 0.062 inclusive.

Figure 5

Forest Plot for Distribution of Effect Sizes of Acceptance Studies on MOOCs



Note. ES = Effect size.

Table 4 shows the heterogeneity results obtained using different statistical metrics to compensate for the weakness of a single metric. The result of Cochran's Q test obtained has affirmed the significance of heterogeneity in effect sizes. The test gave a value of Q = 555.68, $p < .05$ with 35 degrees of freedom to indicate strong evidence of statistical homogeneity of effect sizes. The homogeneity value of $\tau^2 = 0.03$ indicates the extent of variability across studies as compared to the effect sizes. The percentage of total variation across the included studies is large for $I^2 = 93.00\%$ (Kavvoura & Ioannidis, 2008; Rücker et al., 2008). These findings generally imply that the proportion of total variance in the included studies can be attributed to the heterogeneity of true effect sizes.

Table 4

Heterogeneity Results

Metric	Value	*df*	*p*
Cochran's Q	555.68	35	.00
τ^2	0.03	-	-
I^2	0.93	-	-

Table 5 presents the result of subgroup analysis with significant intra-group heterogeneity observed at $p < .001$ with $I^2 = 98.50\%$ and effect size of 61% within a 95% CI [.55, .68] for student satisfaction. This result was followed by intra-group heterogeneity of behavioral intention with $I^2 = 94.53\%$ and effect size of 47% within a 95% CI [.23, .90]. Then student attitude with $I^2 = 88.66\%$ and effect size of 57% within 95% CI [.46, .72]. The intra-group heterogeneity of perceived usefulness was recorded with $I^2 = 51.91\%$ and effect size of 47% within a 95% CI [.29, .65]. However, its Cochran value of 8.32 is low with moderate I^2 and insignificant heterogeneity value at $p = 0.08 > 0.05$. The remaining factors reported no statistical heterogeneity for the subgroup analysis with $I^2 = 0.00\%$ and $p < .001$. This result is not surprising because the meta-analysis parameters of this study show that student satisfaction had the highest path coefficient with six different studies proving that it is the strongest significance factor (Chen et al., 2018; Joo et al., 2018; Daneji et al., 2019; Lu et al., 2019; Pozón-López et al., 2020; Wan et al., 2020). Moreover, considering the path coefficients of the included studies, we have discovered that the average path coefficient (0.542) of studies on student satisfaction is higher than the average path coefficient (0.460) of non-student satisfaction studies and higher than the average path coefficient (0.471) of the entire studies. The high overall statistical heterogeneity of this study can be attributed to multiple sources, including study population, sample size, study design, number of included studies, and data analysis method applied (Borenstein et al., 2010; Melsen et al., 2014). The test for subgroup differences has suggested a statistically significant subgroup effect with $p < .05$ to imply that factors influencing student acceptance of MOOCs significantly modify the acceptance effect. However, there is substantial unexplained statistical heterogeneity within the four subgroups of factors. The validity of the pooled effect size estimate for each subgroup is uncertain because the results of the included studies are inconsistent.

Table 5

Subgroup Analysis of Factors Influencing Student Acceptance of MOOCs

Factor	Cochran's Q	*df*	*p*	I^2	Effect Size	95% CI
Bint	73.13	3	0.00*	94.53	0.57	[0.23, 0.90]
Csef	0.00	0	0.00	0.00	0.33	[0.25, 0.43]

Factor	Cochran's Q	*df*	*p*	I^2	Effect Size	95% CI
Cqua	0.00	0	0.00	0.00	0.45	[0.35, 0.55]
Enjo	0.00	0	0.00	0.00	0.50	[0.40, 0.60]
Eotp	0.00	0	0.00	0.00	0.73	[0.63, 0.81]
Fcon	0.00	2	0.00	0.00	0.43	[0.34, 0.51]
Flow	0.00	0	0.00	0.00	0.66	[0.55, 0.74]
Icap	0.00	0	0.00	0.00	0.56	[0.46, 0.66]
Imot	0.00	1	0.00	0.00	0.57	[0.50, 0.64]
Kout	0.00	0	0.00	0.00	0.54	[0.44, 0.64]
Pexp	0.00	0	0.00	0.00	0.33	[0.24, 0.44]
Prep	0.00	0	0.00	0.00	0.25	[0.18, 0.35]
Puse	8.32	4	0.08	51.91	0.47	[0.29, 0.65]
Satt	35.28	4	0.00*	88.66	0.59	[0.46, 0.72]
Scom	0.00	0	0.00	0.00	0.36	[0.27, 0.46]
Shab	0.00	0	0.00	0.00	0.66	[0.55, 0.75]
Ssat	199.60	4	0.00*	98.50	0.61	[0.55, 0.68]
Tskn	0.00	0	0.00	0.00	0.35	[0.26, 0.45]
Overall	555.68	35	0.00	93.70		

Note. MOOCs = massive open online courses; CI = confidence interval; Bint = behavioral intention; Csef = computer self-efficacy; Cqua = course quality; Enjo = perceived enjoyment; Eotp = engagement on platform; Fcon = facilitating conditions; Flow = flow experience; Icap = intellectual capital; Imot = intrinsic motivation; Kout = knowledge outcome; Pexp = performance expectancy; Prep = perceived reputation; Puse = perceived usefulness; Satt = student attitude; Scom = social competence; Shab = student habit; Ssat = student satisfaction; Tskn = teacher subject knowledge.

* $p < .05$.

The result of meta-regression analysis in Table 6 shows that both "model applied" and "sample size" came up to be statistically significant sources of heterogeneity of effects. The regression coefficients are the estimated increase in log risk ratio per unit increase in covariate. The log risk ratio was estimated to increase by 0.023 per unit increase in the models applied to identify factors influencing student acceptance of MOOCs. This finding is expected because the importance of theoretical models in any research cannot be overemphasized. The application of a wrong model to solve a given problem can lead to an erroneous interpretation, judgment, and conclusion. Previous studies have affirmed that sample size is an imperative consideration for research. The larger the sample size, the more robust is the study result. Moreover, the effect of within-study estimation error variance under the random-effects model will diminish with large sample size, it can precisely vary the effect sizes in few studies and identify outliers that could skew the findings of a smaller data sample (Borenstein et al., 2010).

Table 6

Examination of Sources of Heterogeneity in Effect Sizes of the Included Studies

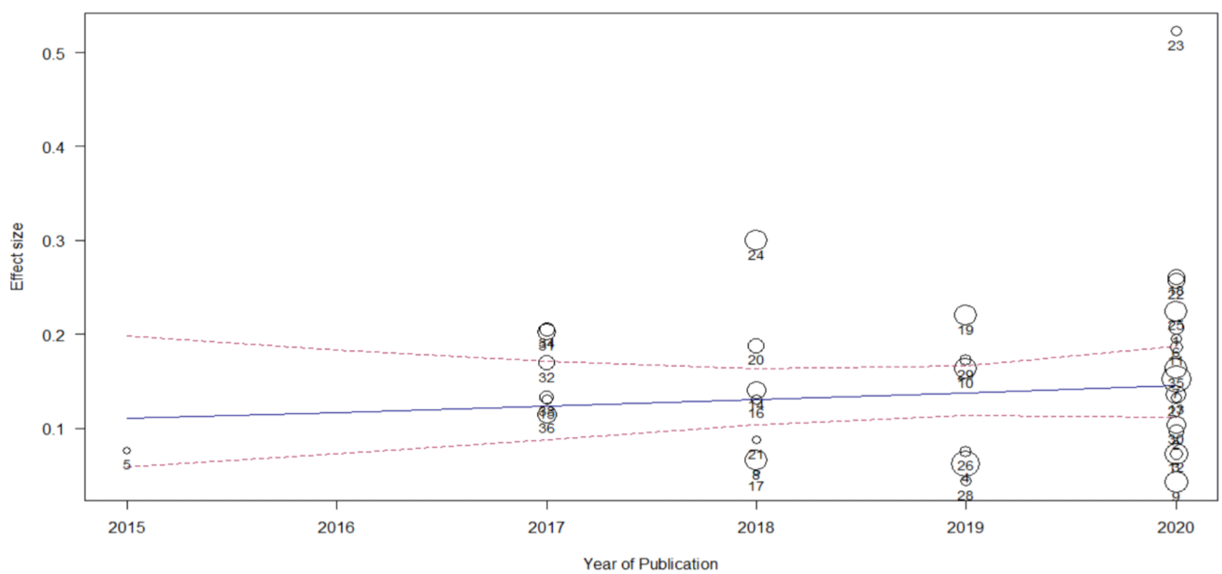
Source	Estimate	*SE*	95% CI	*p*
Year	0.063	0.085	[-0.104, 0.229]	0.459
Model	0.023	0.015	[0.055, 0.144]	0.026
Type	-0.089	0.048	[-0.368, 0.037]	0.076
Country	0.0005	0.018	[-0.037, 0.040]	0.978
Size	0.105	0.038	[0.027, 0.184]	0.010

Note. CI = confidence interval.

Figure 6 shows the scatter plot reporting the result of the meta-regression analysis of this study. It can be seen from the plot that the magnitude of the differences in the included studies slightly increases with the year of publication.

Figure 6

A Scatter Plot Reporting the Result of the Meta-Regression



Significant Biases in Studies on Student Acceptance of MOOCs

Figure 7 shows the funnel plot revealing an asymmetrical distribution of the included studies, which is an indication of potential publication bias (Crocetti, 2016; Lin & Chu, 2018). Studies 33-36 had the largest log odds ratio on the right, studies 1-8 had the smallest log odds ratio on the left and the remaining studies were quite symmetric in distribution.

The visual examination of a funnel plot can be generally subject to interpretation for which the Egger asymmetry method has been suggested as a complementary statistical test for publication bias

(Borenstein et al., 2010; Nakagawa et al., 2017). The purpose of the Egger test was to perform a simple linear regression to determine whether the intercept of the relationship between standardized effect sizes and standard error differs significantly from zero at $p < .05$. The result reported in Table 7 confirms the presence of insignificant publication bias at $p = .433$ to show the effectiveness of our inclusion and exclusion criteria in eliminating publication bias.

Figure 7

Funnel Plot with Pseudo 95% Confidence Limits Indicating Publication Bias Across the Included Studies

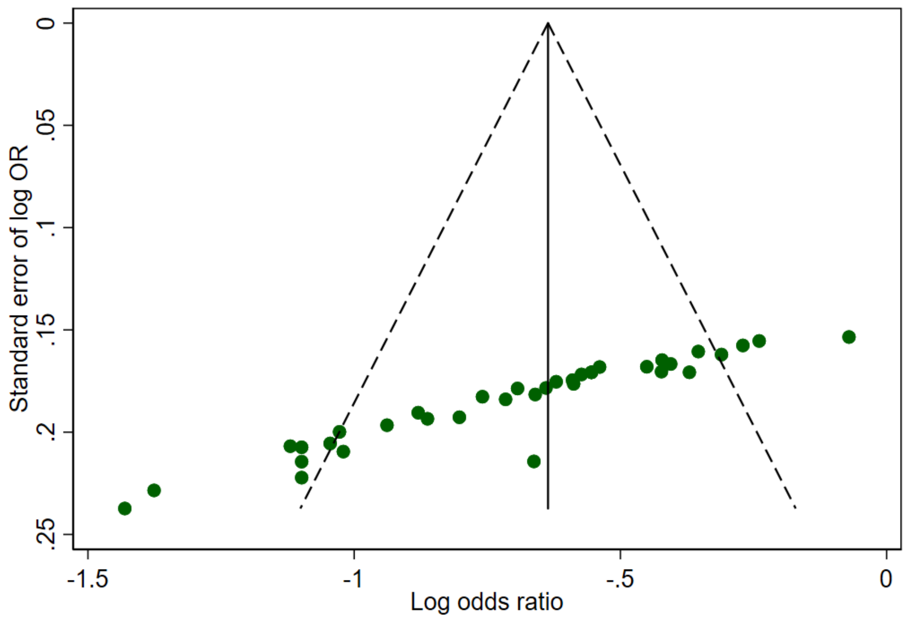


Table 7

Egger Test for Examining Publication Bias

Parameter	Estimate	*SE*	*t*	*p*	95% CI
Slope (coefficient)	1.990	0.149	13.37	0.000	[1.688, 2.293]
Bias (intercept)	-14.552	0.820	-17.75	0.433 [a]	[-16.218, 11.885]

Note. CI = confidence interval.

[a] indicates the presence of insignificant publication bias.

DISCUSSION

Three research questions on the main significant factors, sources of variations, and publication bias were comprehensively formulated to achieve the study aim of discovering the main significant factors influencing student acceptance of MOOCs for ODL. Several research articles published from 2010 to 2020 were meticulously scrutinized, but 36 of them that met our inclusion criteria were eventually selected for meta-analysis. This research has affirmed the increasing curiosity on MOOC studies, and it is the first to attempt a meta-analysis of the existing studies on student acceptance of MOOCs. The findings from the included studies with precisely 14233 participating students show satisfaction, intention, and attitude to be the most significant factors influencing student acceptance of MOOCs. The results of this study have affirmed the recent studies that satisfaction has a strong direct influence on student acceptance of MOOCs (Chen et al., 2018; Joo et al., 2018; Daneji et al., 2019; Lu et al., 2019; Pozón-López et al., 2020; Wan et al., 2020). The study by Joo et al. (2018), although not included in the meta-analysis because of the missing parameter of factor validity, recorded an impressive factor reliability score of 0.930 and a path coefficient of 0.861 for the relationship between student satisfaction and continual intention to use MOOCs. In addition, the results of the current study have affirmed that intention (Yang & Su, 2017; Khan et al., 2018; Arpaci et al., 2020; Haron et al., 2020) and attitude (Wu & Chen, 2017; Hsu et al., 2018; Al-Rahmi et al., 2019; Teo & Dai, 2019; Razami & Ibrahim, 2020) have strong direct influences on student acceptance of MOOCs.

The random-effects model assumption of this current study has revealed the presence of statistical heterogeneity in effect sizes of the included studies, which was caused by models applied and sample sizes. Besides, there were recognizable differences in statistical heterogeneity of effects. The subgroup analysis of the included studies has found an effect size of 61% within the 95% CI [.55, .68] in student satisfaction. The pooled effect size of 54% within the 95% CI [.48, .60] was found in this study. The possible explanation for the variations is based on sample sizes and the theoretical model applied by an individual author for exploring factors influencing student acceptance of MOOCs.

This study has examined the possibility of publication bias in the included studies, considering the diverse reasons that can inject biases. The finding using the funnel plot has avowed a possible indication of publication bias, but further statistical test based on the Egger regression has shown that publication bias is insignificant. This finding is not shocking because previous authors have argued that funnel asymmetry detection may be an artifact of too few effect sizes that can emerge from statistical heterogeneity (Nakagawa et al., 2017). In the subgroup analysis, effect sizes were zero for 14 factors, but greater than zero for factors of student satisfaction, behavioral intention, student attitude, and perceived usefulness. This result is an indication of statistical homogeneity for those 14 factors to justify the absence of biases in the included studies.

The findings of this study generally show the dearth of quality research works on MOOC technology acceptance in the context of Africa when compared to the numerous studies from Asia. Moreover, there is a lack of sufficient African-based publishers on the theme of technology acceptance theories, models, and applications when compared to Europe and America. In this paper, we are making a clarion call for more distinctive research contributions in this area of the Africa continent to resolve our precarious situation and significantly contribute to the African education system through the application of MOOC for distance learning.

Implication

This study has theoretical and practical implications. Theoretically, it is the first meta-analysis of the existing studies on factors influencing student acceptance of MOOCs for ODL. This study has found satisfaction, intention, and attitude to be strong significant factors influencing student acceptance of MOOCs. The impact of student satisfaction is not surprising because previous authors have judged it to be an influential factor contributing to the successful completion of distance learning (Au et al., 2018), and for predicting student acceptance of MOOCs (Chen et al., 2018; Joo et al., 2018; Daneji et al., 2019; Lu et al., 2019; Pozón-López et al., 2020; Wan et al., 2020). It can be affirmed that the greater the satisfaction of students with MOOCs, the greater their acceptance of the system (Wan et al., 2020).

Moreover, student attitude towards distance learning intervention has been identified as one of the challenges of ODL (Malangu, 2018). Previous results have confirmed that attitude has a strong direct influence on student acceptance of MOOCs (Wu & Chen, 2017; Hsu et al., 2018; Al-Rahmi et al., 2019; Teo & Dai, 2019; Razami & Ibrahim, 2020). This meta-analysis study has confirmed the importance of the influence of behavioral intention on the use of MOOCs (Yang & Su, 2017; Khan et al., 2018; Arpaci et al., 2020; Haron et al., 2020). These previous authors relied on the technology acceptance model, theory of planned behavior, technology task fit model, self-determination theory, and unified theory of acceptance and use of technology to infer their results. However, the authors did not investigate the influence of student satisfaction in their research models. The other authors have confirmed a direct linkage between student satisfaction and behavioral intention to use MOOCs (Pozón-López et al., 2020), and the link between student satisfaction and the continuous intention was found to be positively significant (Chen et al., 2018; Joo et al., 2018; Daneji et al., 2019; Lu et al., 2019; Wan et al., 2020). This finding implies that the more students are satisfied with MOOCs, the more they are likely to use the system.

The current study has confirmed the suitability of technology acceptance models with satisfaction, intention, and attitude as important precursors for predicting or explaining student acceptance of MOOCs for ODL. However, since intention and attitude are behavioral patterns to use MOOCs, satisfaction comes out to be the main significant factor of student acceptance of the system. Satisfaction was previously found to be a precursor of attitude (Dai et al., 2020) and intention (Pozón-López et al., 2020). In addition, student satisfaction with MOOCs was found recently to mediate the direct relationship between flow experience and behavioral intention to use the system (Mulik et al., 2020). The satisfaction to attitude sequence found in the general information technology usage (Bhattacherjee & Premkumar, 2004) was further confirmed recently in the context of MOOCs (Dai, et al., 2020). The satisfaction of students with the usage of MOOCs can lead to changes in their attitudes and behaviors toward learning using the system. The positive attitude and behavioral change may influence student retention in MOOCs through appropriate intervention. Such an intervention may include espousing a problem-solving instructional strategy, changing instructional methods, evolving novel pedagogy for learning assessment, transforming student management strategies, promoting cooperative learning among students, a grouping of diverse students in discussion fora for building rapport and collaborative creation of knowledge (Dai, et al., 2020).

The detection of statistical heterogeneity in study effect sizes can provide valuable information for further research. This is because it might allow us to redesign MOOCs to provide relevant interventions for surmounting ODL challenges in the context of students. The direct implication of the findings from the meta-regression analysis is that models applied, and sample sizes can be used to explain the possible sources of statistical heterogeneity. It might relate to issues of methodological design, and sample size of the study participants. This present study has affirmed a communal result of six previous studies that satisfaction is the most significant factor influencing student acceptance of MOOCs (Chen et al., 2018; Joo et al., 2018; Daneji et al., 2019; Lu et al., 2019; Pozón-López et al., 2020; Wan et al., 2020). However, we found one study contradicting this result that satisfaction does not influence the continuous intention of students to use MOOCs according to an extended ECM (Alraimi et al., 2015). Moreover, Zhou (2017) relying on an extended ECM, found satisfaction to be a significant factor influencing student acceptance of MOOCs with a path coefficient of 0.406, but it was not the strongest significant factor. The factor of knowledge outcome with a higher path coefficient of 0.495 was found to be the strongest predictor of student acceptance of MOOCs (Zhou, 2017). The contradicting results of previous studies on student satisfaction with MOOCs may be the consequence of using an extended ECM (Alraimi et al., 2015; Zhou, 2017) instead of the orthodox ECM (Bhattacherjee, 2001).

This study can pragmatically provide policymakers and software companies specializing in the development of educational information systems with an impetus to overcome the intrinsic challenges of ODL. It will provide useful insights to those planning to implement MOOCs to understand how teaching and learning should be delivered to promote student satisfaction with ODL activities. The outcome of this study can provide useful guidelines when making decisions on the implementation of MOOCs for ODL. It suggests that attention be given to the factor of satisfaction to surmount student challenges of ODL. It is important to raise an awareness among ODL practitioners and policymakers on what is required to improve student acceptance of MOOCs. Practitioners and policymakers should formulate comprehensive student satisfaction policies, guidelines, and the specification of requirements that would help surmount the challenges of ODL. The MOOC platform designers would be able to transform the specification of requirements into component systems to improve student satisfaction with the system.

Student satisfaction with MOOCs can be hypothesized as an important driver for surmounting the intrinsic challenges of ODL. Previous studies have highlighted the precursors of student satisfaction to be course quality (Pozón-López et al., 2020), interaction (Chen et al., 2018), and motivation (Chen et al., 2018). The factor of satisfaction with its precursors was judged to be among the prime challenges of ODL for individual students. They include course quality (Au et al., 2018), a lack of interaction (Arasaratnam-Smith & Northcote, 2017; Kara et al., 2019; Li & Wong, 2019; Sadeghi, 2019), a lack of motivation (Kebritchi et al., 2017; Au et al., 2018; Budiman, 2018; Sánchez-Elvira & Simpson, 2018) and a lack of satisfaction (Au et al., 2018; Sánchez-Elvira & Simpson, 2018). It is possible to mitigate these challenges through an effective MOOC intervention, provided the issue of student satisfaction and its immediate precursors can be satisfactorily resolved in the system. MOOCs can allow students to exchange innovative ideas, support the collaborative design of novel solutions to challenging issues, and promote the collaborative creation of new knowledge using the available engagement functions in the system. Hence, student satisfaction can be enhanced by increasing the degree of interactivity and providing inspirational teaching through MOOCs (Chen et al., 2018). The perspective of motivation as explicated by previous findings has indicated that students are motivated to register for MOOCs to improve work efficiency, satisfy their curiosity, and acquire knowledge. Moreover, an adequate degree of functionalities of MOOCs and specific learning tasks will enable students to perceive a higher level of satisfaction. Students are more satisfied with course content and course quality if they can derive real benefits (Wan et al., 2020).

Limitation

The one apparent limitation of meta-analysis as observed in this study is the exclusion of articles that do not satisfy all the inclusion criteria. Such excluded articles may contain useful information. In addition, only the perspective of students was considered, but extending the study to capture the perspectives of teachers and administrators could have yielded more insightful findings. However, this is a general limitation of the included studies because they mainly focused on student acceptance of MOOCs. Some excluded studies delved on factors influencing teacher acceptance of MOOCs, but student opinion counts in the education system.

Nevertheless, this meta-analysis study has provided valuable information regarding the main significant factors influencing student acceptance of MOOCs. The intrinsic limitations of this study could be addressed in future research because we might have missed a few relevant studies in the process of article selection. Further research is needed to explore the interdependencies among factors influencing student acceptance of MOOCs for ODL. In the future, we plan to explore ways to analyze missing data in primary articles to cover the important information that may have been lost. Moreover, we wish to extend this study to a general episode of e-learning acceptance by different populations of participants across varying technology platforms. It would also be interesting to investigate the effects of gray literature on meta-analysis results. In addition, it is prudent to investigate data analytic methods that could help to conduct a more detailed analysis of the quantitative aspect of this study. Moreover, it is interesting for future research to correlate the voices of students with instructors on their acceptance of MOOCs for ODL.

CONCLUSION

The methodology of meta-analysis has been applied in this study to discover and analyze significant factors influencing student acceptance of MOOCs for ODL. Effect sizes, statistical heterogeneity, subgroup analysis, meta-regression analysis, and publication bias were examined for the included studies. This was because of varying sample sizes and theoretical models that were previously applied to identify factors influencing student acceptance of MOOCs. The results obtained in this study show that the pooled effect size estimate of factors influencing student acceptance of MOOCs was highly prevalent. Moreover, they have revealed that satisfaction is the main significant factor influencing student acceptance of MOOCs. Resolving the germane issue of satisfaction with MOOCs can have a significant transformation effect on the behavioral intention and attitude of students to effectively use the technology for ODL. The outcome of this paper can significantly contribute to a better understanding and advancement of technology acceptance models in information systems and related disciplines.

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