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REVIEW ARTICLE

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Delving into instructor-led feedback interventions informed by learning analytics in massive open online courses

Paraskevi Topali[1] | Irene-Angelica Chounta[2] | Alejandra Martínez-Monés[3] | Yannis Dimitriadis[4]

[1]Department of Pedagogy, Universidad de Valladolid, Valladolid, Spain

[2]Department of Computer Science and Applied Cognitive Science, University of Duisburg-Essen, Duisburg, Germany

[3]Department of Computer Science, Universidad de Valladolid, Valladolid, Spain

[4]Department of Signal and Communication Theory and Telematic Engineering, Universidad de Valladolid, Valladolid, Spain

Correspondence
Paraskevi Topali, Department of Pedagogy, Universidad de Valladolid, Paseo de Belén 15, 47011 Valladolid, Spain.
Email: evi.topali@gsic.uva.es

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Abstract

Background: Providing feedback in massive open online courses (MOOCs) is challenging due to the massiveness and heterogeneity of learners' population. Learning analytics (LA) solutions aim at scaling up feedback interventions and supporting instructors in this endeavour.

Paper Objectives: This paper focuses on instructor-led feedback mediated by LA tools in MOOCs. Our goal is to answer how, to what extent data-driven feedback is provided to learners, and what its impact is.

Methods: We conducted a systematic literature review on the state-of-the-art LA-informed instructor-led feedback in MOOCs. From a pool of 227 publications, we selected 38 articles that address the topic of LA-informed feedback in MOOCs mediated by instructors. We applied etic content analysis to the collected data.

Results and Conclusions: The results revealed a lack of empirical studies exploring LA to deliver feedback, and limited attention on pedagogy to inform feedback practices. Our findings suggest the need for systematization and evaluation of feedback. Additionally, there is a need for conceptual tools to guide instructors' in the design of LA-based feedback.

Takeaways: We point out the need for systematization and evaluation of feedback. We envision that this research can support the design of LA-based feedback, thus contributing to bridge the gap between pedagogy and data-driven practice in MOOCs.

KEYWORDS

distance education and online learning, feedback interventions, learning analytics, MOOCs, systematic literature review

1 | INTRODUCTION

This paper focuses on instructor-led feedback mediated by learning analytics (LA) in massive open online courses (MOOCs). We are interested in feedback designed by MOOC instructors (i.e., feedback providers) aiming at learners (i.e., feedback receivers) who may face problems during the course enactment. In this context, feedback provision can happen either automatically by LA tools and/or by the instructors themselves, supported potentially by LA (Figure 1).

Feedback is among the cornerstones of learning fostering students' decision-making on their progress (Al-Bashir et al., 2016) and enhancing teaching practices (Molloy & Boud, 2014). Here, we adopt the widely accepted definition of feedback proposed by Hattie and Timperley (2007) according to whom feedback is "*the information*

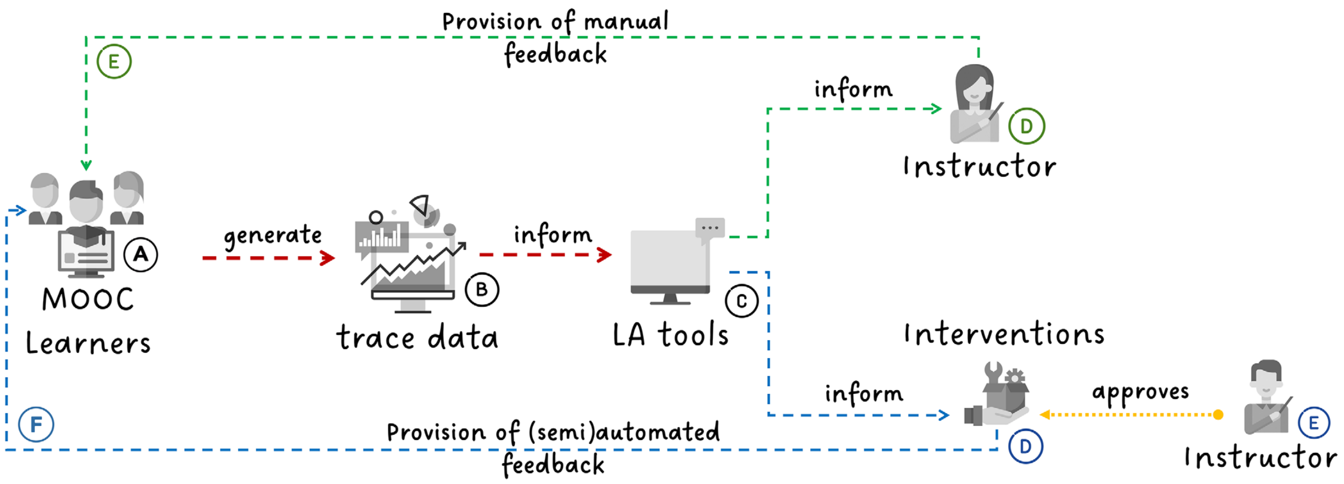

FIGURE 1 Overview of the process of learning analytics-informed instructor-led feedback in massive open online courses. Source: Flaticon.com.

provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding" (pp.8). Feedback is conceptualized as the process of mitigating the inconsistency between the current and the desired understanding/performance stage of the learners (Hattie & Timperley, 2007; Molloy & Boud, 2014).

Successful feedback interventions require the provision of concrete and timely information tailored to learners' needs (Dawson et al., 2019; Hattie & Timperley, 2007; Leibold & Schwarz, 2015). Thus, awareness about the individual learners' state, through the interpretation of diverse verbal and non-verbal sources, is needed to personalize scaffolding (Henderson et al., 2019). Such awareness may be effectively achieved in face-to-face tutoring due to the directness of students-teacher interactions. However, when shifting to online learning, especially in massive and asynchronous settings, such as MOOCs, the provision of timely and personalized feedback raises multiple challenges (Leibold & Schwarz, 2015; Ryan et al., 2019) due to:

a. the vast learners-to-instructors ratio, which increases instructors' workload (Almatrafi et al., 2018),
b. the heterogeneous learners' population in terms of knowledge background, goals, and preferences (DeBoer et al., 2013), and,
c. the asynchronous interaction among the participants.

These issues may result in delayed assistance, not aligning with the needs of learners, and influencing retention (Onah, Sinclair, & Boyatt, 2014).

Previous works systematically explored feedback interventions in MOOCs. Zheng et al. (2018) performed an analysis of 621 MOOCs in China. According to their findings, provided feedback was low, both in terms of quality and quantity, and it depended on the course-teaching model. For example, MOOCs that followed flipped classroom or inquiry-based learning designs offered more support possibilities, such as alerts and recommendations. Wei et al. (2021) conducted a systematic review regarding assessment methods -with feedback as a parameter of assessment- in MOOCs. Their findings showed that feedback rubrics were helpful in assisting and motivating learners' performance in assignments, such as essays. These reviews do not focus explicitly on how literature faces the challenges of providing feedback at scale.

The use of LA has been explored as means to support the provision of scalable feedback tailored to learners' needs in MOOCs (Khalil & Ebner, 2014). LA is defined as the "*measurement, collection, analysis and reporting of data about learners and their con- texts, for purposes of understanding and optimizing learning and the environments in which it occurs*" (Long et al., 2011). Previous studies explored the use of LA to inform feedback interventions. Wang et al. (2017) suggested automatically generated feedback for correcting assignments through LA-informed tools. Liu et al. (2017) and Pardo et al. (2018), discussed instructor-led interventions supported by LA to guarantee the scalability of feedback. Both proposed the involvement of educators in the design of metrics of the LA tools to contextualize feedback interventions. Pardo (2018) proposed a framework for personalized feedback at scale mediated by computer and human feedback agents, where the feedback depends on the data-driven evidence derived from learners' course behaviour and performance. Systematic reviews on LA for online and massive learning explored: (a) learners' engagement and (b) the efficiency and limitations of LA-informed tools, such as dashboards. These reviews highlight the potential of LA to support timely and personalized feedback interventions (Avella et al., 2016; Banihashem et al., 2018; Chiappe & Rodríguez, 2017; Sunar et al., 2016). Yet, they highlight the lack of theoretical and pedagogical underpinning. Considering the importance of learners' support in MOOCs and the limitations of manual feedback provision, a review of LA initiatives informing semi-automated feedback interventions in MOOCs could help understand how support practices are implemented and how they address the challenges posed in MOOCs.

Over the last 2 years MOOCs gained much attention for formal educational purposes due to COVID-19 pandemic (Chen et al., 2020;

FIGURE 2 Interest in massive open online courses over time: the *y*-axis represents the search interest on the chart for the given time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Source: Google Trends.

Ma & Rindlisbacher, 2020; Shah, 2020). Udemy (2020) reported the global growth of the creation of new courses. According to Shah (2020), is considered the "*second year of MOOCs*". Google Trends[1] (Figure 2) depicts the increasing interest in MOOCs during 2020. Given such wide use of MOOCs, we deem that a better understanding of this topic could provide insights to researchers and instructional designers of MOOCs for future research directions and substantial theoretical and practical implications.

The main contribution of the paper is to uncover the way LA-informed feedback is provided in MOOCs, its extent, and its impact. Accordingly, we conducted a systematic literature review answering the following Research Question (RQ): *What is the current landscape of LA-informed instructor-led feedback in MOOCs?*

2 | RELATED WORK

2.1 | Feedback in education

Literature conceptualizes feedback as the information conveyed to learnrs to enhance their understanding and performance and to foster educational improvement considering their current state and the desired state (Hattie & Timperley, 2007; Henderson et al., 2019; Molloy & Boud, 2014; Shute, 2008). To achieve the shift from the current learners' state to the desired one, related research focuses on developing models and theories for effectively guiding the feedback process.

Wood and Wood (1996) proposed the Contingent Tutoring Theory for instructional scaffolding. According to the authors, educators must meet learners' needs by providing them with the necessary support based on their current performance. Then, depending on learners' progress and understanding, the theory proposes a taxonomy of five levels of feedback (for example, hints, general feedback messages, concrete instructions).

Henderson et al. (2019) framed feedback as a process that may impact learners at various levels during learning. Concretely, feedback may influence the: (a) learning outcomes (i.e., learners' progress and performance), (b) cognitive aspects (i.e., understanding of a skill, self-regulation), (c) affective/motivational aspects (i.e., aspects related with negative–positive emotions, etc.), (d) relational aspects (i.e., the relationship between the educator and the learner), (e) values, beliefs and identity (i.e., serving the social theory of learning, boosting socialization).

Other theoretical approaches explored feedback aspects that should be considered to increase the effectiveness of the interventions. For instance, Hattie and Timperley (2007) deemed that constructive feedback is necessary to meet the following: (a) definition of the learner goals (i.e., feed-up), (b) concretization of the approach needed to reach the set goals (i.e., feedback), (c) identification of the future steps needed to enhance the progress (i.e., feed-forward). Likewise, Molloy and Boud (2014) listed three aspects that influence feedback quality related to the: (a) content, (b) timing and (c) provider qualities of feedback.

2.2 | Systematic reviews on learning analytics-based feedback

Literature reports previous systematic literature reviews (SLRs) discussing the potential of LA for feedback in education. Avella et al. (2016), Chiappe and Rodríguez (2017) and Banihashem et al. (2018) conducted SLRs exploring the use and challenges of LA in the educational landscape. All authors stressed the added value of LA in reshaping feedback processes regarding personalization and timing. Yet, Avella et al. (2016) criticized the lack of contextualization that often accompanies LA tools and proposed the inclusion of educational stakeholders in the design and consideration of LA information for contextualized feedback. Similarly, Chiappe and Rodríguez (2017) highlighted that the contextualized pedagogical features should accompany LAs to facilitate well-informed decision making. Mangaroska and Giannakos (2019) performed an SLR exploring the use of LA for learning design to increase data-driven pedagogical interventions and achieve better learning outcomes. The authors discussed the research efforts done to consider learning design and the contextual parameters of a course to achieve actionable LA-driven feedback that is feedback tailored to the real needs of the learners. The SLR pointed to the need to guide educators in the process of sense-making of the information provided by the LA tools to facilitate successful interventions.

[1]https://www.google.com/trends

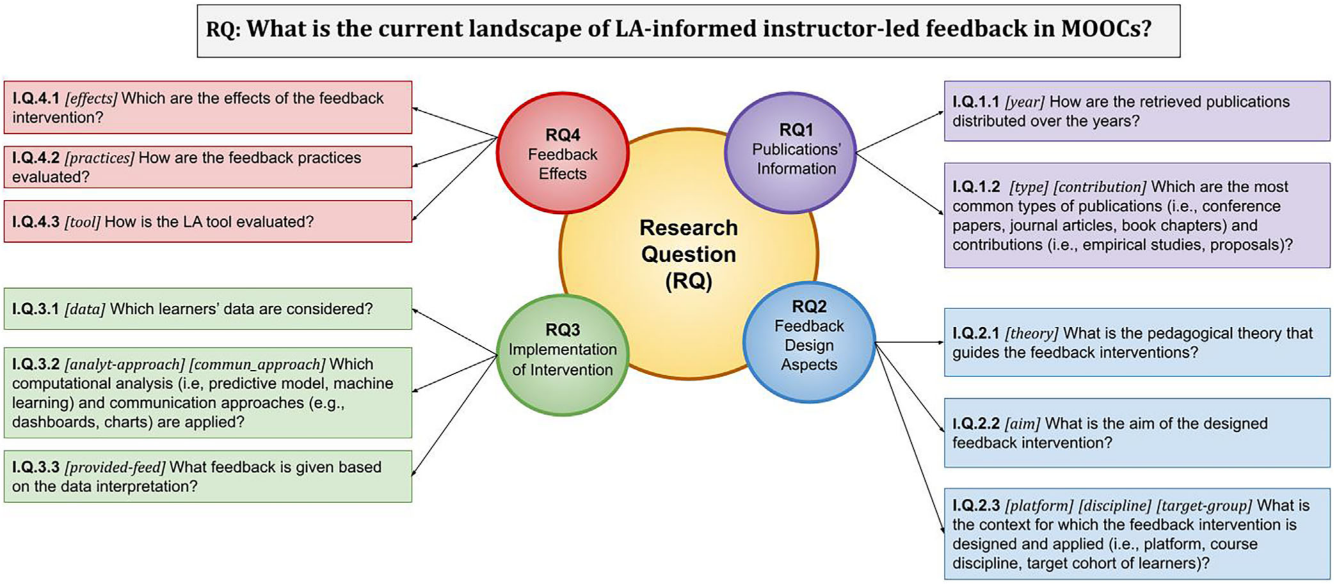

FIGURE 3 Anticipatory data reduction schema including the Research Question, the four sub-questions (circles) and informative questions (rectangles) guiding the systematic literature review.

Sharma & Giannakos (2020) carried out an SLR on the benefits of multimodal LA on human learning. The authors stated the need for further research on tools that provide actionable feedback for learners. Schwendimann et al. (2017) and Matcha et al. (2020) conducted SLRs on the use of LA-dashboards. Matcha et al. (2020) systematically explored the use of LA dashboards as a form of feedback supporting learners' self-regulation. According to the results, the information provided by the analysed dashboards, which consisted of decontextualized visualization of aggregated data, was not always informative enough for the learners. Schwendimann et al. (2017) highlighted the lack of alignment between the visualized data and the learning context, a fact that might affect the quality of the feedback interventions. Focusing on MOOCs, Sunar et al. (2016) conducted an SLR exploring personalization and adaptation in MOOCs. This review revealed the interest in attracting the provision of personalized feedback in massive learning contexts. The authors highlighted the potential of LA tools in enabling targeted interventions and enhancing the course quality. A recent SLR by Cavalcanti et al. (2021) explored automatic feedback in online learning environments. The findings highlighted the lack of educational research to inform the design of tools for automatic feedback and the lack of attention to the teachers who are the ones shaping the feedback practices.

The SLRs presented in this section highlight the importance of the topic of feedback. These studies—with the exception of Cavalcanti et al. (2021)—do not discuss automatic or semi-automatic feedback regarding the design, use, and evaluation aspects of the feedback interventions in authentic cases. However, Cavalcanti et al. (2021) did not focus explicitly on MOOCs and their study did not cover the most recent period, and especially 2020 and later, which is of special interest since MOOCs were more intensively used due to the COVID-19 pandemic.

We envision that the contribution of this work is to bridge this gap and to address the aforementioned limitations. To do so, we performed a systematic review of the state of the art on LA-informed feedback interventions in the context of MOOCs. The works of Wood and Wood (1996) and Henderson et al. (2019) inspired our research and helped us to structure the analysis based on four questions. We present these questions and our methodological approach in the following section.

3 | METHODOLOGY

3.1 | Review questions

To warrant a thorough analysis, we have identified four sub-questions and divided them further into 11 informative questions (IQ) (see Figure 3), following an anticipatory data reduction process (Miles et al., 2014):

> **RQ1.** *What is the overall research state of the LA-informed feedback in MOOCs?* RQ1 delves into research aspects of the reviewed contributions. It aims to analyse the temporal distribution of the studies, the publication venues (i.e., conference papers, or journal articles) (I.Q.1.1) and the type of contributions (i.e., empirical studies, proposals) (I.Q.1.2).

> **RQ2.** *What are the pedagogical theories that inform feedback in MOOCs?* Feedback design requires a priori consideration of pedagogical theories to shape adequate interventions. RQ2 aims to provide insights into the

pedagogical theories that guide the feedback design (I.Q.2.1), the intentions behind the application of feedback in MOOCs (I.Q.2.2) and the course learning context (i.e., MOOC platform, course discipline, cohort of targeted learners) (I.Q.2.3).

RQ3. *How LA is applied and employed in MOOCs in order to result in relevant information for feedback provision?* Feedback depends on the information gathered about learners' behaviour and is influenced by learning design. RQ3 focuses on the data used as input for the LA-supported feedback processes (I.Q.3.1), the applied computational analysis (e.g., machine learning) (I.Q.3.2) and the feedback given based on the collected data (I.Q.3.3).

RQ4. *What are the reported effects of the feedback interventions in MOOCs?* RQ4 aims to provide information regarding the effects of feedback on learners (I.Q.4.1). Additionally, we explore (a) the evaluation of the proposed feedback practices (I.Q.4.2), and (b) the assessment of the LA tools (i.e., tools developed that inform feedback interventions) (I.Q.4.3).

3.2 | Method

The current study employs the guidelines proposed by Kitchenham and Charters (2007). This methodology structures the SLR process in three steps:

1. *Review planning* includes the research questions, the selection of the keywords and the databases, the identification of the exclusion and inclusion criteria.
2. *Review conduction* includes the identification of the search strategy, the selection and quality assessment of the studies and the data extraction and synthesis.
3. *Results reporting* regards the final dissemination of the results.

We performed a literature search through five digital libraries: ACM Digital Library, IEEE Xplore Digital Library, ScienceDirect, Scopus, and Web of Science. These databases were considered as most relevant covering a high number of the contributions in technology-enhanced learning, and they were employed in related works (Alonso-Mencía et al., 2020; Cavalcanti et al., 2021).

The search string consisted of the following keywords: (MOOC* OR "Massive Open Online Course*") AND (feedback OR scaffolding OR assistance OR support) AND (tutor* OR teach* OR instructor* OR practitioner*) AND ("learning analytics" OR "data driven" OR "evidence based"). The term *MOOC** refers to the learning setting that is the focus of the current study. The terms *feedback*, *scaffolding*, *assistance*, *support* were chosen since the main interest of the study regards feedback and are in accordance with related works (Economides & Perifanou, 2018; Konert et al., 2016). The terms *tutor**, *teach**, *instructor**, *practitioner** reflect the study's focus on the perspective of tutoring or teaching. These terms are used in MOOC terminology describing the role of instructor-led actions (Gil-Jaurena & Domínguez, 2018; Vegliante & Sannicandro, 2020). The terms *learning analytics*, *data driven*, *evidence-based* were chosen to reflect the focus on LA-informed feedback (Mangaroska & Giannakos, 2019; Meleg & Vas, 2020). This search string facilitates the detection of publications including variants of the chosen terms, e.g., tutor or tutoring or tutors. The synonyms applied typically cover words frequently utilized in the MOOC literature. We performed the search on the title, abstract, or keywords of publications since these sections most likely contain representative information on the topic. The search phase spanned from 2010 to 2022 covering all related publications from the beginning of research in MOOCs until the submission of this manuscript.

We collected in total 227 publications. We searched papers employing three inclusion criteria and further filtered the results based on five exclusion criteria:

- Inclusion: Peer-reviewed articles about MOOCs dealing with one of the following topics:
  - Design of feedback interventions to deliver appropriate support to learners
  - Use of data to identify when/what/how to offer support (data-driven decision making)
  - Evaluation of data-driven feedback practices
- Exclusion: We rejected papers that correspond to one of the following cases:
  - Duplicate reports of the same study. We used the complete version of the publications.
  - Secondary and tertiary studies (e.g., systematic literature reviews)
  - Abstracts
  - Papers written in other languages than English
  - Publications dealing with the topics presented in the inclusion criteria without involving MOOCs

Figure 4 provides an overview of the review process. After removing the overlapping papers among the different databases ($N = 84$ duplicates), we performed a screening based on the inclusion and exclusion criteria by reading initially the title and abstract and, when necessary, the introduction and conclusion sections. We added 12 topic-related papers cited in the accepted papers (snowball references). After fully reading the documents, we concluded with a list of 38 publications.

Two reviewers participated in the filtering and data analysis process. First, each reviewer examined the papers individually. Then, the reviewers went over the results and spotted potential discrepancies. To address these discrepancies, the reviewers discussed their arguments by referencing related work and citing

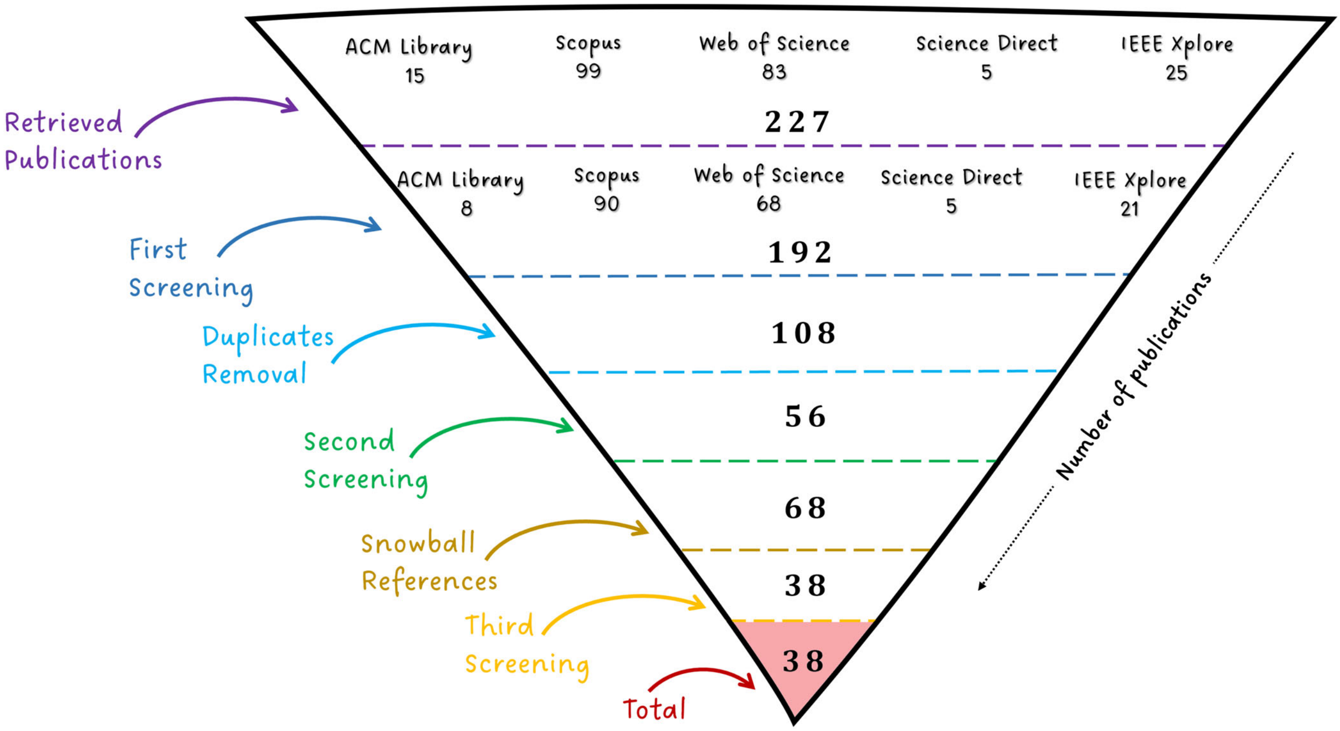

FIGURE 4 Overview of the systematic literature review process followed.

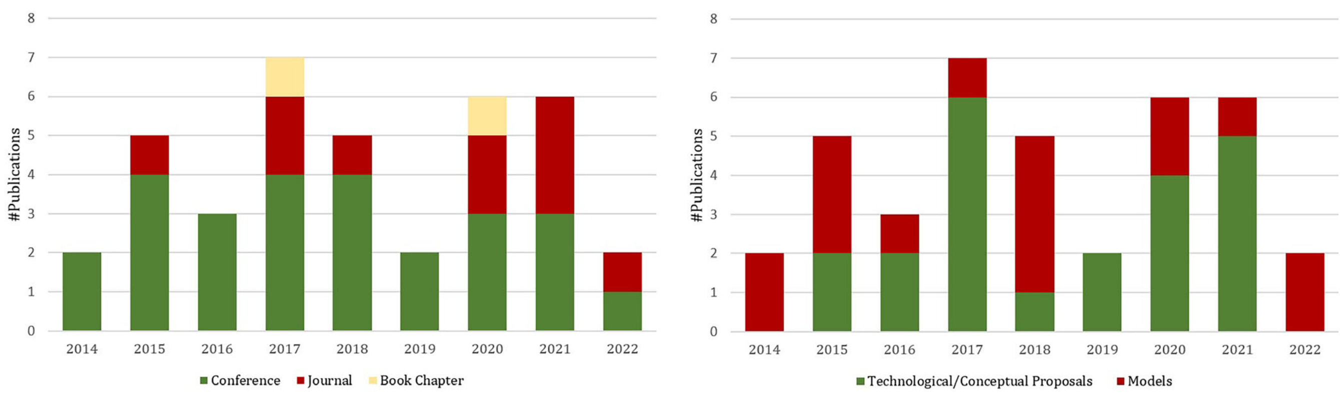

FIGURE 5 Left: Publications included attending to the year of publication and publication type. Right: Publications included attending to the year of publication and contribution type.

relevant examples until they reached an agreement. Both reviewers kept track of the process by recording obtained information digitally using Google Spreadsheets.

To answer the RQs, we carried out content analysis using etic codes that is, predefined categories established before the data analysis (Given, 2012). The coding scheme was designed based on the established IQs (see Appendix, Tables A.1 and B.1). To warrant the quality and trustworthiness of the results, we took the following measures (Guba, 1981): (a) peer debriefing by the research team of the employed coding scheme, and (b) triangulation among the investigators to ensure the data interpretation.

4 | RESULTS

This section presents the results organized along with the four RQs. The list of retrieved papers is presented in Table B.1 (Appendix B), that summarizes the bibliographic data related to the authors, title, published year, and venue of the paper.

4.1 | RQ#1: Publications' information

We analysed the papers based on the year of publication, the publication type, and the contribution type (see Figure 5). The first

TABLE 1 Learning theories identified from the final pool of the retrieved papers.

Learning theories	Studies	Type of contribution
Self-regulated learning	Konert et al. (2016)	Conference paper
	Rohloff et al. (2019)	Conference paper
Constructivism	van den Beemt et al. (2018)	Conference paper
Cognitive theory of multimedia learning	Sharma et al. (2020)	Journal article
Collaborative learning	Ferschke et al. (2015)	Conference paper
	Tomar et al. (2017)	Conference paper
Dynamic/interactive assessment	Yılmaz et al. (2021)	Conference paper
First principles of instruction	Frick et al. (2022)	Journal article

publication regarding LA-informed feedback in MOOCs was in 2014. Although instances of MOOCs exist since 2008, we hypothesize that our results started in 2014 because MOOC platforms started to offer courses systematically in 2012 (Moe, 2015). An increased interest in the topic was noted between 2015 and 2018, with a peak in 2017 ($N = 7$). In 2019, the number of publications decreased significantly. However, in 2020 and 2021 ($N = 7$ and $N = 6$ respectively) the attention on LA-informed feedback in MOOCs was raised again.

Most of the papers were published in conference proceedings ($N = 26$), with fewer journal publications ($N = 10$) and book chapters ($N = 2$). Journal publications increased from 2018 on. Typical venues for the published papers regarded conferences such as LAK[2] ($N = 4$), L@S[3] ($N = 3$), CSCL[4] ($N = 2$) and others such as TEEM,[5] LWMOOCS,[6] ICICI,[7] IEEE TALE and ICALT.[8]

Proposals of system prototypes and conceptual tools (e.g., frameworks) were the most frequent types of contributions ($N = 22$), followed by computational models, such as predictive or network analysis ones ($N = 16$). Only four (4) papers presented empirical studies performed in MOOC environments (Cobos & Ruiz-Garcia, 2020; Ferschke et al., 2015; Teusner et al., 2018; Tomar et al., 2017). This data shows an interest in LA systems and models that may generate and manage feedback. Considering the growth of MOOCs with the plethora of MOOC platforms and providers, our findings suggest that there is an interest in providing systems and solutions to inform the design of tools. However, this interest is still at an early stage since no empirical evidence is reported.

4.2 | RQ#2: Feedback design aspects

Concerning I.Q.2.1, from the 38 papers retrieved, only eight define a theory that drives the proposed feedback strategies. Table 1 summarizes the identified learning theories.

Two papers mentioned self-regulated learning (SRL)—that is, learners should be supported to become independent during their learning process (Zimmerman, 2000)—as the theoretical basis for the development of learner dashboards to support course participants. Two papers that aimed at designing peer feedback reported the use of Collaborative Learning as a theoretical guide. Others mentioned the Cognitive Theory of Multimedia Learning (Mayer & Moreno, 2003) which draws upon Cognitive learning, Constructivism focusing on knowledge building based mainly on learner-to-learning material interaction, and the First Principles of Instruction (David Merrill, 2002). Finally, the Dynamic/interactive Assessment approach (DA) is mentioned, which is grounded in Vygotsky's Zone of Proximal Development (Tzuriel, 2000).

Regarding I.Q.2.2, the results revealed various purposes of the LA-informed feedback interventions. Building on the taxonomy of feedback impact (Henderson et al., 2019), we associated the findings with the five categories proposed by the authors (see Section 2.1). Figure 6 presents the various purposes of feedback, as mentioned in the reviewed papers, and connected to the categories by Henderson et al. (2019). Seventeen publications intended to promote awareness about learners' progress and course behaviour. Ruiz et al. (2014) proposed an LA visualization aiming at generating feedback information to help instructors shape interventions. Several researchers motivated their studies by highlighting instructors' difficulties in delivering feedback adapted to the learners' needs. Their contributions focus on tools delivering personalized and timely support ($N = 14$). Four publications explored community building via enhancing message exchange. Twenty-five publications aimed at providing support to instructors by generating information about learners' progress. Twenty-three studies regarded automated feedback intervention delivered directly to learners. Among them, two studies propose computer agents to deliver feedback, while the conditions that trigger the feedback are decided by the course instructors (Reza et al., 2021; Yılmaz et al., 2021).

Attending I.Q.2.3, 22 publications focused on shaping feedback interventions for all participants without reporting a specific cohort as a target of the designed interventions. Twelve publications focused on learners disengaged and at risk of dropping out. Vinker and Rubinstein (2022) suggested visualizations of learners' submission trajectories to reveal disengaged learners and thus, alert instructors. Four publications specified their target cohort. Teusner et al. (2018) focused on “struggling learners” (i.e., learners with problems in programming activities) and Sharma et al. (2016, 2020) targeted learners with low attention and concentration during the course run-time.

[2]Learning Analytics & Knowledge
[3]Learning at Scale
[4]Computer Supported Collaborative Learning
[5]Technological Ecosystems for Enhancing Multiculturality
[6]Learning with MOOCs
[7]International Conference on Intelligent Data Communication Technologies and Internet of Things
[8]IEEE International Conference on Advanced Learning Technologies

Paper ID	Feedback about learning outcomes		Cognitive Feedback		Affective Feedback	Relational Feedback	Feedback changing values
	Increase awareness	*Improve Retention*	*Support learning*	*Boost SRL*	*Stimulate motivation*	*Provide person. feedback*	*Foster message exchange*
Almeda et al. (2018)						☻	
Caballe et al. (2014)			☻		☻		
Cobos & Soberón (2020)	☻☺						
Cobos & Ruiz-Garcia (2020)	☻☺						
Crossley et al. (2017)		☻					☻
Du et al. (2018)						☻	
Eradze & Tammets (2017)	☻☺						
Ezen-Can et al. (2015)						☻	
Ferschke et al. (2015)							☺
Frick et al. (2022)		☺					
Klusener & Fortenbacher (2015)	☻						
Konert et al. (2016)				☺			
Lafifi et al. (2020)		☻			☻	☻	
Lan et al. (2015)						☻	
Lee et al. (2021)	☻						
Li et al. (2022)	☻					☻	
Malekian et al. (2020)			☻				
Meku Fotso et al. (2020)	☻						
Reza et al. (2021)						☻	
Rohloff et al. (2019)				☺			
Ruipérez-Valiente et al. (2017a)	☻☺						
Ruipérez-Valiente et al. (2017b)	☻☺						
Ruiz et al. (2014)	☻☺						
Sharma et al. (2016)			☺		☺		
Sharma et al. (2020)	☺				☺	☺	
Singelmann et al. (2019)						☺	
Smith (2015)	☺	☺	☺				☺
Tegos et al. (2021)		☺					☺
Teusner et al. (2018)		☺					
Thankachan (2017)	☻						☺
Tomar et al. (2017)							
van den Beemt et al. (2018)	☻						
Vinker & Rubinstein (2022)	☻	☻				☻	
Wang et al. (2017)						☺	
Xing & Du (2018)	☺					☻	
Xing et al. (2016)	☺						
Yılmaz et al. (2021)		☺				☻	
Yu et al. (2021)			☻				

FIGURE 6 Purposes of learning analytics-informed feedback in massive open online courses. Feedback agents: ☺—LA tools, ☻—Instructors.

TABLE 2 Identified learner cohorts reported at the final pool of retrieved papers.

Targeted learner cohorts	Studies
General learner cohort	Caballe et al. (2014), Eradze and Tammets (2017), Ezen-Can et al. (2015), Ferschke et al. (2015), Frick et al. (2022), Konert et al. (2016), Lafifi et al. (2020), Lan et al. (2015), Lee et al. (2021), Li et al. (2022), Meku-Fotso et al. (2020), Reza et al. (2021), Rohloff et al. (2019), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017); Ruiz et al. (2014), Singelmann et al. (2019), Smith (2015), Thankachan (2017), van den Beemt et al. (2018), Wang et al. (2017), Yılmaz et al. (2021), Yu et al. (2021)
At-risk of dropout learners	Almeda et al. (2018), Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Crossley et al. (2017), Du et al. (2018), Klusener and Fortenbacher (2015), Malekian et al. (2020), Tegos et al. (2021), Tomar et al. (2017), Vinker and Rubinstein (2022), Xing et al. (2016), Xing and Du (2018)
More specific cohorts	
Struggling learners	Teusner et al. (2018)
Learners with Low attention and concentration	Sharma et al. (2016), Sharma et al. (2020)
Cohorts that behave differently	Du et al. (2018)

Du et al. (2018) designed LA-informed feedback interventions for groups that behave differently from the norm. Table 2 presents all the identified learner cohorts.

Regarding the context in which LA solutions are designed, the MOOC platform itself is of great importance since it captures learners' trace data. Most interventions were proposed, designed, and implemented in platforms of popular MOOC providers, such as Coursera, Canvas, Open EdX (Figure 7). Other platforms regarded Moodle, Open HPI, NextThought platform, Iversity and XuetangX platform, MiriadaX. In 11 publications, the course delivery platforms were not defined, either because the study was not empirical or because the developed technological tool for feedback was not platform dependent.

Figure 8 and Table 3 display the distribution of the publications over five academic disciplines according to Wu et al. (2012): Humanities, Social Sciences, Natural Sciences, Formal Sciences, and Applied Sciences. Most of the studies regarded Formal Sciences (i.e., Programming, Mathematics). Many studies related to Applied Sciences (i.e., Engineering and Technology) and Humanities (i.e., Education, Languages and Philosophy). Finally, six publications did not define the academic area where their proposal applied or aimed to be applied.

4.3 | RQ#3: Implementation of the proposed intervention

Answering I.Q.3.1, Table 4 indicates the log data collected for informing LA-based interventions. The main data source was click-stream data from system logs, occasionally accompanied by self-reported data. Most studies relied on data provided by interactions in forums, and other MOOC-related aspects (answering quizzes, watching videos, etc.) Most studies capture learner activity in forums regarding post creation (i.e., posts entries and post replies) and views of other posts ($N = 19$). Few studies reported to capture further information, such as the number of comments created to learners' entries and number of comments to post replies (Almeda et al., 2018), positive and negative votes on the posts where the platform permitted it (Klusener & Fortenbacher, 2015), initiation of threads and sub-threads and posts' density and length (Crossley et al., 2017). Reviewed works used data from course assignments (e.g., scores or number of passed quizzes, and tests), «honour» pasted (task high marks) and failed tasks, video activity (e.g., video replays). Malekian et al. (2020) and Thankachan (2017) explored the impact of the sequence on the activities to learners, by checking their progress in terms of repetition of wrong answers in submitted quizzes and scores of past activities. A less frequent source of data regarded learners' information from surveys (e.g., previous knowledge level, demographic information, learners' goals, objectives and expectations) (Cobos & Ruiz-Garcia, 2020; Cobos & Soberón, 2020; Du et al., 2018; Sharma et al., 2016; Singelmann et al., 2019; Smith, 2015).

Attending IQ.3.2, the most frequent computational approaches are machine learning and process mining techniques ($N = 25$), especially predictive modelling ($N = 8$). Xing et al. (2016) and Xing & Du, 2018 proposed temporal predictive models which prioritized learners at risk of dropping out. Du et al. (2018) employed the framework of Exceptional Model Mining (EMM) to detect exceptional learner behaviours, that is learner patterns that may require the instructors' attention. Sharma et al. (2016, 2020) used multi-modal LA for eye-tracking analysis aiming at capturing indicators of learners' performance to give feedback to learners about their reading behaviour and to course instructors about learners' attention. Thirteen studies did not specify the analytical approach to inform feedback interventions.

Figure 9 shows the relationship between the feedback techniques proposed or applied and the feedback purposes (IQ.3.3). All publications highlighted the contribution of LA as a way of providing timely and personalized support to MOOC learners and instructors. Nevertheless, 14 publications (out of 38) did not specify the type of feedback practices. From the rest of the studies, we meet 12 studies discussing implicit feedback through visual aids and 13 studies proposing textual feedback for supporting participants' awareness, promoting SRL and personalized support, improving course retention,

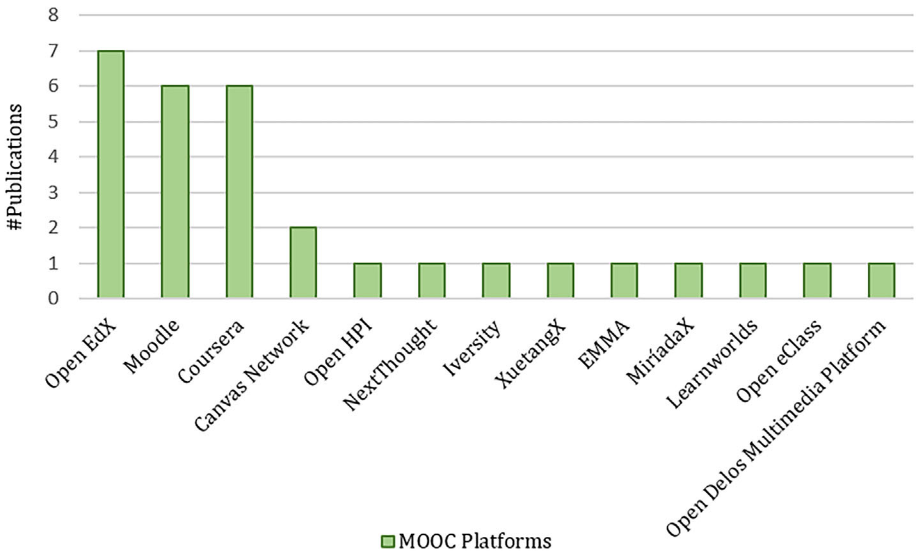

FIGURE 7 The different massive open online course platforms reported at the final pool of the retrieved papers.

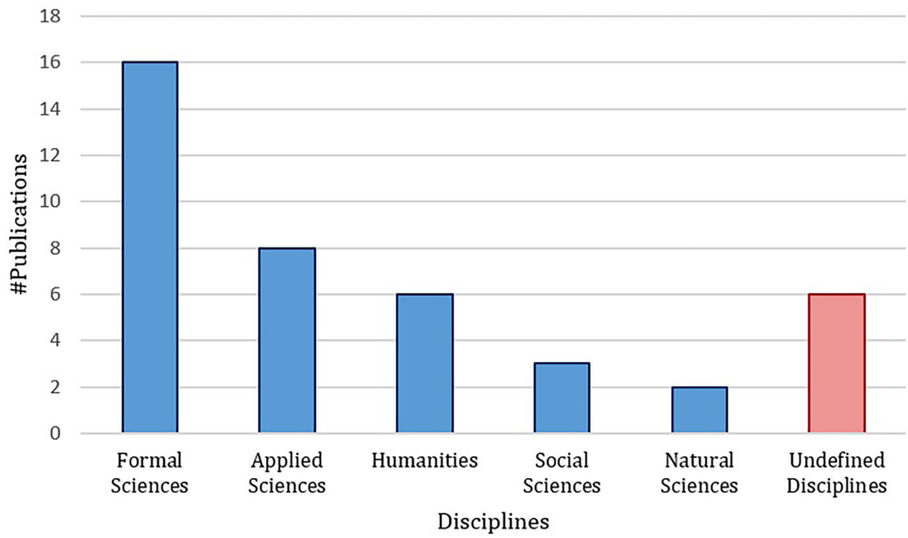

FIGURE 8 Distribution of the studies over the five thematic areas.

and stimulating learners' motivation. Dashboards were the main means of visual support (Eradze & Tammets, 2017; Konert et al., 2016; Rohloff et al., 2019; Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo & Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al., 2017; Ruiz et al., 2014; Smith, 2015; Teusner et al., 2018; Yu et al., 2021). Four studies proposed different kinds of visualizations (Klusener & Fortenbacher, 2015; Sharma et al., 2016, 2020; Vinker & Rubinstein, 2022) for increasing awareness, motivating the learners and improving the learning experience. Klusener and Fortenbacher (2015) reported the use of scatterplots and Sankey diagrams for instructors' awareness and stimulation of engagement.

The textual support regarded text messages, hints and prompts, tips and personalized links or recommender systems and systems for automated corrections on provided solutions (Almeda et al., 2018; Caballe et al., 2014; Ferschke et al., 2015; Frick et al., 2022; Lafifi et al., 2020; Lan et al., 2015; Meku-Fotso et al., 2020; Reza et al., 2021; Singelmann et al., 2019; Teusner et al., 2018; Wang et al., 2017; Yılmaz et al., 2021; Yu et al., 2021). Almeda et al. (2018) proposed sending reminders with course-related material and praising the top-level discussion forum commenters. Wang et al. (2017), Lan et al. (2015) and Teusner et al. (2018) recommended the provision of specific suggestions to low-performing learners for correcting their assignments and exercises' errors and for practicing with additional material. Ferschke et al. (2015), Wang et al. (2017) and Singelmann et al. (2019) proposed the use of tools, such as peer recommender systems and data-driven automatic graders to facilitate the feedback provision, to promote message exchange among peers and to provide support tailored to learners' needs. Teusner et al. (2018) and Almeda et al. (2018) stressed the importance of self-communication and proposed messaging the non-active learners to encourage them to contribute to discussions and to motivate them to ask for help when struggling. Ferschke et al. (2015); Tomar et al. (2017); Tegos et al. (2021) perceived as feedback the dialogue-based support given by peers or agents via conversational channels. Klusener and Fortenbacher (2015) and Xing et al. (2016) focused on designing effective interventions for dropout learners. They recommended informing

TABLE 3 Presentation of the studies over the five thematic areas.

Disciplines	Studies
Formal sciences	Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Crossley et al. (2017), Ferschke et al. (2015), Klusener and Fortenbacher (2015), Konert et al. (2016), Lan et al. (2015), Lee et al. (2021), Malekian et al. (2020), Meku-Fotso et al. (2020), Sharma et al. (2020), Tegos et al. (2021), Teusner et al. (2018), Tomar et al. (2017), van den Beemt et al. (2018), Vinker and Rubinstein (2022), Wang et al. (2017)
Applied sciences	Du et al. (2018), Eradze and Tammets (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), Singelmann et al. (2019), Tegos et al. (2021), Xing and Du (2018), Xing et al. (2016)
Humanities	Almeda et al. (2018), Eradze and Tammets (2017), Frick et al. (2022), Klusener and Fortenbacher (2015), Teusner et al. (2018)
Social cciences	Eradze and Tammets (2017), Ezen-Can et al. (2015)
Natural Sciences	Meku-Fotso et al. (2020), Sharma et al. (2016)
Undefined disciplines	Caballe et al. (2014), Lafifi et al. (2020), Li et al. (2022), Reza et al. (2021), Rohloff et al. (2019); Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruiz et al. (2014), Smith (2015), Thankachan (2017), Yılmaz et al. (2021), Yu et al. (2021)

instructors about potential dropouts and the reasons for which learners abandon the course, facilitating instructors to prioritize support for such learners. Ferschke et al. (2015) presented the Quick Helper, a help-seeking tool that connects learners with peers to respond to unsolved questions. Lafifi et al. (2020) proposed a tool, TutMOOC, to empower instructors' role in tutoring. According to the learners' problem, different feedback agents can be employed, such as computer agents for simple automated solutions or teacher agencies for pedagogical and learning problems. Tegos et al. (2021) proposed the use of conversational agents in dialogue-based MOOC activities, where the agent can trigger conversations among peers and scaffold participants' learning.

4.4 | RQ#4: Feedback effects

The number of empirical studies reporting effects of the implementation of interventions in MOOCs (IQ.4.3) was limited (N = 4), thus not allowing conclusions about the impact of feedback supported by LA. Cobos and Ruiz-Garcia (2020) presented an LA dashboard, which informed instructors about learners' progress and helped them deliver feedback to learners via personal messages. The intervention had positive effects on learners' motivation and persistence during the course. Teusner et al. (2018) found that the learners who received recommended material as automated feedback, performed better during the course compared to those who did not receive material tailored to their needs. Learners' self-reported satisfaction was positively affected as well. Ferschke et al. (2015) and Tomar et al. (2017) studied the feedback given via collaborative chat interventions. In Ferschke et al. (2015), the conversational support given on various channels helped the interactions and communication among peers. However, orchestrating learners' interactions over multiple communication media was demanding. Tomar et al. (2017) shed light on the number of peers participating in conversational interactions. The results suggested that small peer groups (i.e., dyads), formed by the automated computer assistance, were more effective than larger groups (e.g., more than two learners).

Some publications reported preliminary evaluations of the LA tools (IQ.4.2) ($N = 17$), or the delivered feedback (IQ.4.1) ($N = 3$). The evaluation methods employed post-analysis of the participants' trace data testing for tool accuracy ($N = 17$), surveys examining the aspects of usability, usefulness, and user experience ($N = 3$) and lab experience ($N = 1$). Out of the 21 system proposals (Figure 5), 8 studies evaluated the technological tool presented. Rohloff et al. (2019) conducted user surveys with 217 MOOC learners regarding their self-perceived usefulness, the value of the dashboard and the feedback given in the form of textual information. The findings showed positive results for learner satisfaction and tool usability. All the studies ($N = 13$) used learners' logs from past MOOCs to explore the efficiency of their approach. Ezen-Can et al. (2015) applied an unsupervised student model to shed light on learners' posts in discussion forums. The results were positive regarding the provision of automated discourse analysis. The authors concluded that such findings could shape tools for real-time support for MOOC learners. Almeda et al. (2018) developed predictive models exploring the course success of two different cohorts of learners. The authors tested the predictive accuracy of the models and reported positive results on the prediction of learners' grades. They highlighted that their model could help instructors and instructional designers to detect learners at risk of dropping out and provide tailored support to such a cohort. Yılmaz et al. (2021) gathered students' perceptions about the use of a tool for providing scaffolding and tips when learners cannot overcome their problems. Authors conducted questionnaires to 53 undergraduate students exploring ease of use, disliked aspects, and features to improve the tool.

5 | DISCUSSION

In this section, we provide a contextualized discussion from the perspective of our research questions.

5.1 | RQ1: What is the overall research state of the LA-informed feedback in MOOCs?

According to the distribution of publications over the years, LA systems informing feedback in MOOCs increased from 2015 to 2018 and during 2020 and 2021. The interest in the topic follows the

TABLE 4 Summary of the log data reported in the reviewed papers.

Learners' data gathered	Studies
Platform	
Log-in/log-out (e.g., sessions registered, days connected, inactive days)	Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Lafifi et al. (2020), Lee et al. (2021), Li et al. (2022), Meku-Fotso et al. (2020); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), van den Beemt et al. (2018), Xing et al. (2016)
Time spent in course	Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Eradze and Tammets (2017), Frick et al. (2022), Konert et al. (2016), Lee et al. (2021), Li et al. (2022), Meku-Fotso et al. (2020), Reza et al. (2021), Rohloff et al. (2019), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), Ruiz et al. (2014), Teusner et al. (2018), Thankachan (2017), Vinker and Rubinstein (2022), Yu et al. (2021)
Sequential data-submissions	Lee et al. (2021), Malekian et al. (2020)
Overview of failed submissions	Malekian et al. (2020), Thankachan (2017), Vinker and Rubinstein (2022)
Message to Instructor	Lafifi et al. (2020)
Discussion forum activity	
Basic forum activity (i.e., post entries, replies)	Almeda et al. (2018), Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Crossley et al. (2017), Ezen-Can et al. (2015), Ferschke et al. (2015), Klusener and Fortenbacher (2015), Lafifi et al. (2020), Malekian et al. (2020), Rohloff et al. (2019), Ruiz et al. (2014), Tegos et al. (2021), Thankachan (2017), Tomar et al. (2017), van den Beemt et al. (2018), Xing and Du (2018), Xing et al. (2016)
Up-votes/down-votes given or received per post	Klusener and Fortenbacher (2015)
Post length	Crossley et al. (2017), Klusener and Fortenbacher (2015)
Post content	Crossley et al. (2017), Ezen-Can et al. (2015), Ferschke et al. (2015), Lee et al. (2021), Smith (2015)
Forums visits without further action	Meku-Fotso et al. (2020)
Assignment/quiz activity	
Scores	Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Du et al. (2018), Frick et al. (2022), Lee et al. (2021), Li et al. (2022), Meku-Fotso et al. (2020), Reza et al. (2021), Rohloff et al. (2019), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), Ruiz et al. (2014), Tegos et al. (2021), Thankachan (2017), van den Beemt et al. (2018), Vinker and Rubinstein (2022), Wang et al. (2017), Xing and Du (2018), Xing et al. (2016), Yu et al. (2021)
Submissions	Eradze and Tammets (2017), Lafifi et al. (2020), Lee et al. (2021), Li et al. (2022), Rohloff et al. (2019), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), van den Beemt et al. (2018), Vinker and Rubinstein (2022), Yu et al. (2021)
Submission length	Ezen-Can et al. (2015)
Number of failed-passed submissions	Cobos and Soberón (2020), Cobos and Ruiz-Garcia (2020), Lee et al. (2021), Malekian et al. (2020), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), Vinker and Rubinstein (2022), Wang et al. (2017), Yu et al. (2021)
Number of passed submissions with honour	Crossley et al. (2017), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017)
Repetition of wrong answers	Thankachan (2017), Vinker and Rubinstein (2022)
Assignment attempts	Cobos and Ruiz-Garcia (2020), Lee et al. (2021), Meku-Fotso et al.(2020), Rohloff et al. (2019), Ruiz et al. (2014)
Hints used	Li et al. (2022), Thankachan (2017)
Content activity (videos, pdf)	
Visit of course material	Almeda et al. (2018), Eradze and Tammets (2017), Rohloff et al. (2019), van den Beemt et al. (2018), Xing et al. (2016)
Eye tracking logs (i.e., student gaze)	Sharma et al. (2016), Sharma et al. (2020)
Number of downloaded course material	Malekian et al. (2020)
Number of watched videos	Malekian et al. (2020), van den Beemt et al. (2018)
Number of finished videos	Lee et al. (2021), Yu et al. (2021)

TABLE 4 (Continued)

Learners' data gathered	Studies
Repeated video	Li et al. (2022), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017)
Video events (e.g., pause forwarding)	Lee et al. (2021), Li et al. (2022), Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017); Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017), Tomar et al. (2017), Yu et al. (2021)

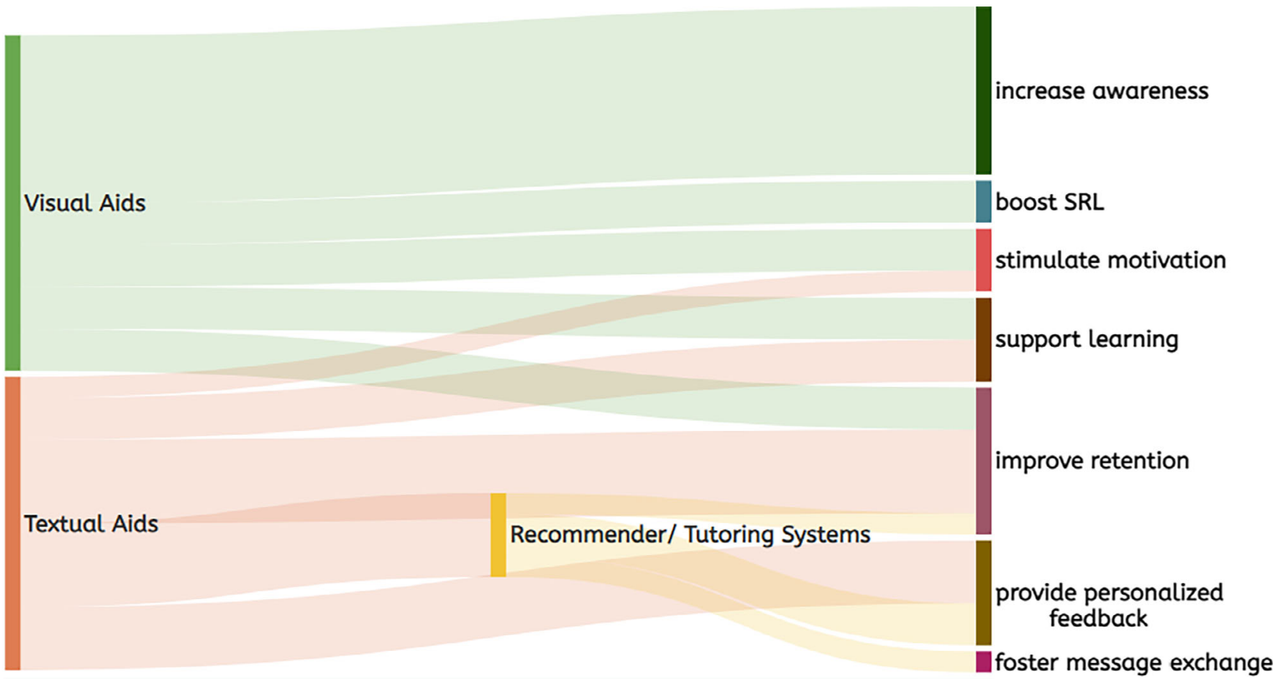

FIGURE 9 Relationship between the feedback techniques applied and/or proposed and the feedback purposes.

research attention on MOOCs, with a peak during 2015–2018. Under the COVID-19 pandemic, Chen et al. (2020) and Ma and Rindlisbacher (2020) reported a significant adoption of MOOCs at all educational levels. We hypothesize that this situation may have boosted the research on feedback practices in MOOCs. Recent efforts from the LA community to provide actionable and human-centered feedback informed by LA (Shum et al., 2019) could be another reason for the interest in MOOCs.

Attending the maturity of contributions, our findings suggest the early state of research on MOOCs and LA-informed interventions in the scope of feedback provision. Most works presented proposals without empirical application and evaluation in authentic settings. Thus, there is a need for elaborated proposals applied in context to draw conclusions about the effects of LA for feedback provision in MOOCs.

5.2 | RQ#2: How is feedback designed in MOOCs in terms of the pedagogical theories followed?

Most contributions aimed to increase the motivation or self-awareness of learners and to provide automated and personalized instruction. The massive character of MOOCs, which requires self-regulated and independent learners (Alonso-Mencía et al., 2020), may explain why most proposals aim at improving self-regulation. Still, the role of instructors remains critical; instructors' active presence and support are valued positively by the learners and relate to retention (Gregori et al., 2018). In two studies, the automated and personalized feedback aimed at enhancing self-regulation was designed by the instructors (Reza et al., 2021; Yılmaz et al., 2021).

From 38 studies, only eight grounded their research on a pedagogical framework or theory associated with feedback and learning. The most common pedagogical theory regarded the principles of SRL (Zimmerman, 2000). Our results agree with the findings of Khalil et al. (2022) of SRL as the dominant theory informing LA proposals. MOOC participants are required to have an autonomous profile (Alonso-Mencía et al., 2020), explaining the adoption of SRL principles as a guide for the design of feedback. Min and Jingyan (2017) argued that learners' logs in MOOCs relate well with SRL-related constructs while recent papers question it (Van Der Graaf et al., 2021). Further work is necessary to study this matching. The lack of theoretical grounding in most contributions indicates pedagogical limitations of the foreseen interventions. Our results agree with Cavalcanti et al. (2021), who highlighted the lack of an educational basis for the online learning feedback systems.

The absence of pedagogical frameworks in MOOCs is associated with learners' disengagement (Ferguson & Sharples, 2014). Previous works emphasized the need of informing tools' development with pedagogical theory to result in meaningful feedback (Ryan et al., 2019; Vieira et al., 2018; Wise & Cui, 2018). Gašević et al. (2017) highlighted the importance of learning theory in LA and proposed a consolidated model for the inclusion of the learning theory into LA research and practice. Our findings confirmed the need for research on theoretically informed LA-based tools that mediate feedback.

Most publications regarded courses related to formal sciences ($N = 17$), such as Programming or Math. According to Najafi et al. (2015), the course discipline is a factor affecting the instructors' effort to provide support. The authors observed that formal and applied sciences tend to include more computer-graded assignments and the social science courses include assignments that require textual analysis. Thus, it is probably easier for formal science courses to employ data-driven feedback, due to data captured by computer-based assignments. This raises important challenges related to the nature of LA-based interventions, which should aim to provide feedback in real-life problems and not only on what can be measured.

5.3 | RQ#3: How is LA applied and employed in MOOCs in order to result in relevant information for feedback provision?

The technological tools developed for informing visual feedback interventions were primarily dashboards. The most frequent data source were learners' logs from MOOC platforms. Still, 18 out of the 38 studies did not define any support strategy. The rest suggested mainly textual support, such as reminders, recommendations to weak learners, motivational messages for encouraging learners to self-report their challenges and stimulation of dialogic peer feedback. Thus, there is a tendency to provide visual feedback, but other forms of textual feedback may be effective.

The reviewed studies provided no input on how to use the LA tools meaningfully to provide feedback. Klusener and Fortenbacher (2015) proposed a tool where its output needs to be interpreted towards an appropriate intervention. While this is reasonable, it might result in less support. LA tools can scale up information about learners' progress facilitating instructors to deliver targeted interventions. However, instructors often find it complex to make sense of LA-based information due to lack of background (Fernández-Nieto et al., 2022; Rienties et al., 2018). Mangaroska and Giannakos (2019) reported that although there are plenty of LA tools, instructors need guidance to comprehend and use them in practice. According to Ryan et al. (2019), LA tools should facilitate the users' sense-making without focusing simply on the transmission of the information to result in effective interventions. Previous works (Liu et al., 2017; Pardo et al., 2018) proposed to place the instructors in the centre of decision-making, involving them in the selection of data features that they consider meaningful for actionable feedback interventions.

5.4 | RQ#4: What are the reported effects of the feedback interventions in MOOCs?

Our findings suggest a gap in terms of the evaluation of feedback interventions in MOOCs that hinders a deep understanding of the impact of LA-based feedback on learning and its usefulness. The scarcity of evaluation approaches for LA empirical interventions in MOOCs is in accordance with the current state of LA interventions in Higher Education (Viberg et al., 2018). This finding points towards a discrepancy between research attention and actual contributions delivered in the educational landscape. In MOOCs, the scarcity of LA-based empirical studies can potentially be attributed to the increased difficulty of implementing and evaluating technological proposals due to the massive character of MOOCs and the limited resources (in terms of time and effort) that MOOC stakeholders can offer. Alternatively, the dominant learning paradigm of MOOCs, where instructors transferred their minor scale learning practices (e.g., face-to-face learning) to MOOCs, without considering the new requirements of this massive environment, contributed to the low interest in empirical assessments of tools.

Most studies ($N = 34$) did not provide empirical evaluation of the tools in practice, while 20 studies offered a preliminary assessment of their contributions exploring mainly the users' satisfaction and the tool's usability. This finding suggests that the field is in its infancy, with little evidence and studies in early stages. At the same time, there is potential, and the limited results so far are positive.

6 | THEORETICAL AND PRACTICAL IMPLICATIONS

We envision that the theoretical and practical implications of this systematic literature review extend into two directions:

1. The systematization of feedback designs in MOOCs based on the learning goals, feedback aims, learning topic, and context;
2. The need for rigorous empirical evaluation of the overall impact of LA-based feedback in MOOCs.

The design and implementation of evidence-based feedback in MOOCs appears to be a developing line of research if we consider the prominent publications' venues and contributions' type. Most research contributions are in the phase of proposing or demoing and have not shifted to practice. Thus, there is still need for large-scale, systematic research regarding one of the main expected benefits of LA in MOOCs—the possibility to empower MOOC instructors in scaling up feedback interventions.

Regarding the design of LA-based feedback in MOOCs, our findings suggested several limitations. The reviewed proposals do not consider pedagogical theories and they do not frame the feedback design in an a priori reflection about learning goals, feedback aims, learning topic, and context. These aspects could be covered, if the design of feedback tools was contextualized within the course design. Such contextualization can be achieved by following a participatory approach when gathering requirements or designing technical solutions and actively involving instructors. Prior research highlighted that data visualizations are not always meaningful for instructors, especially when these visualizations are not connected with the course design. Another critical limitation is the lack of support when interpreting the information provided by tools. Previous literature reports that MOOC instructors often need additional support in interpreting the evidence presented to them regarding their learners' progress (Fernández-Nieto et al., 2022; Rienties et al., 2018).

Together with the a priori systematization of feedback design, there is the need for insights about the impact of feedback on learning and other dimensions that may affect learning in MOOCs, such as participation, motivation, and social engagement. Impact is an essential aspect of feedback that should be further defined within context and together with instructors, technology designers and researchers. This implies a close synergy among researchers and educators to specify: (a) the expected feedback impact and, (b) the metrics to measure it (metrics that will effectively allow to capture changes in learners' behaviours and learning outcomes as a result of feedback).

Our findings indicate the need for conceptual tools to guide the LA-based feedback design. Zheng et al. (2016) highlighted the central role of MOOC instructors in learning. Estrada-Molina and Fuentes-Cancell (2022) pointed out the challenges that instructors face when aiming to provide timely and personalized feedback. LA can generate information to shape scalable and personalized feedback interventions, yet previous works uncover the difficulties of MOOC instructors to comprehend data-driven information (Fernández-Nieto et al., 2022; Rienties et al., 2018).

6.1 | Limitations

This work presents limitations that can serve as pointers for future research. The SLR considered as the search period for identifying relevant studies, a specific timeframe (2010–2022). Any paper published after that point is not included in this review. Additionally, the limited sample size does not allow statistical analysis.

This SLR followed established guidelines proposed by Kitchenham and Charters (2007). However, we made specific decisions while conducting the review that may have impacted the final selection of papers, such as the variety of the terms describing similar concepts related to data-driven evidence or learners' support. Additionally, the article selection was based on papers written in English. Non-English publications with potentially relevant results were excluded.

Finally, we consider the scarcity of the literature on the topic as an important limitation. Despite the rich research on LA-informed feedback in other contexts, such as in higher or online education, the lack of prior work on LA-informed instructor-led feedback in MOOCs does not permit the generalization of results.

7 | CONCLUSIONS

We presented a systematic review of 38 papers exploring contributions to LA-informed feedback in the context of MOOCs during the last 12 years. We analysed the findings based on four topics: the current research state of the art of the field, the design of LA-based feedback interventions in MOOCs, the employment of such interventions and the interventions' impact. The results suggest that the field is still evolving, given the increasing rest on the topic, the variety of proposed solutions and the growing number of journal papers. Nevertheless, the review showed a lack of empirical studies exploring the use of LA to inform feedback in MOOCs and measure the effects of this feedback on students' learning.

The findings suggested limited attention to pedagogical issues related to actual participants' learning and feedback practices in MOOCs. The retrieved publications presented tools that did not provide guidance to their users (i.e., course instructors) on how to treat the data to result in actionable feedback. That is, MOOC instructors are expected to know how to interpret the information provided by dashboards or the outcomes of predictive models. Our work highlighted the need for: (a) contextualization of the feedback design under several course conditions, such as the learning topic and goals and (b) the systematization on the evaluation of the feedback effects.

The above limitations (i.e., the lack of evaluation of the interventions in real cases and the lack of pedagogical underpinning of the developed tools) pose the question of how we can effectively support MOOC instructors and researchers to design and deliver data-driven interventions in massive contexts. Further work and empirical studies are needed to understand the effectiveness of LA-based instructor-led feedback in MOOCs. Additionally, future lines could regard how to set the basis for collaboration among instructors and researchers when designing LA-based feedback tools. To address the limitations above, we propose to work towards a conceptual framework to facilitate instructors in the design of the interventions.

AUTHOR CONTRIBUTIONS

Paraskevi Topali, Irene-Angelica Chounta: Conception and design, or acquisition of data, or analysis and interpretation of data. Paraskevi Topali, Irene-Angelica Chounta, Alejandra Martínez-Monés, Yannis Dimitriadis: Been involved in drafting the manuscript or revising it critically for important intellectual content. Paraskevi Topali, Irene-Angelica Chounta, Alejandra Martínez-Monés, Yannis Dimitriadis: Given final approval of the version to be published. Paraskevi Topali, Irene-Angelica Chounta, Alejandra Martínez-Monés, Yannis Dimitriadis: Agreed to be accountable for all aspects of the work in ensuring

that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/jcal.12799.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Paraskevi Topali https://orcid.org/0000-0002-1951-2327

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APPENDIX A

A.1 | Coding scheme

TABLE A1 The applied coding scheme for the systematic literature review purposes.

I.Q.	Category	Description
General information		
	[title]	Title of the paper
	[authors]	Authors of the paper
RQ1: Publications' information		
I.Q.1.1	[year]	Year in which the paper was published
I.Q.1.2	[type]	Type of the publication (i.e., journal, conference, book)
I.Q.1.2	[contribution]	Type of the paper contribution (i.e., system/technological proposals, models, empirical studies in MOOCs)
RQ2: Feedback design aspects		
I.Q.2.1	[theory]	Theory that guides the design of feedback interventions
I.Q.2.2	[aim]	Aim of the feedback intervention (i.e., general one: to support learners, specific one: to motivate self-regulated learning)
I.Q.2.3	[platform]	MOOC Platform
I.Q.2.3	[discipline]	Course discipline that the proposed intervention and LA-tool are designed and applied
I.Q.2.3	[target-group]	Learners' cohort that the proposed intervention and LA-tool (e.g., dropout learners, lower background knowledge)
RQ3: Implementation of intervention		
I.Q.3.1	[data]	Data that is collected for the design of the proposed intervention/ LA tool (e.g., clickstream data)
I.Q.3.2	[analyt-approach]	How the collected data is analysed (e.g., predictive models, NLP)
I.Q.3.2	[commun-approach]	How the collected data is communicated to inform the instructors/learners (i.e., dashboards, charts)
I.Q.3.3	[provided-feed]	Type of feedback given based on the collected data (e.g., hints, recommendations)
RQ4: Feedback effects		
I.Q.4.1	[effects]	Effects of feedback interventions
I.Q.4.2	[practices]	Evaluation of the types of feedback practices
I.Q.4.3	[tool]	Tool evaluation

APPENDIX B

B.1 | Systematic literature review papers

TABLE B1 The retrieved papers included in the current systematic literature review along with their key properties.

ID	Authors and year	Title	Venue
1	Almeda et al. (2018)	Comparing the factors that predict completion and grades among for-credit and open/MOOC students in online learning	Journal
2	Caballe et al. (2014)	A Methodological Approach to Provide Effective Web-based Training by using Collaborative Learning and Social Networks	Conference
3	Cobos & Soberón (2020)	A proposal for monitoring the intervention strategy on the learning of MOOC learners	Conference
4	Cobos & Ruiz-Garcia (2020)	Improving learner engagement in MOOCs using a learning intervention system: A research study in engineering education	Journal
5	Crossley et al. (2017)	Predicting success in massive open online courses (MOOCs) using cohesion network analysis	Conference
6	Du et al. (2018)	ELBA: Exceptional learning behavior analysis	Conference
7	Eradze & Tammets (2017)	Learning analytics in MOOCs: EMMA case	Book chapter
8	Ezen-Can et al. (2015)	Unsupervised modeling for understanding MOOC discussion forums: A learning analytics approach	Conference
9	Ferschke et al. (2015)	Fostering discussion across communication media in massive open online courses	Conference
10	Frick et al. (2022)	Analysis of patterns in time for evaluating effectiveness of first principles of instruction	Journal
11	Klusener & Fortenbacher (2015)	Predicting students' success based on forum activities in MOOCs	Conference
12	Konert et al. (2016)	PeerLA—Assistant for individual learning goals and self-regulation competency improvement in online learning scenarios	Conference
13	Lafifi et al. (2020)	Intelligent Tutoring of Learners In E-Learning Systems and Massive Open Online Courses	Book chapter
14	Lan et al. (2015)	Mathematical language processing: Automatic grading and feedback for open response mathematical questions	Conference
15	Lee et al. (2021)	Prediction of Student Performance in Massive Open Online Courses Using Deep Learning System Based on Learning Behaviors	Journal
16	Li et al. (2022)	MOOC learners' time-investment patterns and temporal-learning characteristics	Journal
17	Malekian et al. (2020)	Prediction of students' assessment readiness in online learning environments: The sequence matters	Conference
18	Meku-Fotso et al. (2020)	Algorithms for the Development of Deep Learning Models for Classification and Prediction of behavior in MOOCs	Conference
19	Reza et al. (2021)	The MOOClet Framework: Unifying Experimentation, Dynamic Improvement, and Personalization in Online Courses	Conference
20	Rohloff et al. (2019)	Student Perception of a Learner Dashboard in MOOCs to Encourage Self-Regulated Learning	Conference
21	Ruipérez-Valiente, Muñoz-Merino, Gascon-Pinedo, and Kloos (2017)	Scaling to Massiveness with ANALYSE: A Learning Analytics Tool for Open edX	Journal

(Continues)

TABLE B1 (Continued)

ID	Authors and year	Title	Venue
22	Ruipérez-Valiente, Muñoz-Merino, Pijeira Díaz, et al. (2017)	Evaluation of a learning analytics application for Open EdX Platform	Journal
23	Ruiz et al. (2014)	Towards the development of a learning analytics extension in open edX	Conference
24	Sharma et al. (2016)	A Gaze-based learning analytics model: In-Video visual feedback to improve learner's attention in MOOCs	Conference
25	Sharma et al. (2020)	Eye-tracking and artificial intelligence to enhance motivation and learning	Journal
26	Singelmann et al. (2019)	Design and Development of a Machine Learning Tool for an Innovation-Based Learning MOOC	Conference
27	Smith (2015)	Output from statistical predictive models as input to e-learning dashboards	Journal
28	Tegos et al. (2021)	Towards a Learning Analytics Dashboard for Collaborative Conversational Agent Activities in MOOCs	Conference
29	Teusner et al. (2018)	Effects of Automated Interventions in Programming Assignments: Evidence from a Field Experiment	Conference
30	Thankachan (2017)	Adaptive Learning	Conference
31	Tomar et al. (2017)	Coordinating collaborative chat in massive open online courses	Conference
32	van den Beemt et al. (2018)	Do instrumentation tools capture self-regulated learning?	Conference
33	Vinker & Rubinstein (2022)	Mining Code Submissions to Elucidate Disengagement in a Computer Science MOOC	Journal
34	Wang et al. (2017)	Data-driven feedback generator for online programming courses	Conference
35	Xing & Du (2018)	Temporal predication of dropouts in MOOCs: Reaching the low hanging fruit through stacking generalization	Journal
36	Xing et al. (2016)	Dropout Prediction in MOOCs: Using Deep Learning for Personalized Intervention	Journal
37	Yılmaz et al. (2021)	Students' Preferences and Views about Learning in a Smart MOOC Integrated with Intelligent Tutoring	Conference
38	Yu et al. (2021)	Adopting software product lines to implement an efficient learning analytics framework in MOOCs	Journal