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Original research paper

A BIBLIOMETRIC AND META-ANALYTIC REVIEW OF THE IMPACT OF MOOCS IN HIGHER EDUCATION*

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ABSTRACT

Massive Open Online Courses (MOOCs) have gained increasing attention in higher education. This study presents a systematic review using bibliometric analysis and meta-analysis to examine the impact of MOOCs on learning outcomes. Bibliometric analysis identifies key themes, while meta-analysis synthesizes findings for a comprehensive understanding. A total of 116 publications from the Scopus database were analyzed to visualize the conceptual structure and emerging themes. Twelve experimental studies were further examined to assess MOOCs' effects on Actual Learning, Perceived Learning, and Satisfaction. Data analysis using OpenMEE calculated aggregate mean differences, forest plots, and publication bias. Results show that MOOCs significantly impact learning outcomes, with an overall effect size of 0.683 (strong). Specifically, Actual Learning had a strong effect (0.847), while Perceived Learning (0.354) and Satisfaction (0.284) had moderate effects. These findings confirm that MOOCs can significantly improve learning outcomes in higher education. The study concludes that both the theoretical development and practical implementation of MOOCs should consider these differentiated impacts across learning dimensions. The findings of this study are expected to offer meaningful pedagogical contributions to curriculum development, instructional practices, and institutional policies aimed at enhancing the effective integration of MOOCs in higher education settings

Key words:
bibliometric, higher education, learning outcomes, meta-analysis, MOOCs.

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INTRODUCTION

Higher education has undergone significant transformation in recent decades, especially with the emergence of Massive Open Online Courses (MOOCs). MOOCs have become a popular alternative for higher education institutions to provide broad and flexible educational access for students around the world (Boonroungrut et al., 2022; Kannadhasan et al., 2020; Li, 2019). MOOCs promise access to high-quality learning materials at low or even free costs and flexibility in time and place that enables personalized learning (Barman et al., 2019; Pilli et al., 2018; Rambe & Moeti, 2017).

One of the main attractions of MOOCs is their flexibility (Eradze et al., 2020; Karunanayaka et al., 2018). Students can access learning materials any time and anywhere without being physically present in class. This allows for self-directed learning, tailored to individual schedules and needs. In addition, MOOCs also offer a variety of learning materials, from natural sciences to humanities, allowing students to explore their interests and expand their knowledge in various fields. Despite having great potential, the implementation of MOOCs is also faced with several challenges, such as issues of participant retention (Badali et al., 2022; Goopio & Cheung, 2021), content quality (Albelbisi et al., 2023; Buhl & Andreasen, 2018; Margaryan et al., 2015), interaction and support, and the digital divide (Badiuzzaman et al., 2023; Loh et al., 2024; Patra et al., 2024; Rajam et al., 2024). Some courses may need to be more structured or adequate to provide an in-depth understanding. MOOCs tend to lack direct interaction between instructors and participants and support for participants who need additional assistance. In addition, access to the internet and technology may still be an obstacle for some individuals participating in MOOCs. Many students enroll in MOOCs but still need to complete the course (Gregori et al., 2018; Patra et al., 2024; Xia & Qi, 2024). This can be caused by factors such as a lack of motivation (Al-Shabandar et al., 2018; Hew & Cheung, 2014). In addition, the challenge of assessing students' understanding and mastery of material remains an issue that needs attention. Unclear evaluation or lack of interaction between students and instructors can also affect the effectiveness of learning through MOOCs (Loh et al., 2024; Sari et al., 2020; Zhu et al., 2023). Overall, MOOCs have significantly changed higher education, providing broader and more flexible access for students worldwide. However, to maximize their potential, efforts must be made to overcome their challenges. Thus, MOOCs have the potential to become an essential part of the future of inclusive and innovative higher education.

As MOOCs grow, questions arise about their impact on learning outcomes, particularly in higher education. Several studies have revealed the benefits of participation in MOOCs in higher education, including increased independent learning abilities (Delita et al., 2022; Onah et al., 2024), mastery of subject matter (Deng & Benckendorff, 2021; Hew & Cheung, 2014), and digital skills development (Edelsbrunner et al., 2022; Sinha, 2024). However, there is also research exploring the low retention rates of participants and the challenges in measuring the real impact of MOOCs on higher education (Borrella et al., 2022; Goopio & Cheung, 2021; Shah et al., 2022). These studies try to understand whether MOOCs can provide a learning experience equivalent to traditional classroom teaching and how certain factors, such as course design, social interaction, evaluation, and participant characteristics, can influence learning outcomes. Several other studies show that MOOCs can significantly impact participants in terms of learning outcomes (Alhazzani, 2020; Khan et al., 2021; Wei et al., 2023; Yu et al., 2024). Thus, although MOOCs have become a popular alternative in higher education, further research is still needed to understand how their effectiveness can be optimized to improve learning outcomes.

Meta-analysis can be a practical approach to answer this question. Meta-analysis is a statistical method used to combine and analyze the results of various relevant studies to identify general patterns or consistent effects (Chang et al., 2013). This study conducts a meta-analysis that examines actual learning, perceived learning, and satisfaction with learning outcomes. Actual learning reflects changes in knowledge identified through rigorous learning measurement (Bacon, 2016). Perceived learning indicates students' self-reported increased knowledge, generally based on reflection and introspection. Meanwhile, satisfaction is an affective measure generally studied and describes fulfilling someone's expectations or needs. Additionally, bibliometric analysis defined as the quantitative evaluation of academic literature through publication and citation metrics, can provide valuable insights into themes and concepts related to MOOCs in higher education. This analysis can help us see developments in the field, identify essential contributions, and identify knowledge gaps that need further research.

In this context, this article aims to conduct a meta-analysis of existing studies to identify the impact of MOOCs in higher education on learning outcomes, including Actual Learning, Perceived Learning, and Satisfaction. In addition, we will also conduct a bibliometric analysis to look at themes and concepts related to MOOCs in higher education. The results of this research can provide a deeper understanding of how MOOCs influence student learning outcomes in higher education. In addition, the results of this research can also serve as a guide for researchers and practitioners interested in better understanding the role and impact of MOOCs in improving the quality of higher education.

METHOD

Samples and Search Criteria

We systematically reviewed the literature on the impact of MOOCs on learning outcomes in higher education, using the Scopus database. We were searching for publications that are primarily focused on the influence of MOOCs on learning outcomes, specifically actual learning, perceived learning, and satisfaction. The keywords used include a series of synonyms for "MOOC" (i.e., "MOOCs," "Massive open online courses") combined with a series of synonyms for "learning outcome" (i.e., "actual learning," "Perceived Learning" and "Satisfaction"), and "higher education." The search scope was limited to peer-reviewed academic publications, such as journal articles and conference proceedings. After the initial search, we retrieved 1,698 citations from the database, the search results being based on the first four inclusion criteria listed in Table 1.

TABLE 1. Inclusion criteria

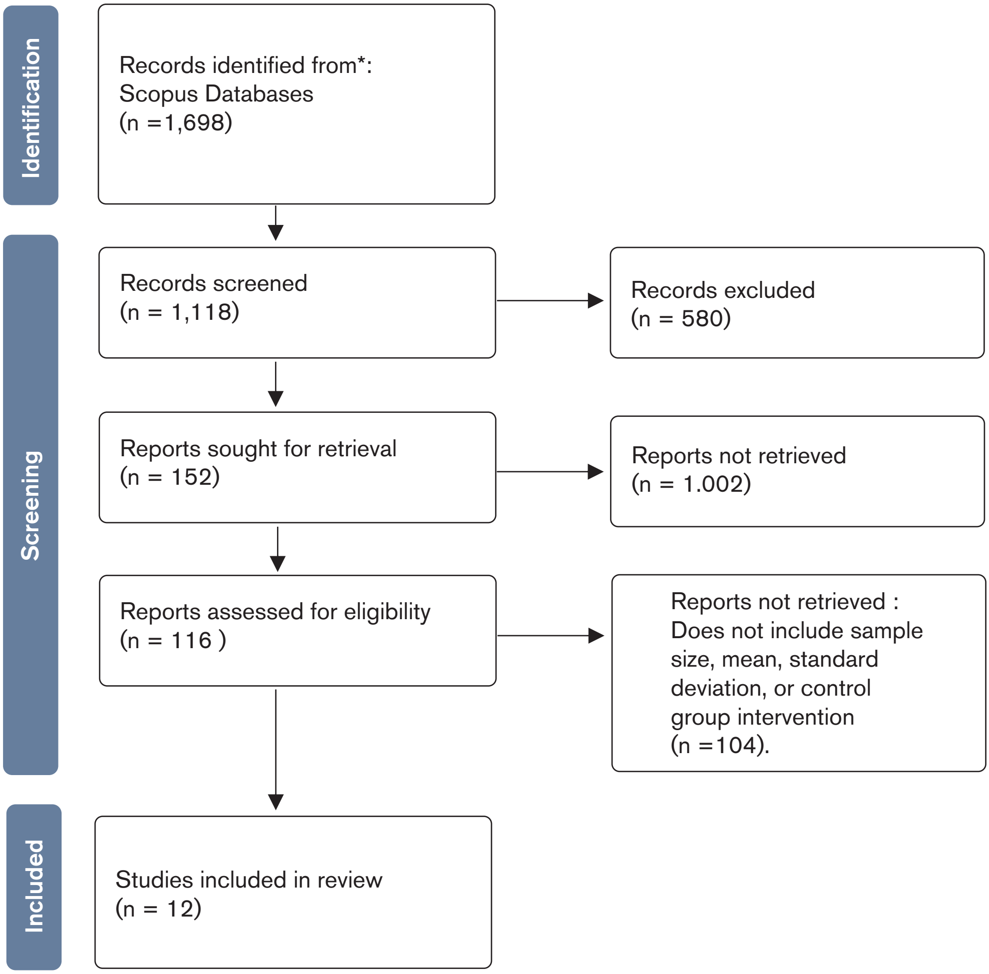
Inclusion criteria	Description
Publication type	Original research scientific articles from peer-reviewed journals and proceedings
Environment relevance	Studies conducted in environments relevant to the use of MOOCs in higher education
Participant relevance	Studies involved participants relevant to the MOOCs context in higher education, such as students or college course participants.
Language relevance	Studies published in English
Research design	Studies that use robust research designs, such as randomized controlled trials (RCTs) or quasi-experiments, to ensure the validity of the results.
Results of research	Data were sufficient to calculate an effect size
Learning outcomes	Clear learning outcomes (Actual Learning, Perceived Learning, or Satisfaction)

We ultimately included 116 articles for bibliometric analysis. We further screened the articles for meta-analysis and selected 12 articles. Figure 2 shows a PRISMA flow diagram illustrating this review's data collection and evaluation procedures.

Process Flow

We used the PRISMA flow model (Figure 1) to document the process flow of identification, screening, eligibility, and inclusion of studies. The PRISMA guidelines were proposed by the Ottawa Methods Center for reporting items for systematic reviews and meta-analyses (Page et al., 2021).

FIGURE 1. A flow diagram of PRISMA



A total of 1,698 articles were identified and screened in three stages. The first stage filtered articles based on title, abstract, keywords, publication year (2012–2023), language (English), and source (journals and proceedings). Articles failing these criteria were excluded. The second stage selected experimental studies on the impact of MOOCs in higher education on learning outcomes (actual learning, perceived learning, and satisfaction). In the third stage, non-experimental studies and those lacking sample size, mean, standard deviation, or control group intervention were excluded, leaving 12 articles for review. Among them, five contained multiple research results, resulting in 19 studies analyzed using meta-analysis techniques.

Data Analysis

Bibliometric Analysis. This systematic review employs two analytical approaches: bibliometric analysis and meta-analysis. Bibliometric analysis examines publication patterns by analyzing citation distribution and interconnections among scientific works. This approach helps assess the impact of MOOCs on higher education and guides future research (Aria & Cuccurullo, 2017; van Eck & Waltman, 2014). We used Bibliometrix and VOSviewer, two open-source tools that visualize conceptual relationships in academic literature. To explore the conceptual network of MOOCs research, we applied thematic mapping and thematic network analysis, grouping conceptual themes into a two-dimensional matrix to illustrate their interconnections and influence.

Meta-Analysis. Meta-analysis involves calculating the effect size to measure differences between experimental and control groups. In the context of this research, effect sizes reflect the impact of MOOCs on various learning outcomes, namely actual learning, perceived learning, and satisfaction, as reported in the included studies. Effect sizes from individual studies are combined using the Random Effects Model, which generalizes findings to broader populations (Barr et al., 2013; Borenstein et al., 2010; Cohen, 1992). This model is selected based on heterogeneity ($p < 0.001$). In this study, effect sizes were calculated using Hedges' formula (Borenstein & Higgins, 2013) and analyzed with OpenMEE. OpenMEE was originally developed for ecology and evolutionary biology; it applies general statistical models that are widely used in meta-analyses across various disciplines, including education. Its core functionalities, such as calculating effect sizes, heterogeneity indices (Q and I^2), and testing for publication bias, are standard procedures in meta-analytic research. Furthermore, OpenMEE is an open-source software (Wallace et al., 2017), which enhances transparency and accessibility, making it a practical and replicable tool for researchers in the field of educational science. The random effects model assumes variability in true effect sizes across studies, reflecting differences in sampled populations (Borenstein et al., 2010). Table 2 presents the effect size interpretation.

TABLE 2. Cohen's classification of effect sizes (Cohen et al., 2018)

Effect Sizes	Interpretation
ES≤0,20	Weak
0,20<ES≤0,50	Moderate
0,50<ES≤1,00	Strong
ES>1,00	Very Strong

The heterogeneity test in this study was carried out using a random effects approach to find whether there were differences in each effect size used. If the p-value <0.001, then each study used shows heterogeneity. Furthermore, according to Wilson & Lipsey (2001), if the p-value from the heterogeneity test is smaller than the significance level (typically 0.05), it indicates significant heterogeneity among the included studies, meaning that the effect sizes vary beyond what would be expected by chance. This suggests that the studies are drawn from different populations or have different effect distributions. To test for publication bias, we used the File Safe N (FSN) approach. According to Borenstein et al. (2010), if the FSN value is greater than (5k + 10), where k is the number of studies included in the meta-analysis, the results are considered robust and not likely to be affected by publication bias.

FINDINGS

Bibliometric Analysis

A total of 116 articles were included in the bibliometric analysis to examine publication trends on MOOCs in higher education. As shown in Figure 2, the ACM International Conference Proceedings Series is the most productive academic source for publishing articles about MOOCs in Higher Education (n=6). The Sustainability journal (n=5) was ranked second, followed by the journals Lecture Notes in Networks and Systems (n=4), Advances in Intelligent Systems and Computing (n=3), Frontiers in Psychology (n=3), International Journal of Educational Technology in Higher Education (n=3), and Lecture Notes in Computer Science (n=3). Figure 2 shows the frequency of academic resources publishing one or more documents in the bibliometric data sample.

FIGURE 2. Top cources of publications in the sampled bibliometric data

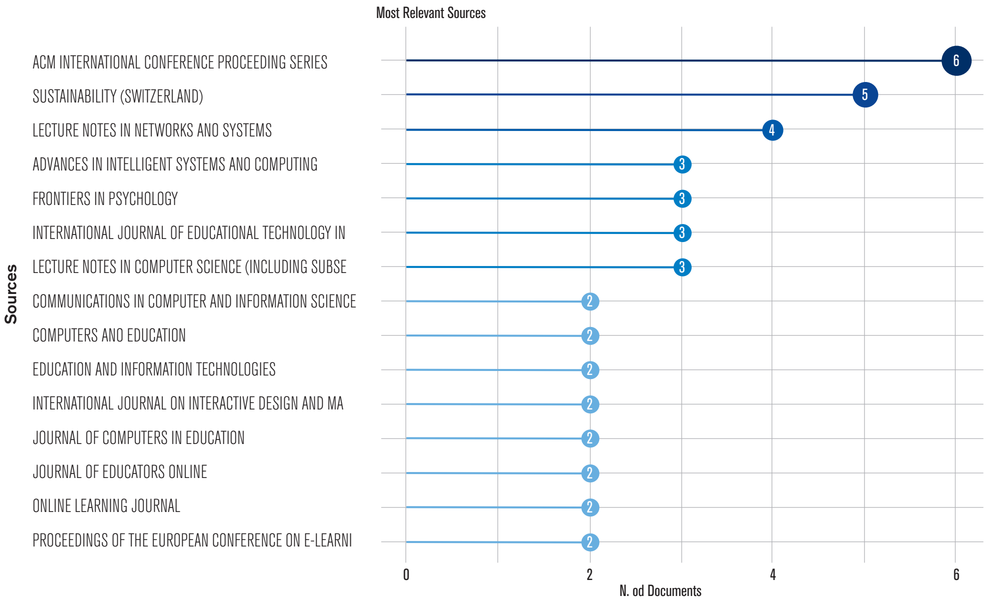
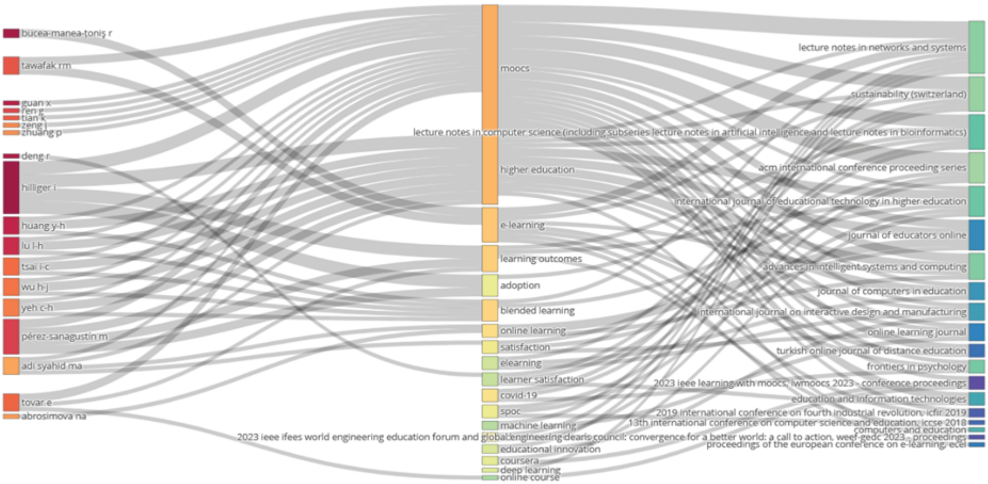


Figure 3 shows a Sankey diagram, showing which keywords are most discussed about the journals and authors cited. In this diagram, the width of the gray arrows proportionally represents the strength of the association between keywords.

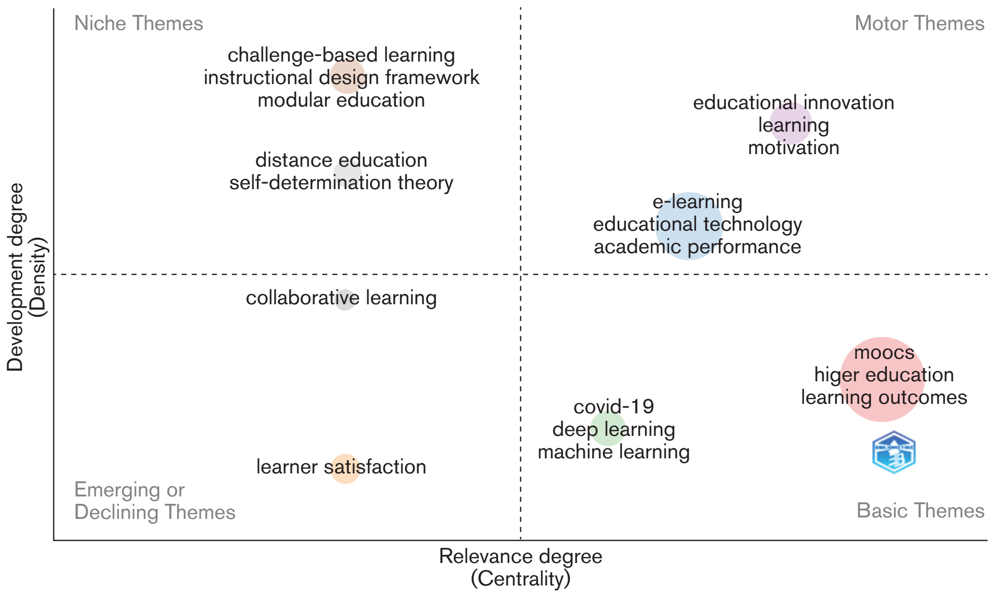
FIGURE 3. Three-field plot to indicate relations among authors, cited sources, and keywords



Thematic Map Analysis

Thematic map analysis is used to visualize key themes by identifying clusters of related keywords that reveal underlying conceptual structures in the literature (Hallinger & Kovačević, 2019). First, we narrowed the range of data extraction to thematic clusters with at least two keywords. Second, we only included 250 keywords from articles collected with high frequency on the network to reduce data visualization noise. Figure 4 shows a thematic map of the main concepts.

FIGURE 4. Quantitative Thematic Map of Keywords in Clusters



Thematic maps centralize research topics by grouping them based on co-word occurrences, following a specific genre framework (Yu et al., 2020). In this study, the thematic map was generated using the Biblioshiny interface of the Bibliometrix R-package, which applied a co-occurrence network analysis of author keywords. The resulting clusters were visualized into four thematic quadrants based on Callon's et al. (1991) centrality and density metrics. These quadrants are: Motor Themes, which are well-developed and strongly connected to other themes, representing the driving force of the research field; Niche Themes, which are internally well-developed but only weakly linked to the broader domain, reflecting specific yet relevant subtopics; Emerging or Declining Themes, which show both low centrality and density, indicating topics that are either evolving or losing relevance; and Basic Themes, which are fundamental to the field but remain underdeveloped in terms of research depth.

The Motor Themes quadrant includes key topics such as educational innovation, learning motivation, e-learning, educational technology, and academic performance, areas that are both highly relevant and extensively discussed in the literature. For instance, prior research has explored the use of MOOCs in engineering education, such as smart grid technologies, to improve accessibility and instructional quality (Martinez-Ríos et al., 2022). Mobile technologies have also been shown to enhance learning outcomes by offering accessible, high-quality content (Jouicha et al., 2022). In the domain of learning motivation, studies on K-MOOCs highlight that system usability significantly increases student satisfaction (Joo et al., 2018). The Niche Themes quadrant comprises challenge-based learning, instructional design frameworks, distance education, and self-determination theory. Although these topics are less frequently addressed, they offer unique theoretical contributions. A notable example is the CMODE framework, which integrates challenge-based and modular learning in MOOCs, resulting in increased student engagement and academic performance (Mesutoğlu et al., 2021).

The Emerging or Declining Themes quadrant features topics such as collaborative learning and learning satisfaction, which indicate evolving or diminishing research interest. One study investigated the use of conversational pedagogical agents in MOOCs to foster more interactive learning environments (Caballé et al., 2021). Another examined student satisfaction during COVID-19, emphasizing the role of video design, content quality, assessments, and peer interaction, while instructor-related factors were found to have minimal influence (Suriyapaiboonwattana & Hone, 2023). Finally, the Basic Themes quadrant includes fundamental concepts such as MOOCs, higher education, learning outcomes, COVID-19, deep learning, and machine learning. Although central to the field, these topics remain underdeveloped. For example, Jiang and Ma (2021) proposed a blended teaching model that integrates deep learning techniques into MOOC-based environments, improving both student engagement and analytical skills. Similarly, Edalati et al. (2022) applied machine learning to enhance sentiment analysis in MOOCs, achieving high accuracy in aspect-based opinion mining.

The Keywords Analysis

In addition to the thematic map analysis, we also analyzed the subsequent networks of each theme. We draw the interconnections between subordinate networks in each cluster on a thematic map. Cooccurrence analysis revealed that keywords were grouped in eight clusters or groups, as shown in Figure 5. After a thorough review, we finalized the main thematic network containing meaningful keywords that explain the study of MOOCs in higher education.

FIGURE 5. Network visualization map of keywords' co-occurrence

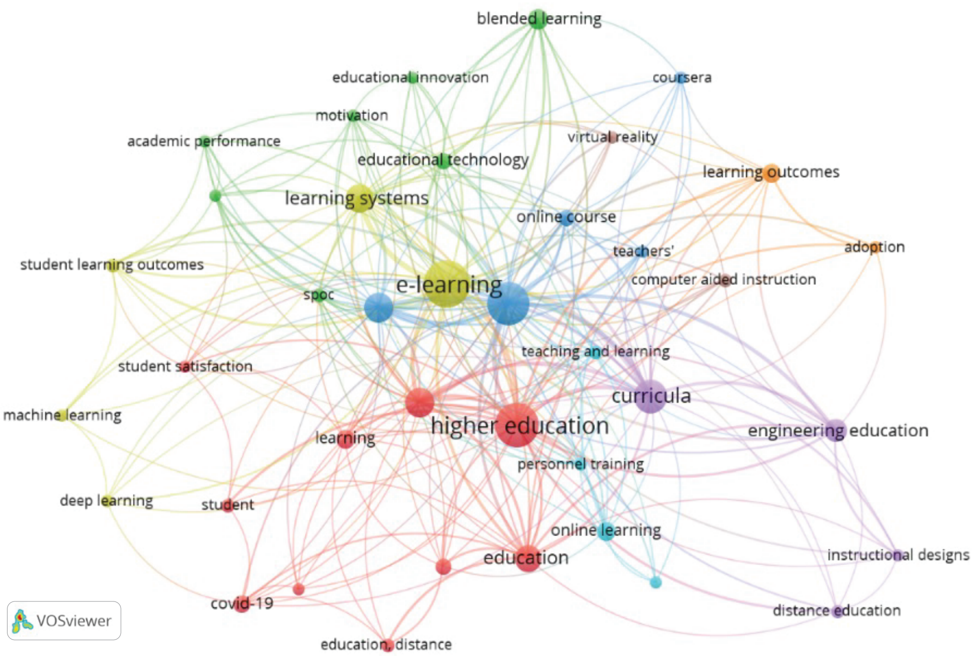


Figure 5 shows the thematic network of keywords. The clusters were generated using VOSviewer, a software tool designed for constructing and visualizing bibliometric networks. The clustering algorithm in VOSviewer is based on modularity optimization, which groups keywords that frequently co-occur across publications. Cluster 1 includes terms related to MOOCs in higher education that have been researched, namely higher education, teaching, education, learning satisfaction, covid 19, distance education, and student. These keywords reflect the high interest in using MOOCs in higher education, especially during the COVID-19 pandemic.

Cluster 2 includes academic performance, blended learning, educational innovation, educational technology, motivation, spoc and student satisfaction. This shows that research in the context of MOOCs also highlights the importance of innovation in education, the use of technology in learning, and motivational factors that influence learning success.

Cluster 3 includes Coursera, education computing, online courses, students, and teachers. Cluster 3 highlights terms related to specific online learning platforms, such as Coursera, computing education, and the relationship between learners and teachers in online learning environments. Cluster 4 includes e-learning, deep learning, learning systems, machine learning, and student learning outcomes. This reflects an interest in using advanced technology to increase the effectiveness of learning in MOOCs. Cluster 5 includes curriculum, distance education, engineering education, and instructional designs. Cluster 6 includes online learning, personnel training, professional development, and teaching and learning. Cluster 7 includes adoption and learning outcomes. Cluster 8 includes computer-aided instruction and virtual reality. Clusters 5 to 8 show the diversity of research conducted in the context of MOOCs in higher education and the importance of developing innovative and effective learning practices in the digital era.

Meta-Analysis

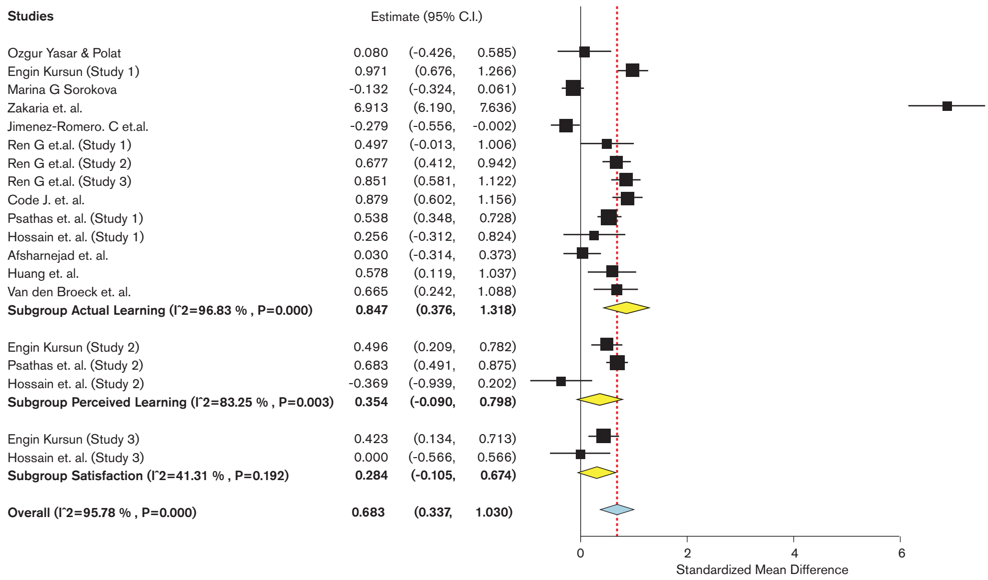
This research analyzes 19 research results taken from 12 articles. Four studies produced several research results. The first step is to calculate the effect size of each study. To be more accurate, the effect size of each study in this research was calculated using OpenMEE software. Table 2 summarizes the effect sizes and variances for each study and country. The inclusion of country information helps contextualize the findings, as educational systems, cultural factors, and MOOC implementation can vary significantly across region.

TABLE 3. Cohen's classification for effect sizes

No	Study	Region	Effect Size	Varians	Criteria
1	Özgür Yaşar & Polat	Turkey	0.080	0.067	Weak
2	Engin Kursun (Study 1)	Turkey	0.971	0.023	Strong
3	Engin Kursun (Study 2)	Turkey	0.496	0.021	Moderate
4	Engin Kursun (Study 3)	Turkey	0.423	0.022	Moderate
5	Marina G Sorokova	Russia	-0.132	0.010	Weak
6	Zakaria et al.	Malaysia	6.913	0.136	Very Strong
7	Jimenez-Romero. C et al	Colombia	-0.279	0.020	Weak
8	Ren G et al. (Study 1)	China	0.497	0.068	Moderate
9	Ren G et al. (Study 2)	China	0.677	0.018	Strong
10	Ren G et al. (Study 3)	China	0.851	0.019	Strong
11	Code J.et al.	America	0.879	0.020	Strong
12	Psathas et al (Study 1)	Greece	0.538	0.009	Strong
13	Psathas et al (Study 2)	Greece	0.683	0.010	Strong
14	Hossain et al (Study 1)	Bangladesh	0.256	0.084	Moderate
15	Hossain et al (Study 2)	Bangladesh	-0.369	0.085	Weak
16	Hossain et al (Study 3)	Bangladesh	0.000	0.083	Weak
17	Afsharnejad et al.	Australian	0.030	0.031	Weak
18	Huang et al.	China	0.578	0.055	Strong
19	Van den Broeck et al.	Belgium	0.665	0.047	Strong

Figure 5 presents a forest plot that summarizes the overall effectiveness of MOOCs on student learning outcomes, based on 19 research results. This visualization displays the standardized mean differences and confidence intervals for each study, enabling comparison across different outcome types such as actual learning, perceived learning, and satisfaction.

FIGURE 6. Forest plot effect size overall



The results of data analysis in the image show an overall effect size of 0.683 (0.50<ES≤1.00), included in the strong category. The second stage is to test heterogeneity and select an appropriate estimation model. Heterogeneity tests were carried out to prove whether each study's effect sizes differed. The heterogeneity test in this study was carried out using the Q parameter approach with degrees of freedom (df=25). Table 4 shows the results of the heterogeneity test using OpenMEE software.

TABLE 4. Heterogeneity test data summary

Q	Df	p	I^2
426.205	18	0.001	95.777

Analysis shows that the Q value = 426.205 and p<0.001. The degree of variation in effect sizes between studies is reflected in the I-Squared value (I2=95.777), which indicates that 95% of the effect size reflects the percentage of variability due to true heterogeneity. So, the distribution of effect sizes in the studies analyzed is heterogeneous. This indicates the potential for analyzing moderator variables to uncover sources of differences between effect sizes. Because each effect size is heterogeneous, the model used to calculate the combined effect size is a random effect model. The following are the results of the moderator variable analysis in this meta-analysis study.

TABLE 5. Moderator variable analysis results

Variable	Estimate	Lower bound	Upper bound	Std. error	p-Val
Overall	0.683	0.337	1.030	0.177	< 0.001
Learning Outcomes					
Actual Learning	0.847	0.376	1.318	0.240	< 0.001
Perceived Learning	0.354	-0.090	0.798	0.226	0.118
Satisfaction	0.284	-0.105	0.674	0.199	0.153
Subject					
English Language & Literature	0.231	-0.566	1.028	0.407	0.570
History	0.629	0.295	0.962	0.170	< 0.001
Mathematics	0.243	-0.536	1.023	0.398	0.541
Accounting	6.913	6.190	7.636	0.369	NA
Biology	0.711	0.545	0.876	0.084	< 0.001
Computer Science	0.610	0.469	0.751	0.072	< 0.001
Physiology	-0.037	-0.391	0.318	0.181	0.839
Education	0.030	-0.314	0.373	0.175	NA
Source					
Journal	0.767	0.324	1.209	0.226	< 0.001
Proceedings	0.324	-0.181	0.830	0.258	0.209
Country					
Turkey	0.525	0.196	0.853	0.168	0.002
Russia	-0.132	-0.324	0.061	0.098	NA
Malaysia	6.913	6.190	7.636	0.369	NA
Colombia	-0.279	-0.556	-0.002	0.141	NA
China	0.711	0.545	0.876	0.084	< 0.001
America	0.879	0.602	1.156	0.142	NA
Greece	0.610	0.469	0.751	0.072	< 0.001
Bangladesh	-0.037	-0.314	0.318	0.181	0.839
Australian	0.030	0.242	0.373	0.175	NA
Belgium	0.665	0.242	1.088	0.216	NA

The analysis of the moderator variable „learning outcomes“ was conducted by dividing it into three subgroups: actual learning, perceived learning, and satisfaction. Among these, actual learning showed the strongest effect size (g=0.847), indicating a high impact of MOOCs on students' measured academic performance. In contrast, perceived learning and satisfaction demonstrated lower effect sizes (g=0.354 and g=0.284, respectively), suggesting a more modest but still meaningful influence. These findings highlight that while MOOCs strongly enhance actual learning outcomes, they also contribute to learners' perceptions and satisfaction with the learning experience, albeit to a lesser extent.

The third step is to calculate the combined effect size from the experimental studies. Using OpenMEE software, a combined effect size of g=1.061 was obtained from k=26 study results. The lower bound (LBg) was 0.690, while the upper bound (Ubg) was 1.302. This combined effect size is classified as a moderate effect. Table 6 presents the summary of these combined effect size estimates. This combined effect size is classified as a moderate effect. Table 6 presents the results of this study's combined effect size estimates.

TABLE 6. Combined effect size using random effect

Effect Size (g)	Lower Bound	Upper Bound	Std. error	p-Value
1.061	0.745	1.378	0.162	<0,001

Next, the publication bias test is carried out to find out whether the data that has been collected can be used as a representative sample of the population or not. The analysis results show that the fail-safe N value is 1572 (α=0.05; p<0.001). The number of studies (k) is 19, so the value of 5k + 10 = 5(19) + 10 is 105. Because the fail-safe N is 1572 and is higher than the value of 5k + 10, it can be concluded that there is no publication bias in this meta-analysis.

DISCUSSION

What themes emerge from the study of MOOCs in higher education?

Using bibliometric analysis, we explored emerging themes related to MOOCs in higher education. Researchers collected various types of observable evidence to understand emerging themes related to studying MOOCs in higher education. Based on the exploration of thematic maps related to MOOCs in higher education, we can observe that educational innovation, learning motivation, e-learning, educational technology, and academic performance are the topics most widely discussed and relevant in the context of MOOCs. This research covers innovation in education, learning motivation, the use of technology, and academic outcomes. In the context of educational innovation, other research also highlights how using mobile technology and integrating MOOCs can improve student learning outcomes (Jouicha et al., 2022). Collaborative concepts in the context of Massive Open Online Courses (MOOCs) have been explored through the use of conversational pedagogical agents, which are AI-driven tools designed to facilitate interaction between students and instructors, as well as among peers, through natural language dialogue. These agents aim to enhance engagement and improve the learning experience in MOOCs (Caballé et al., 2021).

The Niche Themes quadrant, comprising challenge-based learning, instructional design frameworks, distance education, and self-determination theory, represents areas of unique but focused scholarly interest within the context of MOOCs in higher education. Studies in this cluster have proposed innovative frameworks for course redesign that positively affect learning outcomes. For example, the CMODE framework integrates challenge-based and modular education in MOOCs and has demonstrated improvements in student engagement and perceived course value (Mesutoğlu et al., 2021). The Emerging or Declining Themes quadrant, which includes collaborative learning and learning satisfaction, reflects evolving or waning research interest. Nonetheless, contributions in this area remain significant. Notably, the integration of conversational pedagogical agents in MOOCs has been shown to enhance learner interaction and satisfaction, particularly in remote and asynchronous learning environments.

The Basic Themes quadrant, comprising MOOCs, higher education, learning outcomes, COVID-19, deep learning, and machine learning, includes core topics that are highly relevant yet underdeveloped in terms of conceptual refinement. This quadrant offers rich opportunities for future research. Key areas include: enhancing the effectiveness of MOOCs through interactive and participatory teaching strategies; applying deep learning and machine learning to optimize content delivery, automated assessment, and personalized learning pathways; developing more accurate evaluation metrics to assess MOOCs learning outcomes; and integrating MOOCs into formal higher education curricula to expand access and quality.

Recent studies support the role of artificial intelligence in advancing MOOCs. For instance, deep learning models have been shown to improve learning engagement, adaptability, and personalization (Jiang & Ma, 2021). Similarly, machine learning approaches to student feedback analysis have produced promising results in optimizing course content and delivery (Edalati et al., 2022). These technologies enable systems to tailor learning materials based on user behavior, preferences, and performance, helping instructors and institutions refine teaching strategies. Predictive models based on learner data can further inform personalized interventions, improve retention, and ensure alignment with educational goals (Li et al., 2023; Mourdi et al., 2020; Tzeng et al., 2022).

What research focuses emerge from the study of MOOCs in higher education?

The co-occurrence analysis offers a clear overview of the key research focuses in the study of MOOCs in higher education. Frequently connected keywords include higher education, teaching, education, learning satisfaction, COVID-19, distance education, and student. These terms reflect sustained scholarly interest in the use of MOOCs to improve student outcomes through greater access to learning resources, time and location flexibility, and diverse instructional methods. During the COVID-19 pandemic, MOOCs emerged as a vital solution for ensuring educational continuity. Studies have shown that MOOCs facilitate distance learning, reduce access barriers, and support interaction in remote environments.

Additional keyword clusters include academic performance, blended learning, educational innovation, educational technology, motivation, SPOC, and student satisfaction. These themes underscore the multidimensional role of MOOCs in enhancing conceptual understanding, problem-solving, and analytical skills.

Motivation, both intrinsic and extrinsic, has also been shown to significantly influence student participation and performance, making it a critical consideration in MOOC design and management.

Several studies have focused on specific online learning platforms such as Coursera, examining their impact on learning effectiveness and student experience (Ho et al., 2022; Hoić-Božić & Dlab, 2023). Computational education also emerges as a significant theme, highlighting how digital tools can enrich learning experiences (Ruangvanich & Piriyasurawong, 2021). Effective interaction between learners and instructors remains essential for engagement and motivation in online environments (Brooker et al., 2018; Loh et al., 2024; Sun et al., 2019).

MOOCs represent one of the most expansive implementations of e-learning, enabling global access to high-quality educational content. Institutions can broaden their reach and visibility, while students benefit from materials offered by international experts. Emerging technologies such as deep learning and machine learning are increasingly used to develop adaptive and personalized learning systems (Al-Azazi & Ghurab, 2023; Delgado Algarra et al., 2024; Mourdi et al., 2020; Turan & Yilmaz, 2024). These technologies support tailored learning paths based on individual needs and capabilities. Future research should further explore the integration of advanced technologies in MOOCs to enhance learning effectiveness and student experience in higher education.

Based on reports from various studies sourced in this meta-analysis research, MOOCs are empirically proven to have a strong level of effectiveness on learning outcomes in higher education compared to non-MOOC learning. Studies show that MOOCs can provide comparable or even better learning outcomes than conventional learning (Yaşar & Polat, 2021; Zakaria et al., 2019), which we also found in our research (Figure 5, in this report). Another study explored using a blended classroom model that combines elements from MOOCs (Ren et al., 2022). They found that students who participated in the blended classroom model achieved higher academic performance than those who received traditional classroom instruction.

The study results also show that learning designs that consider student self-efficacy in MOOC learning can improve learning outcomes (Code et al., 2021). This research recommends that institutions adopt more flexible learning options, including online and blended learning options that give students choice and control in their learning experience. This will also help institutions be better prepared to face an educational future full of uncertainty. Nevertheless, it is essential to continue to develop and improve the design and implementation of MOOCs to be more effective in achieving learning goals in higher education. The integration of innovative technology, the development of relevant and exciting content, and good support for participants can be the key to the success of MOOCs in improving learning outcomes in higher education.

In our research, the analysis results of the moderator variable learning outcomes are divided into three subgroups of variables, namely actual learning and perceived learning and satisfaction. Based on the analysis results, actual learning has a more substantial effect size than perceived learning and satisfaction. This indicates the importance of increasing understanding and mastery of actual learning material in online learning experiences. Although perceived learning and satisfaction are also crucial for understanding student learning experiences, actual learning remains the core of practical learning goals. Therefore, these results provide valuable insights into which aspects should be focused on in designing and managing MOOCs to achieve optimal learning outcomes.

CONLUSSION

From the bibliometric analysis and meta-analysis results, MOOCs positively impact learning outcomes in higher education. Emerging themes in research on MOOCs include educational innovation, learning motivation, use of technology, and academic outcomes. The primary research focuses on developing effective learning strategies, integrating advanced technology in learning, and improving interactions between students and teachers in online learning environments. The moderator variable for learning outcomes shows that actual learning has a stronger effect than perceived learning and satisfaction. This emphasizes the importance of understanding and mastering the learning material in the online learning experience.

This study has two primary limitations. First, the data collection relied exclusively on the Scopus database, which may have resulted in the exclusion of relevant studies indexed in other databases such as Web of Science. Second, the search strategy was based on a predefined set of keywords, including synonyms for "MOOC" (e.g., "MOOCs," "Massive Open Online Courses"), "learning outcome" (e.g., "actual learning," "perceived learning," and "satisfaction"), and "higher education." As a result, studies that employed alternative terminology or addressed similar concepts using different labels may not have been identified and were therefore not included in the analysis.

Based on the findings, there are many suggestions for future research. First, research can be conducted to investigate the long-term effects of using MOOCs on students' learning outcomes, careers, and adaptability after graduation. Second, research could focus on identifying the most effective learning strategies in MOOCs, including using advanced technologies, challenge-based learning models, and MOOC integration. Third, further studies explore using MOOCs platforms such as Coursera, Udemy, and EdX in facilitating learning and improving student performance. We hope this research can empower researchers to understand the related literature on MOOC adoption in higher education from the learners' perspective and its directions and limitations.

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