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Indicators for enhancing learners' engagement in massive open online courses: A systematic review

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ABSTRACT

Massive open online courses (MOOCs) have paved a new learning path for the 21st-century world. The potential to reach a massive geographically dispersed audience is one of the major advantages of MOOCs. Moreover, they can be offered on a self-paced and self-regulated basis and have become an integral part of lifelong learning, especially in workplaces. However, one persistent problem is the lack of learners' engagement. A harmonisation of studies providing a holistic view into aggregating indicators for enhancing learners' engagement in MOOCs is lacking. The coronavirus pandemic has accelerated MOOC adoption, and learners' engagement in MOOCs has become even more essential for the success of this educational innovation. We examine the existing literature to derive indicators important for enhancing learners' engagement in MOOC learning environments. Using a systematic approach, 83 empirical studies were examined, and 10 indicators were identified as important considerations for enhancing learners' engagement while designing MOOCs—from initiatives for individual learners to platform and instructional design perspectives. We also present a table describing these indicators and offer a structured discussion on each one. We believe the results provide guidelines for MOOC designers and instructors, educational policymakers, higher education institutions, and MOOC engagement researchers.

1. Introduction

The twenty-first century has been characterised by significant advances in technological development permeating most spheres of life. Technologies influence how we live, interact, learn, and engage in activities. The advent of social media has also facilitated these advancements in technological developments. For example, learning now takes place in social environments fostered by social media platforms, and the increasing adoption of massive open online courses (MOOCs) is noteworthy. This is because MOOCs can be delivered to learners wherever they live, can be self-paced, and are self-regulated [7]. MOOCs are perceived as a strategic response to the United Nations' Sustainable Development Goal 4, which seeks to 'ensure inclusive and equitable quality education and promote lifelong learning opportunities for all' by 2030 ([117], p.1).

Despite the many benefits of MOOCs and their high adoption rate, this educational innovation still faces many challenges. The central problem – irrespective of a MOOC's pedagogical design and theory – is attrition or high dropout rates [37]. A key contributor to attrition is lack of learners' engagement but existing studies have not actually delved into what it means to make MOOC learning engaging.

Learners' engagement in MOOCs is difficult to define. Some view it as the time learners devote to course materials [15,68], others the time learners spend watching lecture videos, answering quizzes, submitting assignments, and participating in forum discussions [62,96,122]. This arises in particular because that engagement has four components: cognitive, behavioural, emotional (affective), and social [34]. The second school of thought argues that MOOC learning will become a passive activity if tracking learners' activities through clickstreams is all that is required [13,22]. Therefore, measuring learners' engagement in MOOCs is challenging because determining what is to be measured, and how, is difficult due to the multiple components and players that contribute to the online learning process: pedagogy, learners, instructors, teaching assistants, and the learning environment [103].

Based on the observations presented above, engagement is a means to an end regarding MOOC completion, not an end in itself. These insights make it clear that engagement requires full commitment or attention to the learning process, including the components and players

Abbreviation: MOOC(s): Massive Open Online Course(s)

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involved in the process. Our focus is to take a pragmatic approach and determine from the journal articles and conference papers reviewed indicators that have been used for learner's engagement in MOOCs. We will also attempt to offer a definition for active engagement in MOOCs learning environments based on the available evidence.

2. Learners' engagement in MOOCs

Many scholars have systematically examined the challenges associated with learners' engagement in MOOC learning environments. Henrie, Halverson, and Graham's [48] review examined the current approaches to measuring student engagement in technology-mediated learning, finding that quantitative self-report, qualitative measures, quantitative observational measures, and physiological sensors have been used. Similarly, Guajardo-Leal, Navarro-Corona, and González [45] systematically mapped academic engagement in MOOCs to identify and delineate the construct of academic engagement in MOOCs. Their results show the methodological perspectives, designs, and approaches and the types of instruments used, as well as emerging thematic trends in the study of academic engagement in MOOCs. Assami, Daoudi, and Ajhoun's [6] theoretical review identified seven personalisation criteria for enhancing learner engagement in MOOC platforms: personal expectation and learning motivation, preferences and needs, learning outcomes, learning cognitive style, level of knowledge, competence and experience, and pace of work. These criteria are assumed to reduce MOOC attrition via a recommender system. The authors described their proposed intervention as a content recommendation for adaptive learning in MOOCs. Khalid, Lundqvist, and Yates' [56] study on recommended techniques used in MOOCs showed that online thread recommender systems can increase engagement. Similarly, Wei, Saab, and Admiraal [108] revealed that learners' course engagement is measured in three ways: course content engagement, course assessment, and discussion forums.

Despite these scholarly contributions, the literature on learners' engagement in MOOCs still lacks harmonisation and existing systematic reviews on learners' engagement indicators in MOOCs are narrowly focused. Following analysis of the current literature, we decided a systematic review and synthesis of the literature is needed that highlights and harmonises the indicators for achieving learners' engagement in MOOCs and presents emerging issues to explore.

Systematic literature review is an efficient method to synthesise and examine existing knowledge and determine paths for future research [73,76]. This review identifies critical indicators for enhancing learners' engagement in MOOC environments based on studies conducted in the last decade. This will facilitate an overview of the discourse, highlighting indications and implications for the body of knowledge for future pedagogical engagement with MOOCs. We have raised the following research questions to review scholarly contributions on learners' engagement in MOOCs and highlight the indicators:

3. Methodology

We conducted a systematic review of the literature on learners' engagement in MOOCs following the procedure described in Fig. 1.

3.1. Method

A theoretical literature review 'draws on existing conceptual and empirical studies to provide a context for identifying, describing, and transforming into a higher order of theoretical structure and various concepts, constructs or relationships' ([76], p. 188). Its main goal is to extend the current knowledge regarding discourse, highlighting what is known and what still needs to be known [76]. Theoretical reviews frequently result in the development of conceptual frameworks or models that facilitate the discourse being inspected. DeLone and McLean's theoretical review is one good example and, based on our aim and this study's research questions, we followed their insights [33], especially as guides for building taxonomies of approaches for evaluating learners' engagement in MOOCs and the key issues for learners' engagement. Further, their study suggests systematic ways for structuring emerging themes and organising them into tables and provides guidance in building a conceptual model.

3.2. Guidelines for conducting the literature review

The research questions were based on three components for a review question's structure proposed by Kitchenham and Charters [59]:

(1) Population: learners enrolling for MOOCs.
(2) Intervention: empirical studies on learners' engagement in MOOCs, which lead to ways of enhancing engagement or fostering understanding of the discourse.
(3) Outcomes: type of evidence relating to MOOC learner engagement to identify engagement indicators.

We followed Cooper's [27] suggested guidelines to select studies[1] and extract relevant data based on our focus and aim. We collected relevant studies from 2010 to mid-June 2020, estimating that research on learners' engagement in MOOCs began from 2010, and choosing a decade as a suitable time frame.

Our inclusion and exclusion criteria are listed below.

3.2.1. Inclusion criteria

(1) Written in English.
(2) Empirical studies (full articles and papers, notes, extended abstracts, work-in-progress papers).
(3) Peer-reviewed studies.
(4) Strictly focused on MOOCs.
(5) Four-page minimum length.
(6) Explicitly focused on learners' engagement in MOOCs, thereby leading to ways of enhancing engagement or fostering understanding of the discourse.
(7) Published between 1st January 2010 and 15th June 2020.
(8) Must not contain replication of the same idea by the same author (s).
(9) Journal articles or papers included in conference proceedings.

3.2.2. Exclusion criteria

(1) Journal articles and conference papers making a similar contribution by the same authors.
(2) Journal articles and conference papers not written in English.
(3) Blog posts, magazine articles, theses, newsletters, and literature review articles or papers.

3.2.3. Search

We composed a search string—***engagement OR cognitive engagement OR behav* OR social engagement OR emotion* OR affect* AND moocs OR mooc OR 'massive open online courses' OR 'massive open online course' AND [Publication Date: (01/01/2010 TO 15/06/2020)]***—and applied it to each database presented in Table 2, searching titles and abstracts to find relevant articles.

The search was conducted from 18th May to 15th June 2020. Fig. 2 presents an overview of the process and the results.

3.2.4. Selection

Table 2 provides the details of the selection process and results.

[1] In the text, we refer to conference papers as 'papers' and journal articles as 'articles'.

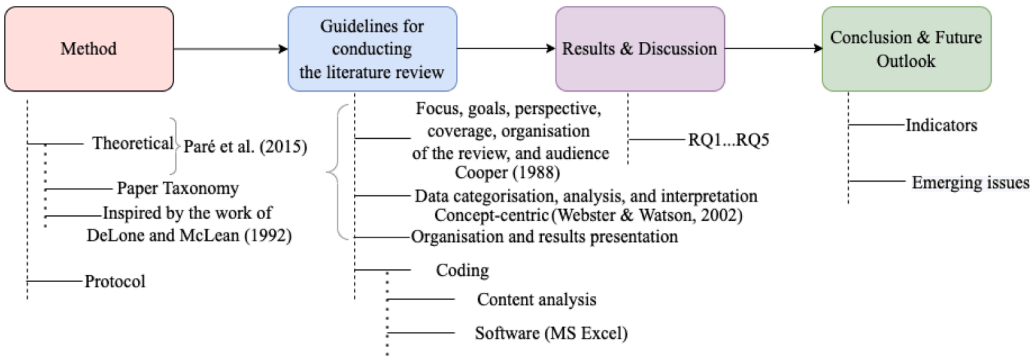

Fig. 1. . Methodological approach to the review [107].

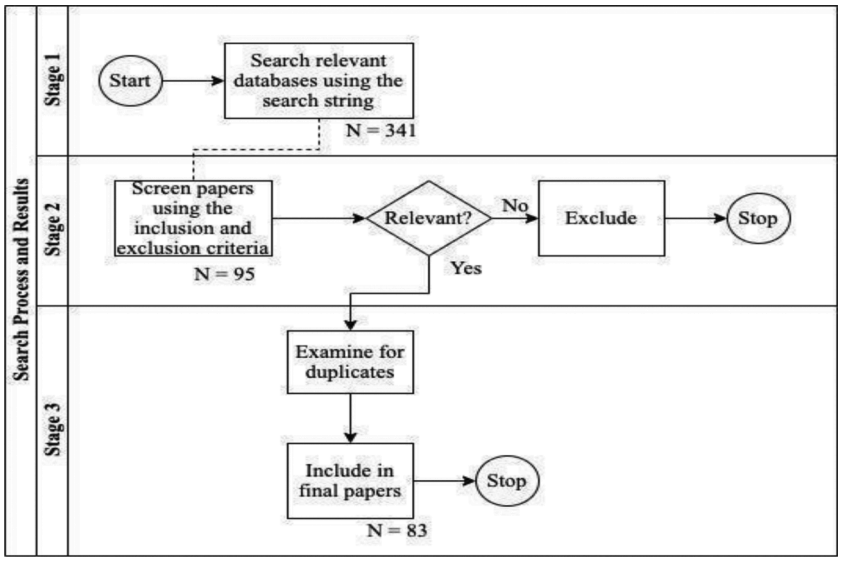

Fig. 2. Search process and results.

The search identified 341 studies. Eliminating duplicates and studies not meeting the inclusion criteria left 83 studies for the review. Google Scholar was selected as it is comprehensive, and we could retrieve more relevant studies than those deposited in our selected digital libraries. Twelve studies found through Google Scholar were also found in other databases (e.g. IEEE Xplore and Springer) and were excluded as duplicates.

3.2.5. Data synthesis and analysis

We created an MS Excel spreadsheet and collected extracts from all the studies, organised in rows and columns. Each row summarised the data extracted from each study. The columns described what data were being extracted, – title, author, year, article or paper type, and so on. To code the content, the three researchers read the articles and papers, keywording them according to the review goals (Table 1), after which we compared results and created themes. Discussion continued until a consensus was reached on the coding.

Table 1
Research questions and goals.

Research questions	Goals
RQ1. What research methods have been used to study learners' engagement in MOOCs?	To determine what research methods have been used to collect data and whether the methods are used retrospectively or concurrently.
RQ2. Which indicators have been investigated and found to enhance learners' engagement in the MOOC learning environment?	To identify and harmonise all existing indicators that enhance learners' engagement in MOOCs.
RQ3. What approaches have been used to determine learners' engagement in MOOCs?	To determine which techniques have been used to determine whether MOOC learners are engaged or not.
RQ4. What issues are associated with MOOC learning pedagogy?	To determine and describe which parts of the learning pedagogy in MOOCs have been most investigated and why.
RQ5. Which pedagogical tools offered by MOOC platforms are employed in an engaging MOOC environment?	To identify all possible pedagogical tools used in the design of MOOC implementation.

3.3. Demographic information about the studies

3.3.1. Year of publication and sources

Fig. 3A provides an overview of the studies collected from 1/1/2010 to 15/6/2020 and shows that the articles and papers included were published from 2013 to 2020. Our rationale for beginning the search in 2010 was that MOOCs were introduced in 2008, and we expected research on learners' engagement in MOOCs to have started slowly from 2010. Our findings justify our assumption because the relevant articles and papers date from 2013 onwards, and 2016 witnessed the highest number of articles and papers ($n = 22$) published and included in our study. Other results are: 2013 ($n = 1$), 2014 ($n = 8$), 2015 ($n = 10$), 2017 ($n = 11$), 2018 ($n = 12$), 2019 ($n = 9$), and 2020 ($n = 10$). Most of the included studies were conference papers ($n = 51$) (Fig. 3B), with 32 journal articles. This is not surprising, conferences being avenues for rapidly disseminating research results, including work-in-progress

Table 2
Details of the search process and results.

Databases or sources	Initial search	Screening by inclusion criteria	Duplicates excluded	Final result
ACM	87	36	0	36
Springer	44	10	0	10
IEEE Xplore	10	9	0	9
Taylor & Francis	4	3	0	3
Emerald Insight	5	0	0	0
Wiley Online	7	5	0	5
Elsevier	11	6	0	6
Google Scholar	173	26	12	14
Total Results	**341**	**95**	**12**	**83**

papers. Conferences also bring relevant stakeholders – researchers, practitioners, policymakers – together to share knowledge and recent findings and discuss their implications.

3.3.2. Sample sizes in studies

Regarding the investigated issues, articles and papers differed in their focus areas, so there is no common unit of analysis among the studies. Sixty-two studies used students as the unit of analysis, sample sizes ranging from five (smallest) to 320,000 (largest) students. The mean sample size was 14,603 students and the standard deviation was 45,132 students. The high standard deviation is due to the variation in the samples and the non-normal distribution. Seven studies did not specify their sample size and four used the word 'participants'; this comprised largely students, instructors, course designers, and teaching assistants. Six analysed forum messages, with sample sizes of 369, 1,002, 2,187, 3,864, 4,050, and 100,000, while two analysed learning activities retrieved from course data logs (sample sizes 18 and 56,800,000 learning activities). One study analysed data on 6.9 million video-watching sessions, another analysed data from nine courses.

4. Results

RQ1 What research methods have been used to study learners' engagement in MOOCs?

The breakdown of data collection methods used indicated the vast majority ($n = 65$) used a single method. Sixteen studies used two data collection methods and two used three data collection methods. Our analysis (see Fig. 4A) reveals eight methods were used to research learners' engagement in MOOCs. Four dominated: experiment ($n = 29$), case study ($n = 22$), mixed ($n = 19$), and survey ($n = 7$). Grouped by methodological approach, there were 39 quantitative studies, 25 qualitative studies, and 19 mixed-methods studies (of which eight used the experimental method in conjunction with other methods, Fig. 4B). One of the mixed-methods studies [93] used netnography to collect observation data from the course discussion forum.

RQ2 What indicators have been investigated and found to enhance learners' engagement in the MOOC learning environment?

Tables 3 (Appendix A) and 4 (Appendix B) depict the results of our examination of the existing literature on indicators for enhancing learners' engagement in MOOCs. Table 3 lists the 10 indicators found. First, we identified all the indicators, described them, and categorised them into types. Then, we classified all the indicators into broad measurement constructs. Input indicators are provisions that must be in place to implement an activity, and there are indicators based on the activity's process and outcomes [90]. Generally, indicators are said to be concise, observable, and measurable [19].

Table 4 presents a detailed analysis of the studies showing the

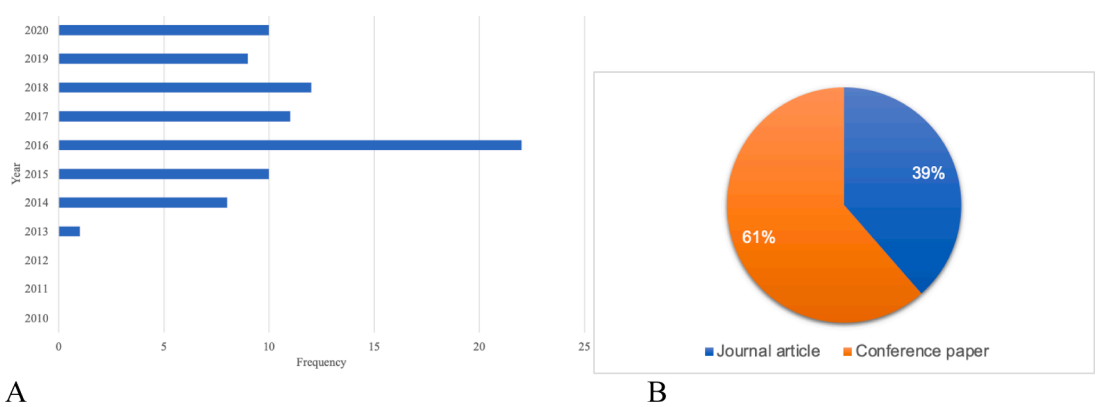

Fig. 3. Publication year (A) and source (B).

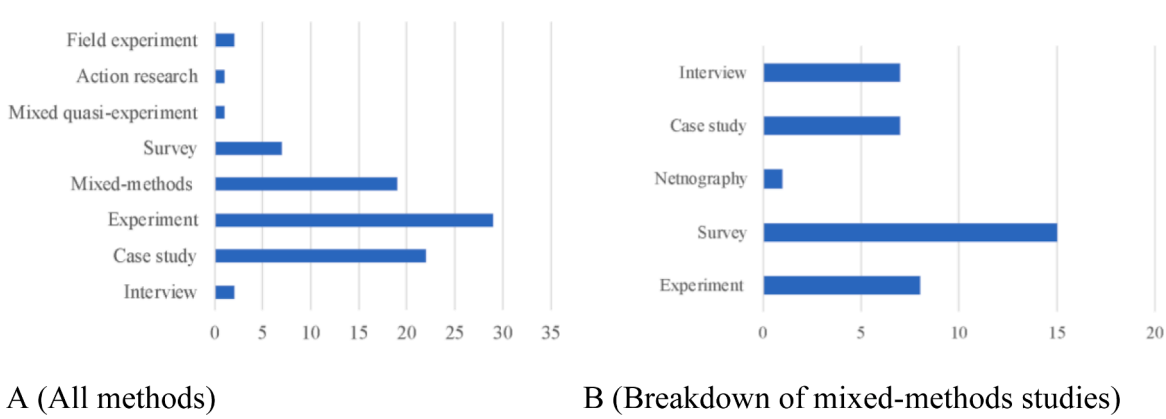

Fig. 4. Research methods used for MOOC engagement studies.

Table 3
Indicators for facilitating engagement in MOOC learning environments.

Indicators	Description	Measurement construct	Indicator type
Learner's personality	Learner's personality assessment (goals, needs, skills, character, cognitive capacity, IQ, expectations, cultural diversity, and motivation)	Learner's profile	**Input**
Engagement pattern	Learner's engagement pattern assessment (e.g., dual-layer (instructor-centred and learner-centred) courses, learning group size)		
Learning materials	Measuring the length of active viewing of the learning material (e.g., audio, video, gamified learning materials, slides, and transcripts). Effectiveness of third-party support tools.	Instructional design	**Process**
Instructor's feedback	Providing, for example, weekly course progress feedback to learners and their open questions. Instructor's adaptive learning guidance for at-risk students using relevant interventions.		
Learner's feedback	Asking for intermittent open feedback from learners		
Course duration	Deploying short- and medium-length courses per time; long courses could break into shorter courses		
Active Participation	Interactivity with peer learners and faculty members (instructors, teaching assistants) (e.g., via commenting in discussion forums and posts, and participation via social media channels)	Platform design	
	Interactivity with the learning materials (e.g., via commenting, bookmarking, annotating on videos, intext search, etc.) Gamifying the learning environment. Learner's reading behaviour.		
Attention loss detection	Cognitive and affective states detection (e.g., boredom, mind wandering, confusion, lack of social communication, and arousal) to provide timely feedback to instructors and intervention for the learners.	Engagement detection	
Performance	Performance assessment (e.g., via taking quizzes, coding exercises, and assignments). Best practices for formative and summative assessments	Active learning Outcomes	**Outcome**
Reward	Awarding digital badges and other gamification elements to stimulate motivation and offering course completion certificates		

indicators' distribution. The results show active participation is the most common indicator for enhancing learners' engagement in MOOCs, the top four being active participation ($n = 35$), learners' personality ($n = 15$), engagement pattern ($n = 10$), and learning materials ($n = 6$).

RQ3 What approaches have been used to determine learners' engagement in MOOCs?

Fig. 5 shows the taxonomy of approaches used. First, approaches are organised in three layers based on our findings, then broadly categorised in four ways (modelling, computer-based data, tools, and self-reporting; depicted in green) and further divided into sub-approaches (in yellow). Finally, we provide specific techniques used or descriptions of the same (in red). Table 5 (Appendix C) presents the results in detail. Computer-based data retrieval is the most commonly used technique ($n = 36$), followed by modelling ($n = 25$), data retrieval using a tool ($n = 12$), and self-reported data ($n = 10$). Overall, deep learning, shallow learning, cluster analysis, regression analysis (including logistic regression), correlation analysis, t-Distributed Stochastic Neighbour Embedding, global sensitivity analysis, visual and auditory cues, scripting in Python, and inter-rater reliability techniques such as Cohen's weighted kappa [25], were used by studies that employed modelling and computer-based data retrieval techniques for analysis ($n = 33$). The remaining results are presented in Table 5.

RQ4 What issues are associated with MOOC learning pedagogy?

We began by categorising all contextual issues covered in the studies into general course activities ($n = 39$), gamifying the learning space ($n = 8$), pedagogy and learning design ($n = 8$), lecture video ($n = 7$), discussion forum ($n = 15$), discussion forum and community assistance ($n = 1$), discussion forum and course social media use ($n = 1$), reading the course materials ($n = 1$), course quality and effectiveness ($n = 2$), and lecture video and discussion forum ($n = 1$) (see full results in Table 6, Appendix D). The results show self-regulated learning ($n = 2$), learning behaviour ($n = 6$), and motivation and engagement ($n = 3$) were some specific issues investigated in the general course activities category. Overall, learning engagement issues in MOOCs varied widely and the results suggest taking a broad perspective when attempting to investigate learners' engagement. Fig. 6 provides a taxonomy of key issues and highlights their central points.

RQ5 Which pedagogical tools offered by MOOC platforms are employed in an engaging MOOC environment?

Simply put, pedagogical tools are tools useful for teaching or learning [91]. We identified all possible pedagogical tools mentioned in each study and classified them as learning material, practising, assessment, communication/community sharing, and stimulator (see full results in Table 7, Appendix E). Discussion forum ($n = 65$) was the most commonly included tool in the MOOC learning environment, not surprising considering that MOOCs are self-regulated and presented via the web to geographically dispersed learners. The result implies communication/community sharing is crucial for successful MOOC learning and engagement. The remaining results showed video ($n = 62$) was the most widely used learning material in MOOC learning environments, assessment was mainly by quiz ($n = 46$), tutorial ($n = 7$) was the preferred mode for practising, and third-party tools (e.g. tutoring system and internet chat relay) ($n = 6$) and gamified mechanics ($n = 5$) were used to stimulate learning and engagement.

5. Discussion

Our findings offer a detailed look at learners' engagement in MOOCs and the indicators for enhancing it. We argue that active learning engagement includes the entire process, beginning when an individual enrols in a course, interacts with the learning materials and its contingencies, performs the required tasks, is assessed, and is deemed to have completed the course and rewarded in some manner. Four factors, all interdependent, are important to achieve the above: motivated learners, active learning activities, engaging pedagogical tools, and learning affordance. However, course completion as an outcome is not an indication that the learner has engaged with the course. The individual learners' goals are key to whether they complete the course, but contingencies such as pedagogical tools and the learning platform can drive motivation to complete the course.

To address our first goal, we extracted data from the included studies pertaining to their methods. Results showed studies of learners' engagement used varied methods, the experimental method being the most popular. Next most common were case studies and mixed-methods studies. Our results also confirm that the choice of research method is based on the kind of problem investigated [111]. Overall, 37 studies investigated issues relating to behavioural, affective, and cognitive components of engagement using the experimental method. All case studies were based on retrospective data collection, the remaining studies involved concurrent data collection. However, 10 studies that collected data by survey were post-course investigations.

Our second goal was to determine the critical indicators for investigating learners' engagement in MOOCs, based on documented evidence, and discover how these indicators are interrelated. We therefore categorised the indicators into input, process, and outcome using Scheerens et al.'s [90] classification. We defined process indicators as

Table 4
Learner's engagement indicators found in the literature.

Studies	Learner's engagement indicators									
	Learner's personality	Engagement pattern	Learning materials	Instructor's feedback	Learner's feedback	Course duration	Active Participation	Attention loss detection	Performance	Reward
Milligan et al. [69]	x									
Bonafini et al. [13]							x			
Labarthe et al. [63]							x			
Borrás-Gené et al. [14]							x			
Sharif and Guilland [93]										x
Sun and Bin [95]				x						
Cook et al. [26]							x			
Cassidy et al. [18]							x			
Crosslin et al. [29]		x								
Khalil et al. [58]				x						
Petronzi and Hadi [79]					x					
Zheng et al. [120]		x								
Ferguson and Clow [37]		x								
Chang and Wei [21]										x
Rodriguez et al. [85]						x				
Walji et al. [105]							x			
Lu et al. [68]				x						
Vaibhav and Gupta [104]							x			
Sunar et al. [97]							x			
Perez-Alvarez et al. [78]			x							
Dubbaka and Gopalan [36]								x		
Anutariya and Thongsuntia [4]						x				
Ramesh et al. [82]				x						
Kaveri et al. [55]							x			
Floratos et al. [40]									x	
Romero-Rodriguez et al. [86]										x
Jung and Lee [54]							x			
Li and Baker [66]		x								
Williams et al. [112]	x									
Phan et al. [80]		x								
Barak et al. [11]	x									
Gregori et al. [44]							x			
Gallego-Romero et al. [41]			x							
Lan and Hew [64]	x									
Alharbi et al. [2]			x							
Balasooriya et al. [9]					x					
Rizzardini and Amado-Salvatierra [83]	x									
Khalil and Ebner [57]		x								
Goldberg et al. [42]	x									
Rebecca Ferguson et al. [39]						x				
Antonaci et al. [3]							x			
Shi and Cristea [94]							x			

(continued on next page)

Table 4 (*continued*)

Studies	Learner's engagement indicators									
	Learner's personality	Engagement pattern	Learning materials	Instructor's feedback	Learner's feedback	Course duration	Active Participation	Attention loss detection	Performance	Reward
Lan and Hew [65]	x									
Ferguson and Clow [38]		x								
Baek and Shore [8]							x			
Crues et al. [30]							x			
Thornton et al. [101]			x							
Coffrin et al. [24]		x								
Bote-Lorenzo and Gómez-Sánchez [15]							x			
Guo et al. [46]			x							
Zhu et al. [121]							x			
Brunskill et al. [17]							x			
Hu et al. [51]							x			
Xiao and Wang [115]			x							
Wong et al. [114]	x									
Houston et al. [50]							x			
Schaffer et al. [89]	x									
Wen et al. [110]	x									
Wen and Rosé [109]	x									
Núñez et al. [72]	x									
Zheng et al. [118]							x			
Nelimarkka and Hellas [71]							x			
Appiah-Kubi and Rowland [5]							x			
Wise et al. [113].							x			
Chen et al. [22]							x			
Brady et al. [16]							x			
Huang et al. [53]							x			
Kizilcec et al. [60]	x									
Zheng et al. [119]	x									
Qiu et al. [81]							x			
Wang et al. [106]							x			
Romero et al. [87]	x									
Coetzee et al. [23]							x			
Davis et al. [31]							x			
Robal et al. [84]								x		
Thaker et al. [100]							x			
Xing et al. [116]								x		
Gong et al. [43]								x		
de Freitas et al. [32]							x			
Deng et al. [34]		x								
Deng et al. [35]		x								
Hew [49]							x			
Sun et al. [96]							x			
Total	15	10	06	04	02	03	35	04	01	03

the various actions taking place during the activity, broadly classifying them into instructional and platform design. Instructional design process indicators are course-based. In all, we found 10 indicators important to learners' engagement in MOOCs.

Further, our findings show that most indicators for MOOC learning engagement are process-related, others are input- and outcome-based. The predominant indicator is active participation – see Table 3 for detailed explanations about all 10 indicators. The indication regarding active participation is that interactivity with learning materials, peer learners, instructors, teaching assistants, and learning environments should be enhanced based on their pedagogical tools (lecture videos, forums, etc.). Participation in a MOOC can only occur virtually and through interaction with digitised learning materials and environments. Participation and interactions are keywords used when attempting to define engagement and they are interdependent.

Existing MOOC engagement studies indicate learners' participation manifests in two major ways: interactions in discussion forums by reading posts, commenting, and spearheading threads, and interactions with learning materials. Interaction with videos can be in the form of annotation and bookmarking. Notably, learners' engagement in MOOC

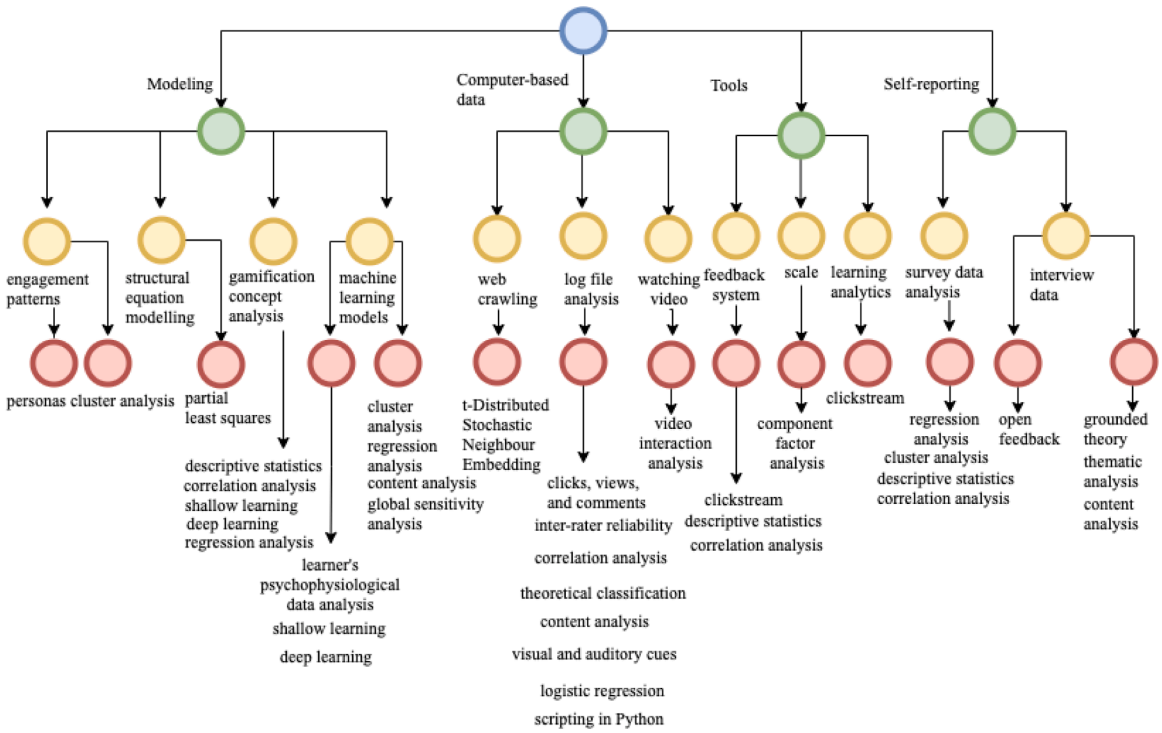

Fig. 5. Approaches used for evaluating learners' engagement in MOOCs. Regression and machine learning model techniques such as convolutional neural networks have been used to analyse facial expression data.

environments has four components – behavioural, cognitive, social, and affective. Learners' participation encompasses these four components. For example, forum discussion participation has been examined from social, cognitive, and behavioural perspectives. MOOCs suffer from passive participation and interaction rates in discussion forums [8]. Quality of posts [13], a reputation system that encourages learners to make useful posts [23], and leadership [97] are crucial for active participation in discussion forums. Bonafini et al. [13] found that MOOC learners' posts in forums are more concerned with acquiring information than engaging in critical thinking. The quality of the learners' posts in forum discussions contributes to learning achievements. Furthermore, active participation and performance are positively correlated [8]. The implication of the correlation between active participation and performance is that individuals seek ways to raise their performance when motivated and deeply engaged [98]. Additionally, video is a predominant pedagogical tool in terms of interactions with learning materials in MOOC environments. High-quality videos are imperative for fostering learners' interaction [44,115] but not sufficient for course completion [13]. Nevertheless, learners' participation increased as MOOC offerings progressed [44].

Summarising the discourse on learners' participation, Bonafini et al. [13] recommend that MOOC designers and instructors design forum discussions so that learners can exhibit critical thinking using relevant interaction prompts to foster sharing of complex concepts learned in courses. This is consistent with Bali [[10], p. 51], who argues that we should consider 'how to develop higher-order thinking and deep learning approaches to MOOCs'. However, participation in forum discussions is also based on the philosophical foundation of the MOOC design, for example, xMOOC (based on cognitive-behaviourist, social constructivism), sMOOC (based on social constructivism only), and cMOOC (based on connectivism pedagogy). Although a study has explored the use of commenting on course videos ([99], cited in Ogunyemi et al. [74]), other innovative interactive gestures – intext search of video transcripts – in MOOCs are scarce. This is why Bonafini et al. [13] recommend the use of interactive videos with features such as segmenting and inserting probing questions to promote students' engagement with videos.

Considering the discourse on process indicators, we can postulate that instructional and platform designs correlate positively. Overall, our findings regarding interaction with course materials and instructors are consistent with Li, Johnson, Aarhus, and Shah's [67] recent study, showing course design and materials are important for learners seeking knowledge and good instructors are important for ensuring successful skill-based learning in MOOCs.

As seen in Table 3, *learners' personality assessment* includes assessments of their goals, needs, expectations, cognitive capability, motivation, and cultural diversity. These assessments are important for addressing learners' heterogeneous nature, especially MOOC learners, in which context Costa and McCrae's [28] Big 5 model of the dominant personality traits – extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience – is especially useful. There is also growing interest in whether learners' personality traits are correlated with their intention to continue using [1] or complete [47] a MOOC. For example, Gupta [47] found a significant link between personality traits and learner's intention to complete a MOOC. These studies might indicate interesting trends for future researchers. Similarly, studies have indicated a relationship between learners' engagement patterns and intention to complete a MOOC. Evaluation of such patterns can help us understand their motivation for enrolling in MOOCs. Although there are no conventional or universally agreed upon descriptions for *engagement patterns*, we found common patterns in the literature reviewed. Examples include 'Samplers, Strong Starters, Returners, Midway Dropouts, Nearly There, Late Completers and Keen Completers' [39], 'Active, Passive, Observer, Drop-in' [79], and 'Active Participation, Passive Participation, Lurking' [69]. However, irrespective of the description, engagement patterns can be broadly grouped into three categories: observers (or lurkers, samplers), passive participants (nearly there), and active participants (keen completers). Observers usually have no intention to enrol. As the description implies, they are usually auditing or sampling courses and have no intention to start one. Passive participants usually start a course but do not complete it, while active participants are enthusiastic about completing the

Table 5
Approaches used to evaluate learner's engagement in MOOCs.

Studies	Evaluation approach category	Evaluation approach sub category	Techniques/ description of techniques used
Milligan et al. [69]	Modelling	Engagement pattern	Cluster analysis
Labarthe et al. [63]	Modelling	Engagement pattern	Cluster analysis
Zheng et al. [120]	Modelling	Engagement pattern	Cluster analysis
Rebecca Ferguson et al. [39]	Modelling	Engagement pattern	Cluster analysis
Shi and Cristea [94]	Modelling	Engagement pattern	Cluster analysis
Ferguson and Clow [38]	Modelling	Engagement pattern	Cluster analysis
Deng et al. [35]	Modelling	Engagement pattern	Cluster analysis
Cook et al. [26]	Modelling	Engagement pattern	Personas
Sun and Bin [95]	Modelling	Structural equation modelling	Partial least square
Kaveri et al. [55]	Modelling	Structural equation modelling	Partial least square
Jung and Lee [54]	Modelling	Structural equation modelling	Partial least square
Sun et al. [96]	Modelling	Structural equation modelling	Partial least square
Chang and Wei [21]	Modelling	Gamification concept analysis	Descriptive statistics
Vaibhav and Gupta [104]	Modelling	Gamification concept analysis	Descriptive statistics
Romero-Rodriguez et al. [86]	Modelling	Gamification concept analysis	Descriptive statistics
Alharbi et al. [2]	Modelling	Gamification concept analysis	Shallow learning, deep learning
Antonaci et al. [3]	Modelling	Gamification concept analysis	Regression analysis, correlation analysis
Dubbaka and Gopalan [36]	Modelling	Machine learning model	Deep learning
Xing et al. [116]	Modelling	Machine learning model	Deep learning
Xiao and Wang [115]	Modelling	Machine learning model	Deep learning
Anutariya and Thongsuntia [4]	Modelling	Machine learning model	Cluster analysis
Ramesh et al. [82]	Modelling	Machine learning model	Regression analysis
Gong et al. [43]	Modelling	Machine learning model	Regression analysis
Bote-Lorenzo and Gómez-Sánchez [15]	Modelling	Machine learning model	Regression analysis
Gregori et al. [44]	Modelling	Machine learning model	Global sensitivity analysis, content analysis
Khalil et al. [58]	Tools	Learning analytics	Clickstream
Ferguson and Clow [37]	Tools	Learning analytics	Clickstream
Rodriguez et al. [85]	Tools	Learning analytics	Clickstream
Walji et al. [105]	Tools	Learning analytics	Clickstream
Lu et al. [68]	Tools	Learning analytics	Clickstream
Phan et al. [80]	Tools	Learning analytics	Clickstream
Coffrin et al. [24]	Tools	Learning analytics	Clickstream
Khalil and Ebner [57]	Tools	Learning analytics	Clickstream
Davis et al. [31]	Tools	Feedback system	Clickstream
Romero et al. [87]	Tools	Feedback system	Descriptive statistics
Coetzee et al. [23]	Tools	Feedback system	Correlation analysis

Table 5 (*continued*)

Studies	Evaluation approach category	Evaluation approach sub category	Techniques/ description of techniques used
Deng et al. [34]	Tools	Scale	Component factor analysis
Wen et al. [110]	Computer-based data	Log file analysis	Logistic regression
Thaker et al. [100]	Computer-based data	Log file analysis	Logistic regression
Zhu et al. [121]	Computer-based data	Log file analysis	Logistic regression
Qiu et al. [81]	Computer-based data	Log file analysis	Logistic regression
Wang et al. [106]	Computer-based data	Log file analysis	Logistic regression
Crues et al. [30]	Computer-based data	Log file analysis	Logistic regression
Bonafini et al. [13]	Computer-based data	Watching video	Logistic regression
Wise et al. [113].	Computer-based data	Log file analysis	Theoretical classification
Brady et al. [16]	Computer-based data	Log file analysis	Theoretical classification
Houston et al. [50]	Computer-based data	Log file analysis	Theoretical classification
Wong et al. [114]	Computer-based data	Log file analysis	Theoretical classification
Goldberg et al. [42]	Computer-based data	Log file analysis	Clicks, views and comments
Rizzardini and Amado-Salvatierra [83]	Computer-based data	Log file analysis	Clicks, views and comments
de Freitas et al. [32]	Computer-based data	Log file analysis	Clicks, views and comments
Brunskill et al. [17]	Computer-based data	Log file analysis	Clicks, views and comments
Wen and Rosé [109]	Computer-based data	Log file analysis	Clicks, views and comments
Hew [49]	Computer-based data	Log file analysis	Clicks, views and comments
Borrás-Gené et al. [14]	Computer-based data	Log file analysis	Clicks, views and comments
Cassidy et al. [18]	Computer-based data	Log file analysis	Clicks, views and comments
Crosslin et al. [29]	Computer-based data	Log file analysis	Clicks, views and comments
Sunar et al. [97]	Computer-based data	Log file analysis	Clicks, views and comments
Perez-Alvarez et al. [78]	Computer-based data	Log file analysis	Clicks, views and comments
Floratos et al. [40]	Computer-based data	Log file analysis	Clicks, views and comments
Baek and Shore [8]	Computer-based data	Log file analysis	Clicks, views and comments
Zheng et al. [118]	Computer-based data, self-reporting	Log file analysis, web crawling interview data	Clickstream, thematic analysis
Schaffer et al. [89]	Computer-based data	Log file analysis	Correlation analysis
Huang et al. [53]	Computer-based data	Log file analysis	Correlation analysis
Williams et al. [112]	Computer-based data	Log file analysis and survey data analysis	Regression analysis
Li and Baker [66]	Computer-based data	Log file analysis	Regression analysis
Gallego-Romero et al. [41]	Computer-based data	Log file analysis	Scripting in Python
Hu et al. [51]	Computer-based data	Log file analysis	Inter-rater reliability
Appiah-Kubi and Rowland [5]	Computer-based data	Log file analysis	Content analysis
Guo et al. [46]	Computer-based data	Watching video	Video interaction analysis
Thornton et al. [101]	Computer-based data	Watching video	Video interaction analysis

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Table 5 (*continued*)

Studies	Evaluation approach category	Evaluation approach sub category	Techniques/ description of techniques used
Robal et al. [84]	Computer-based data	Log file analysis	Visual and auditory cues
Chen et al. [22]	Computer-based data	Web crawling	t-Distributed Stochastic Neighbour Embedding
Balasooriya et al. [9]	Self-reporting	Survey data analysis	Descriptive statistics
Núñez et al. [72]	Self-reporting	Survey data analysis	Descriptive statistics
Nelimarkka and Hellas [71]	Self-reporting	Survey data analysis	Cluster analysis
Sharif and Guilland [93]	Self-reporting	Survey data analysis and interview data	Open feedback
Petronzi and Hadi [79]	Self-reporting	Survey data analysis	Open feedback
Lan and Hew [64]	Self-reporting	Interview data	Content analysis
Lan and Hew [65]	Self-reporting	Survey data analysis	Regression analysis
Kizilcec et al. [60]	Self-reporting	Survey data analysis	Regression analysis
Zheng et al. [119]	Self-reporting	Interview data	Grounded theory
Barak et al. [11]	Self-reporting	Survey data analysis and interview data	Correlation analysis, content analysis

course. Although both learners' personality traits and patterns of engagement in MOOCs are associated with intention to complete the course, a participant's pattern of engagement is not inherent to their personality traits but simply a reflection of one's behaviour in a MOOC learning experience.

Learning materials, feedback mechanisms from both learners and instructors, and course duration should be factored into the process for designing the instructions. These indications were conspicuous in the studies reviewed. Videos are perhaps the most used learning materials in MOOCs. They are pre-recorded, and learners can watch them at their own pace. Some studies indicate that the time spent watching instructional videos determines how engaged learners are with the learning materials: Bonafini et al. [13] used binomial logistic regression models to examine how long MOOC learners engaged with videos and forum posts and assessed how this can predict their learning achievements. Video length is an important aspect of MOOC instructional design as shorter videos tend to increase learners' engagement [46,88]. These findings are congruent with Crosslin, Dellinger, Joksimovic, Kovanovic, and Gasevic's [29] study, which indicate that learners are considered active if they watch the instructional video and post it in a forum during each week of the course. Future researchers might therefore investigate novel ways of making lecture videos interactive and engaging.

Learners' feedback is another integral issue for successfully designing an engaging MOOC. Eliciting learners' feedback helps understand their intrinsic motivation and emotional responses [18]. Furthermore, learners can provide feedback to inform course instructors whether their goals have been met [79], indicate their learning preferences [55], and improve learning [40]. Learners' feedback is mainly established by self-reporting approaches using survey and interview methods, though feedback can also be computer-generated or mediated. For example, feedback on course assignments can use an automatic feedback system [20]. Automatic feedback can be delivered synchronously or asynchronously, or feedback can be processed asynchronously by human agents such as course instructors [52]. Thus, learners' and *instructors' feedback* can be synchronous, asynchronous, or both. While learners provide feedback to convey their experience and expectations, instructors convey feedback to facilitate course progress and stimulate learners'

Table 6
Issues investigated in studies.

Studies	Issue category	Contextual issues
Milligan et al. [69]	General course activities	Self-regulated learning
Lan and Hew [64]	General course activities	Self-regulated learning
Cook et al. [26]	General course activities	Self-assessment for learners
Zheng et al. [120]	General course activities	Small learning groups
Williams et al. [112]	General course activities	Student characteristics and goals
Shi and Cristea [94]	General course activities	Social behaviour
Kizilcec et al. [60]	General course activities	Social identity threat
Davis et al. [31]	General course activities	Social comparison clues
Sun and Bin [95]	General course activities	Learning behaviour
Ramesh et al. [82]	General course activities	Learning behaviour
Kaveri et al. [55]	General course activities	Learning behaviour
Bote-Lorenzo and Gómez-Sánchez [15]	General course activities	Learning behaviour
Qiu et al. [81]	General course activities	Learning behaviour
Khalil and Ebner [57]	General course activities	Learning behaviour
Gallego-Romero et al. [41]	General course activities	Learning by doing
Phan et al. [80]	General course activities	Learner's previous subject knowledge
Barak et al. [11]	General course activities	Learner's personality
Gregori et al. [44]	General course activities	Learner's support strategies
Goldberg et al. [42]	General course activities	Learner's level of education
Jung and Lee [54]	General course activities	Learner, instructor, and the learning environment
Deng et al. [35]	General course activities	Learner factors, teaching context, and engagement patterns
Wen and Rosé [109]	General course activities	Latent study habits
Crosslin et al. [29]	General course activities	Dual layer educational framework
Lu et al. [68]	General course activities	Detecting at-risk students
Floratos et al. [40]	General course activities	Formative assessment and feedback practice
Balasooriya et al. [9]	General course activities	Continuous engagement assessment
Rizzardini and Amado-Salvatierra [83]	General course activities	Continuous follow-up mechanism for learners
Lan and Hew [65]	General course activities	Motivation and engagement
Hew [49]	General course activities	Motivation and engagement
Sun et al. [96]	General course activities	Motivation and engagement
Zheng et al. [119]	General course activities	Motivation and retention
Romero et al. [87]	General course activities	Avoiding procrastination
Xing et al. [116]	General course activities	Affective state detection
Petronzi and Hadi [79]	General course activities	Open feedback from learners
de Freitas et al. [32]	General course activities	Quality and retention
Deng et al. [34]	General course activities	Quality and engagement

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Table 6 (*continued*)

Studies	Issue category	Contextual issues
Brunskill et al. [17]	General course activities	Impact of choice on unsupported learners
Wen et al. [110]	General course activities	Watching video, working on course problems, accessing course modules, participating in forum discussions
Cassidy et al. [18]	General course activities	Workload, task design and level of and nature of facilitation
Borrás-Gené et al. [14]	Gamifying the learning space	Incorporating fun and motivation
Sharif and Guilland [93]	Gamifying the learning space	Service design and gamification
Khalil et al. [58]	Gamifying the learning space	Gamified weekly feedback
Chang and Wei [21]	Gamifying the learning space	Meeting learning objectives
Vaibhav and Gupta [104]	Gamifying the learning space	Retention
Romero-Rodriguez et al. [86]	Gamifying the learning space	Learners' interest and motivation
Alharbi et al. [2]	Gamifying the learning space	Learner's support strategies
Antonaci et al. [3]	Gamifying the learning space	Social presence and sense of community
Ferguson and Clow [37]	Pedagogy and learning design	Learning behaviour
Ferguson and Clow [38]	Pedagogy and learning design	Learning behaviour
Rodriguez et al. [85]	Pedagogy and learning design	Short length MOOCs
Walji et al. [105]	Pedagogy and learning design	Tools and pedagogical affordances
Perez-Alvarez et al. [78]	Pedagogy and learning design	Self-regulated learning and third-party support tool
Anutariya and Thongsuntia [4]	Pedagogy and learning design	Structuring the course length
Ferguson et al. [39]	Pedagogy and learning design	Short and full-length MOOC offering
Coffrin et al. [24]	Pedagogy and learning design	Students' learning process
Dubbaka and Gopalan [36]	Lecture video	Detecting learner's emotions
Li and Baker [66]	Lecture video	Heterogeneous learners
Thornton et al. [101]	Lecture video	Learners' video watching behaviour
Guo et al. [46]	Lecture video	Video production analysis
Xiao and Wang [115]	Lecture video	Intelligent tutoring system
Robal et al. [84]	Lecture video	Privacy-aware system
Gong et al. [43]	Lecture video	Affective state detection
Bonafini et al. [13]	Lecture video and discussion forum	Participation behaviour
Labarthe et al. [63]	Discussion forum	Social learning
Zhu et al. [121]	Discussion forum	Social interaction
Baek and Shore [8]	Discussion forum	Social interaction
Houston et al. [50]	Discussion forum	Social interaction
Sunar et al. [97]	Discussion forum	Social behaviour
Wise et al. [113].	Discussion forum	Social learning networks
Appiah-Kubi and Rowland [5]	Discussion forum	Social presence and peer support
Huang et al. [53]	Discussion forum	Super-poster behaviour
Hu et al. [51]	Discussion forum	Structuring discussion forum
Crues et al. [30]	Discussion forum	Learning behaviour
Schaffer et al. [89]	Discussion forum	Learning behaviour
Wong et al. [114]	Discussion forum	Cognitive learning
Nelimarkka and Hellas [71]	Discussion forum	Internet Relay Chat
Wang et al. [106]	Discussion forum	Higher order thinking
Coetzee et al. [23]	Discussion forum	Reputation points award
Brady et al. [16]	Discussion forum and community assistance	Social incentive and motivation
Zheng et al. [118]	Discussion forum and course social media use	Course social media groups activities
Thaker et al. [100]	Reading the course materials	Reading behaviour
Núñez et al. [72]	Course quality and effectiveness	Community learning
Chen et al. [22]	Course quality and effectiveness	Learning via social media

motivation. Instructors' feedback should be prompt and personalised for online course learners [31,49]. These principles were demonstrated by Khalil, Ebner, and Admiraal's (2017) study, where gamified mechanics were used to provide feedback to students regarding their weekly course activity and stimulate their intrinsic and extrinsic motivation. Furthermore, gamified mechanics and identification of learners' reading patterns [100] can help provide timely, lag-free feedback to learners based on their interactions [86]. Instructors' feedback also manifests when instructors or their teaching assistants respond to learners' questions or comment on posts in discussion forums [54].

Overall, the implication regarding learners' and instructors' feedback is that it is not a straightjacket process. MOOCs differ concerning the goals of their deployments. While the results discussed here can be beneficial for monitored MOOCs, especially those offered by universities to a well-defined learner population, the results differ for unmonitored MOOCs. Nevertheless, gamified mechanics help provide feedback to learners about the course progress, whether the course is monitored or not.

Learners' engagement detection is a feedback mechanism for ensuring learners continue to engage with the learning process. Therefore, we argue that engagement detection is a moderating construct in achieving active learning engagement. Engagement detection in the reviewed studies varied from facial expression recognition to emotional state detection. Webcams are a simple way of determining learners' facial expressions while watching course videos [36,43] and determining attention loss in real time [84] to refocus their attention on the course video. Factors contributing to attention loss in virtual learning environments include mental fatigue [43], isolation [63], and the passive nature of video watching [84]. A lab experiment used music clips to stimulate learners' arousal and valence states and detect their emotions [116]. Course instructors receive the feedback from learners' engagement detection. Engagement detection can moderate the path relationships between instructional design and platform design, learners' profiles and platform design, and between platform design and active learning engagement. The conceptual model is presented in Fig. 7.

Our closing remark regarding engagement detection is the same as for learners' and instructors' feedback: instructional designers should consider that factors such as mental fatigue and non-interactive videos contribute to disengagement.

Course duration is an essential component of instructional design. The literature on whether shorter MOOCs provide more engagement for learners than longer ones is scarce. We only found three studies that explicitly explored this topic and scholars' views on this issue are not aligned. The question regarding course duration was raised by Rodriguez, Armellini, and Nieto [85], who found that learners engaged more in a six-week modularised course divided into two three-week courses than when they had to complete the entire course in one go, adding that condensing long courses into shorter courses, as opposed to merely dividing them, is a more effective pedagogical design approach. However, other studies indicate that offering short courses does not guarantee learners' engagement [34,39]. Ferguson et al. [39] established a correlation between engagement patterns and course duration, finding that learners engaged more in the first three weeks of an eight-week course than in a three-week course, and recommending that decisions about whether courses should be short or long be based on prior understanding of learners' engagement patterns. These findings are further

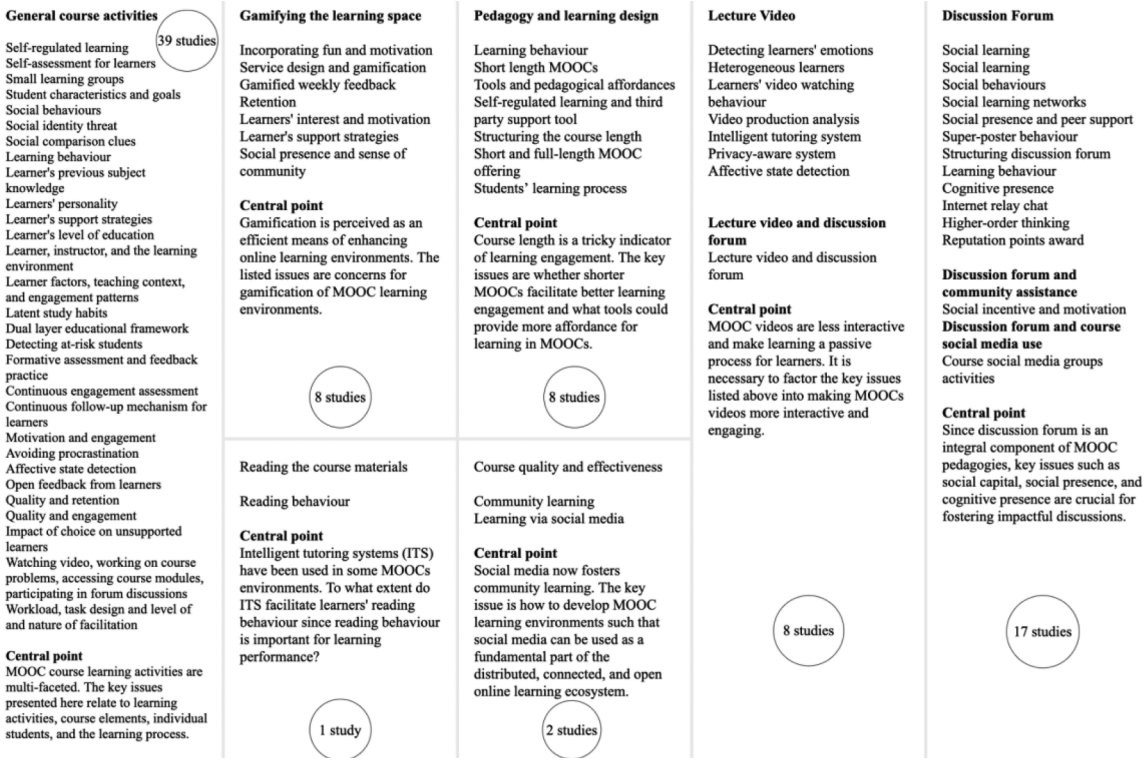

Fig. 6. Taxonomy of learning engagement issues in MOOCs.

exemplified in Anutariya and Thongsuntia's [4] study showing that short- to medium-length courses contribute to good performance and engagement. The monotony of long MOOCs and the mediation of traditional teacher-student interaction by technologies contribute to increased dropout rates [86]. Although we cannot claim that shorter MOOCs are more engaging, we argue that MOOCs benefit from being short- to medium-length courses. This is consistent with studies showing that MOOC learners engage more in the first few weeks of a course [29, 75].

Scheerens et al. [90] divide outcome indicators into output, outcome, and impact indicators. The output indicator is the direct outcome of the learning process, usually measured by standardised achievement tests. Using these descriptions and our findings from the reviewed studies, we define outcome indicators as the tangible evidence that the activity has occurred. For our current discourse, the actions are not measured at the end of the activity but throughout the process. We found that outcomes are measured through performance assessments in the form of taking quizzes, coding exercises, and assignments depending on the course. Furthermore, evidence of the activity achievement or outcome is rewarded through digital progress badges and course completion certificates to stimulate motivation. If completion certificates must be paid for and learners cannot afford this, free digital course completion badges can be awarded. MOOC *rewards* evident in existing studies include digital gamified achievement badges, redeemable points, virtual goods, leadership boards, trophies, reputation, and course completion certificates. These provide enjoyment and motivation for learners, who can also display their learning achievements on their social media pages [14,21,93,104]. Bonafini et al. [13] found that the learner's intention to achieve certification is a key driver of active participation – by watching videos – thereby enhancing their course achievement. Learners' engagement cannot be directly measured from isolated data [82].

Regarding our third goal, our findings show that there is no 'silver bullet' for evaluating learners' engagement in MOOC environments. The reviewed studies indicated that various approaches and interventions have been used, mainly based on the engagement component being investigated and the specific associated problem. As one of the studies argued, it is difficult to measure actual engagement 'without direct observation and questioning, which is infeasible at scale' ([46], p. 43). The following summarises approaches for improving learners' engagement in MOOC learning environments:

- Identification of patterns of engagement to deploy interventions addressing specific clusters of learners' attributes.
- Exploration of interventions using gamification concepts to stimulate learners' motivation and make learning enjoyable.
- Detection of instances where learners feel isolated, bored, distracted, or prone to procrastination, and deployment of interventions to nudge learners to refocus their attention or overcome procrastination through a real-time notification system.
- Solicitation of learners' feedback to determine whether goals and expectations are being met.
- Use of tools such as learning analytics, feedback systems, and measurement scales to determine learners' engagement with the learning materials and other components of the learning system and environment and nudge the learner by providing instant feedback and ensuring alertness.

Regarding our fourth goal, the insights that can be drawn from the results regarding pedagogical issues with MOOCs are broadly threefold: pedagogical design of MOOCs, gamifying the learning space, and learners' social interactivity. Regarding pedagogical design, the overarching issues are self-regulated learning and course learning materials such as videos. By their nature, MOOCs are offered on a self-regulated basis; thus, learners have to manage their time and study. However, learners' heterogeneous nature and their previous knowledge play key roles in their self-regulation of MOOC learning [72,80]. Prior knowledge brought into a course seems to contribute to better learning engagement and performance. This is a key issue course designers need to understand about MOOC learners' heterogeneous nature. The dual-layer framework

Table 7
Pedagogical tools.

Studies	Pedagogical tools															
	Learning material			Practicing		Assessment			Communication/community sharing						Stimulator	
	video	note	textbook	tutorials	coding board	assignment	quiz	exam	discussion forum	survey	social media	blog	leaderboard	email	gamified mechanics	third-party tool (e.g., tutoring system)
Milligan et al. [69].									x							
Bonafini et al. [13]	x								x							
Labarthe et al. [63]									x							
Borrás-Gené et al. [14]									x							
Sharif and Guilland [93]															x	
Sun and Bin [95]																
Cook et al. [26]									x							
Cassidy et al. [18]									x							
Crosslin et al. [29]	x					x										
Khalil et al. [58]							x		x							
Petronzi and Hadi [79]									x							
Zheng et al. [120]									x							
Ferguson and Clow [37]									x							
Chang and Wei [21]															x	
Rodriguez et al. [85]	x					x										
Walji et al. [105]									x							
Lu et al. [68]	x					x										
Vaibhav and Gupta [104]															x	
Sunar et al. [97]									x							
Perez-Alvarez et al. [78]	x	x					x									x
Dubbaka and Gopalan [36]	x															
Anutariya and Thongsuntia [4]	x						x		x							
Ramesh et al. [82]	x					x	x		x							
Kaveri et al. [55]	x					x	x		x							
Floratos et al. [40]	x					x	x		x							
Romero-Rodriguez et al. [86]															x	
Jung and Lee [54]	x					x	x		x							
Li and Baker [66]	x					x	x		x							
Williams et al. [112]						x	x									
Phan et al. [80]	x					x	x		x							
Barak et al. [11]	x					x	x		x							
Gregori et al. [44]	x					x	x		x							
Gallego-Romero et al. [41]	x				x	x	x		x							
Lan and Hew [64]	x					x	x		x							
Alharbi et al. [2]	x					x										
Balasooriya et al. [9]	x					x			x							
Rizzardini and Amado-Salvatierra [83]	x								x			x		x		
Khalil and Ebner [57]	x					x	x		x							
Goldberg et al. [42]	x						x		x		x	x		x		
Rebecca Ferguson et al. [39]	x					x			x					x		
Antonaci et al. [3]	x	x							x						x	
Shi and Cristea [94]	x						x		x							
Lan and Hew [65]	x					x	x		x							
Ferguson and Clow [38]	x					x			x					x		
Baek and Shore [8]	x					x	x		x					x		
Crues et al. [30]	x					x	x		x							

(*continued on next page*)

Table 7 (*continued*)

Studies	Pedagogical tools															
	Learning material			Practicing		Assessment			Communication/community sharing						Stimulator	
	video	note	textbook	tutorials	coding board	assignment	quiz	exam	discussion forum	survey	social media	blog	leaderboard	email	gamified mechanics	third-party tool (e.g., tutoring system)
Thornton et al. [101]	x								x							
Coffrin et al. [24]	x					x	x		x				x			
Bote-Lorenzo and Gómez-Sánchez [15]	x			x		x	x		x							
Guo et al. [46]	x			x					x							
Zhu et al. [121]	x					x	x		x							
Brunskill et al. [17]	x					x	x									
Hu et al. [51]	x	x	x						x							
Xiao and Wang [115]	x			x			x		x							
Wong et al. [114]	x					x	x		x							
Houston et al. [50]						x			x					x		
Schaffer et al. [89]	x					x			x							
Wen et al. [110]	x					x			x							x
Wen and Rosé [109]	x					x	x		x	x						
Núñez et al. [72]	x			x			x		x	x				x		
Zheng et al. [118]	x	x							x		x			x		
Nelimarkka and Hellas [71]	x		x	x		x	x				x					x
Appiah-Kubi and Rowland [5]							x		x							
Wise et al. [113].	x	x				x	x		x							
Chen et al. [22]	x					x	x		x	x				x		
Brady et al. [16]						x	x		x	x				x		
Huang et al. [53]		x				x			x	x						
Kizilcec et al. [60]	x						x	x								
Zheng et al. [119]	x					x	x		x					x		
Qiu et al. [81]	x					x			x							
Wang et al. [106]	x			x			x		x							
Romero et al. [87]	x					x	x									x
Coetzee et al. [23]	x					x	x		x							
Davis et al. [31]	x					x	x		x							
Robal et al. [84]	x						x		x							
Thaker et al. [100]	x	x	x				x	x	x							
Xing et al. [116]	x															x
Gong et al. [43]	x						x									
de Freitas et al. [32]	x	x				x	x	x	x		x					x
Deng et al. [34]	x	x				x			x							
Deng et al. [35]	x	x				x	x	x	x			x				
Hew [49]	x	x		x		x	x		x			x		x		
Sun et al. [96]	x					x	x	x	x							
Total	62	12	03	07	01	46	46	05	65	05	04	04	01	12	05	06

*Please note that in some studies, there is more than one pedagogical tool found.

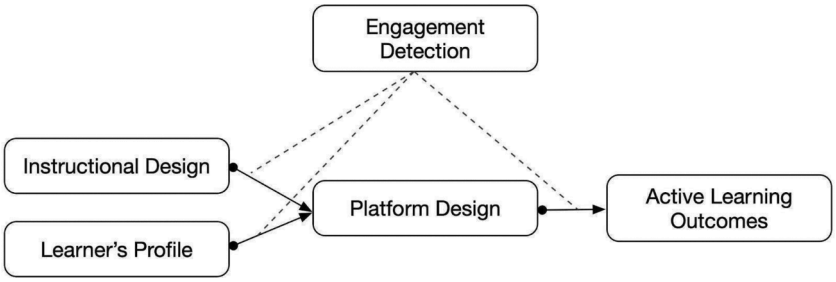

Fig. 7. A conceptual model for achieving learners' active engagement in MOOC environments.

is an approach designed to give learners an alternative option in choosing their learning pathway [29]. The workload, video length, and course duration are other key determinants of effective self-regulated learning. Gamification mechanics play a key role in stimulating fun and engagement for learners. They also enhance learners' motivation. However, the extent to which gamification can stimulate the learning experience needs to be understood. Social engagement is a rarely investigated component of learners' engagement in MOOCs. Social interaction among learners has been found to contribute to both their emotional engagement and their performance and can foster community learning among MOOC participants ([72]; students, instructors, and teaching assistants). Discussion forums being an important MOOC pedagogical design tool, future researchers should explore novel ways to foster social engagement in MOOCs as well as ensure overall course engagement.

Finally, our findings with regard to our fifth goal show that MOOCs' instructional design are determined by their pedagogical aims, consistent with Toven-Lindsey, Rhoads, and Lozano's [102] findings that the array of pedagogical practices in MOOCs 'tends toward an objectivist-individual approach, with some efforts to incorporate more constructivist and group-oriented approaches' (p. 1). Table 7 shows various pedagogical tools used to facilitate learners' engagement in MOOC environments. These are assumed to foster both the presentation of learning materials to students and learning engagement [10]. Apart from generic tools such as videos, quizzes, discussion forums, and textbooks, emails, leaderboards, and coding boards have been used. The nature of the course and the goal of enhancing learners' engagement appear to be the rationale for using these uncommon tools. They can therefore be perceived as interventions for enhancing learners' independent engagement in MOOCs. Although notifications have traditionally been sent to learners by email, Romero, Cerezo, Espino, and Bermudez [87] proposed the use of smartwatches as a better alternative to help learners overcome procrastination. Similarly, Brady, Fisher, and Narasimham [16] used emails to trigger learners' social incentives and motivation to enhance their performance. Incorporating coding boards in MOOC environments helps enhance learners' programming skills through 'learning by doing' (e.g. Gallego-Romero et al. [41]). One significant area of contention is the extensive use of videos and quizzes in MOOCs. It is argued that these do not provide an equivalent experience to university courses as they do not meet the needs of the heterogeneous learners found in MOOC environments [10]. Lecture videos (see Table 7) are integral to MOOC pedagogical design. However, as pointed out in the existing literature, video watching is a monotonous, boring, and passive activity and can make learners prone to disengagement [22,43,70,86,92]. Therefore, future researchers need to find novel ways to make lecture videos more interactive and engaging. The issue with lecture videos appears to be not only their length but poor quality and less interactive affordances.

Furthermore, interactive voice-controlled audio widgets are not popular in MOOCs and could be explored, especially for supporting the lifelong learning needs of field workers and adult learners with few computer skills. We argue that this consideration could be an approach to meeting MOOC learners' heterogeneous needs. Further, voice-controlled pedagogical tools can be used for asynchronous feedback in MOOC environments. Although the argument about not monitoring MOOCs because of their massiveness is clear, we think the learning process is asynchronous and there should be ways to make feedback in MOOCs dynamic and effective. To exemplify our assertion, a recent study revealed that voice-based chatbots can be used for peer-to-peer assessment in monitored MOOCs [77].

5.1. Summary of emerging questions

As authors, we engaged in some personal reflections when reading the articles and documenting the questions arising and other questions raised by some authors to indicate directions for future research. We present the questions as essentially an overview of our reflections as reviewers of the journal articles and conference papers included and as suggestions for future research:

- How do we support the lifelong learning needs of people with low computer literacy and field workers who do not perceive themselves as being in some formal or informal learning environment?
- Are MOOCs being used to address lifelong learning needs in the workplace? What indicators are crucially important for MOOCs to meet such needs?
- What novel instructional design elements could promote learners' engagement in MOOCs, considering that interventions such as gamification, video-based learning, and learning analytics have largely been used?
- Is the principle 'less is better' appropriate for MOOC pedagogical design? Existing knowledge does not converge regarding offering MOOCs as short courses; however, evidence shows learners are more likely to engage during the first few weeks of learning.
- Should we discuss patterns of engagement or learners' individual differences? What informs emerging patterns of engagement?
- Are there novel ways to overcome the limitations of xMOOCs, for example, their monotonous nature that tends to keep learners passive? If the learners' role is merely to watch videos and answer questions, their attention might decrease.
- Gamification provides extrinsic motivation for learners. How do we design MOOCs to support intrinsic motivation?
- What is the interplay between learners' cognitive capabilities and their social engagement in MOOC discussion forums?

5.2. Limitations and future research

First, with respect to our methodology, we selected only studies written in English and may have excluded interesting and relevant studies published in other languages. Our selection was limited to only journal articles and conference papers, thereby possibly excluding studies published as book chapters or theses. Nevertheless, conference papers and journal articles are widely accessed and provide current knowledge of the discourse. Second, we intentionally limited our literature review to education sciences, educational technology, human-computer interaction, computer engineering, information systems, and

psychology to obtain a manageable scope that could be reviewed in detail. However, we acknowledge that there is a growing body of relevant knowledge from the fields of social sciences and humanities (e.g. [61]). This limitation can also be considered a potential future research opportunity complementing the current one. Despite these limitations, we believe that knowledge is a building block, and our study provides a foundation on which future studies can build.

It would also be beneficial to complement this study by considering the findings emerging from the social sciences and humanities. Interest in understanding the broader patterns and attitudinal changes that continuously transforming technologies bring is increasing: how are attitudes and habits going to change? What will be the impact of these changes? We plan to work further with engagement indicators to create a tool for evaluating learners' engagement in online learning environments such as MOOCs.

5.3. Implications

Our findings relate to the instructional and technological designs of MOOCs because these are intertwined, and our results indicate methods to foster research and practice on learners' engagement.

The preliminary guidelines that we can suggest from this study are the following:

1 When designing the learning activities and environment, pedagogical needs must be prioritised over technological possibilities. The intertwined design must consider what should be learned, what methods are fitting, what technology supports these learning methods, learners' potential profiles, and duration. An example could be to include an audio widget in MOOC design, especially for supporting the lifelong learning needs of specialised learners such as field workers and adults with limited computer skills. We believe that this kind of intervention can be used to address some people's need to 'learn as you go'.

2 To understand learning, evaluate success, and identify enhancements needed to improve engagement in MOOCs, we have grouped our indicators as follows:

1.%2 Input indicators (learners' personality and engagement patterns) can be used to personalise materials and tasks for learners. Learning analytics is a current method for creating personalised tasks and process flows in courses.

2.%2 Process indicators (instructors' feedback, learners' feedback, course duration, active participation, attention loss detection) can be used to lessen procrastination, attrition, and the need for remedial action. An example is the use of formative assessment, which can be supported by chatbots, depending on the course topic.

3.%2 Outcome indicators (performance and reward) can be used to stimulate the learning process for increased motivation and interest. Here, the commonly used examples are badges and gamification.

Although our guidelines are appropriate for MOOC instructional and feature designers and facilitators, we also encourage policymakers to examine the following when promoting funding and guiding future learning activities, especially regarding workplace and lifelong learning: (1) promote learning while working on routine tasks; (2) promote short- and medium-length MOOCs; (3) support learning at work by allocating time; (4) use technology to promote scaffolding for reflective processing of such situations in ways that are recognised as beneficial and worth the unavoidable pauses or delays that capturing of the moment may cause for learning (a similar indication is reported in Bauters et al. [12]); and (5) create a motivation to engage in a MOOC. Joint projects between universities and enterprises can be undertaken to design courses with new engagement methods, such as audio, voice control, learners' and instructors' feedback, automatic pattern recognition, voice-controlled discussion forums, and nudges to refocus learners when their attention is fragmented.

6. Conclusion

MOOCs have increasingly been adopted in recent years, especially during the coronavirus pandemic, but learners' engagement is essential for successful learning. This study shows that learners' engagement in MOOCs is a topic of considerable interest to scholars from a variety of angles. Although the pandemic may lead to an increase in the number of studies on MOOCs, the foci may change depending on how the pandemic impacts teaching and learning. Summarising the outcomes using our goals allows us to suggest preliminary guidelines for enhancing engagement in MOOCs.

First, methodological approaches for conducting studies are largely experimental; other approaches include case studies, mixed-methods studies, surveys, and interviews. Case studies are largely based on retrospective data.

Second, 10 indicators were identified as important for fostering the learners' engagement process in MOOCs: learners' personality assessment; learners' engagement pattern assessment; measurement of interaction with the learning materials; provision of timely feedback from instructors; soliciting intermittent open feedback from learners; deployment of short- to medium-length courses; assessment of learners' participation in forum discussions; deployment of interactive elements to stimulate learners' participation; timely detection of learners' engagement to forestall boredom, procrastination, and attention loss during learning; performance assessment; and rewards in the form of digital badges and completion certificates. These 10 indicators support hybrid MOOC learning pedagogy. Future MOOC pedagogy designers might want to consider our indicators for enhancing learner engagement as the shortcomings of existing MOOCs' pedagogical approaches are clear.

Third, the approaches used to determine learners' engagement in MOOCs are broadly grouped into modelling, computer-based data, tools, and self-reporting. Our findings show no consensus regarding how to evaluate learners' engagement. Rather, several attempts to evaluate learners' engagement varied depending on the type of learning engagement component being investigated.

Fourth, the pedagogical issues we found are broadly divided into MOOC pedagogical design, gamifying the learning space, and learners' social interactivity. MOOC discussion forums and lecture videos have been extensively researched because of the underlying philosophical assumptions that guide MOOC learning. Further, MOOCs are largely designed for both cognitive and social learning. Nevertheless, because we cannot classify all MOOC pedagogical issues in a study of this nature, we believe that those we have identified can help to understand what attention should be paid to them.

Finally, the pedagogical design tools used in MOOCs can be broadly categorised into learning materials, practising, assessment, communication/community sharing, and stimulators. Videos and lecture notes are the most common learning materials, tutorials are largely used for practising activities, and quizzes and assignments are the most popular means of assessment. Discussion forums are used to foster communication/community sharing. Third-party tools such as intelligent tutoring systems and internet relay chats are used to stimulate the learning environment and activities.

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CRediT authorship contribution statement

Abiodun Afolayan Ogunyemi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Project administration. **James Sunney Quaicoe:** Validation, Writing – review & editing. **Merja Bauters:** Writing – review & editing, Supervision.

Declaration of Competing Interest

None.

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Appendix A

Table 3

Appendix B

Table 4

Appendix C

Table 5

Appendix D

Table 6

Appendix E

Table 7

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