ISSN: 1309 – 6575
Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi
Journal of Measurement and Evaluation in Education and Psychology
Research Article; 2023; 14(Special Issue); 382-395

Learning Analytics in Formative Assessment: A Systematic Literature Review

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Abstract

This systematic review examines the use of learning analytics (LA) in formative assessment (FA). LA is a powerful tool that can support FA by providing real-time feedback to students and teachers. The review analyzes studies published on Web of Science and Scopus databases between 2011 and 2022 that provide an overview of the current state of published research on the use of LA for FA in diverse learning environments and through different delivery modes. This review also explores the significant potential of LA in FA practices in digital learning. A total of 63 studies met all selection criteria and were fully reviewed by conducting multiple analyses including selected bibliometrics, a categorical meta-trends analysis and inductive content analysis. The results indicate that the number of LA in FA studies has experienced a significant surge over the past decade. The results also show the current state of research on LA in FA, through a range of disciplines, journals, research methods, learning environments and delivery modes. This review can help inform the implementation of LA in educational contexts to support effective FA practices. However, the review also highlights the need for further research.

Keywords: Learning analytics, formative assessment, assessment analytics, bibliometrics

Introduction

Formative Assessment

In the learning process, it is vital for the teacher to ascertain what the student already knows and teach accordingly (Ausubel, 1968). In this sense, assessment is an essential factor in the learning process. Students' performance and progress can be measured by assessment. Also, it shows what needs to be improved in the learning and teaching process. According to Lubinescu et al. (2001), assessment is a key factor for accreditation and evidence in the learning process. It occurs over the course of time by collecting evidence of learning in a systematic and planned way to determine whether a student achieved learning (Harlen et al., 2002). Two types of assessments encompassing assessment for formative and summative purposes have been emphasized in the literature. There is a distinction between these types of assessments. While summative assessment summarizes learning in order to make a decision related to recording, marking or certifying performance and achievements (Harlen & James, 1997), the formative assessment identifies aspects of learning by monitoring student learning during the learning process to provide feedback, modify learning and teaching activities and strengthen subsequent learning.

Formative assessment is a continuous process of evaluating student learning to identify areas of student weakness and make adjustments to instruction for improving student outcomes (Black & Wiliam, 1998). It involves ongoing monitoring and gathering evidence of students' progress during the learning process

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To cite this article:
Zhang, K., Yılmaz, R., Ustun, A. B., & Karaoğlan-Yılmaz, F. G. (2023). Learning analytics in formative assessment: a systematic literature review. *Journal of Measurement and Evaluation in Education and Psychology, 14*(Special Issue), 382-395. https://doi.org/10.21031/epod.1272054

Received: 28.03.2023
Accepted: 8.10.2023

(Yan et al., 2021). Based on collecting evidence of students' progress, feedback is provided to students as a key factor of formative assessment (Black & Wiliam, 1998; Stobart, 2008). Evidence based feedback is a useful strategy to foster students' learning outcomes in different circumstances. Furthermore, one way to extend formative assessment is to incorporate more technology into the process. For example, making online quizzes or assessments can provide immediate feedback to students and can help teachers identify areas of weakness more quickly (Karaoglan-Yilmaz et al., 2020; Ustun & Tracey; 2021). Additionally, using analytical tools in a learning management system (LMS) or any other smart system can allow teachers to track student progress over time and make data-driven decisions about instruction. This process can include the use of data from formative assessments, as well as data from other sources, such as data for demographic, student performance and student engagement (Karaoglan Yilmaz et al., 2022). By analyzing this data, educators can identify patterns and trends that can inform instruction and help to improve student outcomes.

Learning Analytics

The demand of extracting meaningful insights from high-volume data requires automated analytical analyses in order to strengthen and shape the learning environments and experience (Ustun et al., 2022). High-volume data should be turned into meaningful information about the learning and teaching processes through analytical analyses using statistical algorithms and mathematical techniques. Analytical analyses can be performed by Learning Analytics (LA) which provides information about students and the learning environment in order to "access, elicit, and analyse them for modelling, prediction, and optimization of learning processes" (Mah, 2016, p. 288). LA is an emerging field that potentially revolutionizes how we understand and improve learning. It can be defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (The Society for Learning Analytics (SoLAR, http://solaresearch.org/)). In other words, data that students generate can be collected, analyzed and reported to understand and optimize the teaching and learning process and the learning environment. Ultimately, LA uncovers students' learning patterns and behaviors to predict student learning outcomes (Xing et al. 2015) and also discovering their learning patterns and behaviors provides opportunities for teachers to tailor education by offering more personalized experiences or adaptive learning materials (Ndukwe & Daniel, 2020; Siemens, 2013).

One of the key benefits of LA is that it enables teachers to monitor student performance (Ustun et al., 2022). Teachers can gain a complete picture of how students are progressing and identify areas where they may need additional support by collecting data on students' activity, engagement, and achievement. Providing personalized instruction is another key benefit of LA. Teachers can tailor instruction to meet the specific needs of each student by analyzing data on how individual students learn (Schumacher & Ifenthaler, 2018). Therefore, students can more easily adapt to the content, pace, or style of the instruction, and this potentially leads to more effective and efficient learning. LA can also be used in the identification of at-risk students. By analyzing student engagement and performance data, teachers can identify students who may be at risk of falling behind and provide early interventions for these students according to their learning preferences and abilities to help them stay on track. (Gašević et al., 2016). Finally, LA can be utilized to enhance the design of learning environments and resources. The way students interact with learning environment and resources can be analyzed to identify areas where they can be improved to better support student learning. For instance, according to analyzing how students interact with a particular LMS, the interface of the LMS can be redesigned to make it more user-friendly or add features that students have found helpful (Ustun et al., 2021; Ustun & Tracey, 2020).

Assessment Analytics

Assessment analytics (AA) is a burgeoning research field and is considered a subset of LA. Economides (2009) states that 'like any other context-aware system, an AA procedure monitors, tracks and records data related to the context, interprets and maps the real current state of these data, organizes them (e.g., filter, classify, prioritize), uses them (e.g., decide adaptations, recommend, provide feedback, guide the learner) and predicts the future state of these data' (as cited in (Papamitsiou & Economides, 2016, p.118). In this sense, assessment analytics like LA is related to measuring, collecting, analyzing, and reporting data about students and environments in which learning occurs for the purposes of comprehension and optimization of the learning environments where data is extracted from assessment (Cooper, 2015). One of the major aims of assessment analytics is to support the assessment process in an effective and efficient manner (Papamitsiou & Economides, 2016) because assessment data has great potential for students to take advantage of them after meaningful results derive from analyses of assessment data (Ellis, 2013). The assessment analytics explicitly show what students need to invest their time to improve learning and lead teachers on what they need to modify and shape in the learning to improve learning processes. Assessment analytics can be used to predict student performance, improve the detection of students at risk and misconceptions, uncover gaps between what needs to be learned and what is already learned, and reveal students' behavior, cheating, and guessing.

Learning analytics and Formative assessment

LA and FA are closely related, as both involve the use of data to inform instruction and improve student learning. LA and formative assessment can provide an entire picture of student learning. Combining these two concepts informs pedagogical decisions and practices such as providing feedback to students (Taras, 2008). LA can be used to support formative assessment by providing data and insights that can inform instructional decisions and help teachers understand how their students are learning and make more informed decisions about instruction. LA offers opportunities for educational progress and gives formative guidance to students or teachers (Gašević et al., 2022). Specially, using analytical tools help teachers to provide LA based personalized feedback (Pardo et al., 2019). LA and formative assessment can be used to create a more data-driven and personalized approach to instruction, one that is continuously informed by student data and tailored to meet the needs of individual learners (Merikko, 2022). To gain a more comprehensive understanding of student learning, LA can be used in conjunction with formative assessment.

Purpose of the study

There are many studies on FA and LA in the literature. However, a gap exists in the literature in terms of reviews of research on applying LA in formative assessment. In order to fill this gap, the articles that were indexed in the Web of Science and Scopus databases and addressed the use of LA in the formative assessment were pinpointed and analyzed. The Web of Science and Scopus databases were chosen for the study because they provide access to the most relevant and prestigious publications in the related research area.

This review aimed to sketch the current landscape of published studies on LA for FA in a variety of learning environments through various delivery modes. The following questions guided our review and analyses.

1. Bibliometrics of the reviewed articles:
    - 1.1. What were the descriptive bibliometrics like?
    - 1.2. What journals were these studies published in?
    - 1.3 What disciplines or professional fields were these studies conducted in?
    - 1.4 What types of learning environments were these studies conducted in?
    - 1.5. What delivery modes were utilized in these studies?
2. Methodologies of the reviewed articles:
    - 2.1. What research methods were employed in these studies?
    - 2.2. What populations were studied with what types and sizes of participants?

Method

This review focused on the research on learning analytics in formative assessment.

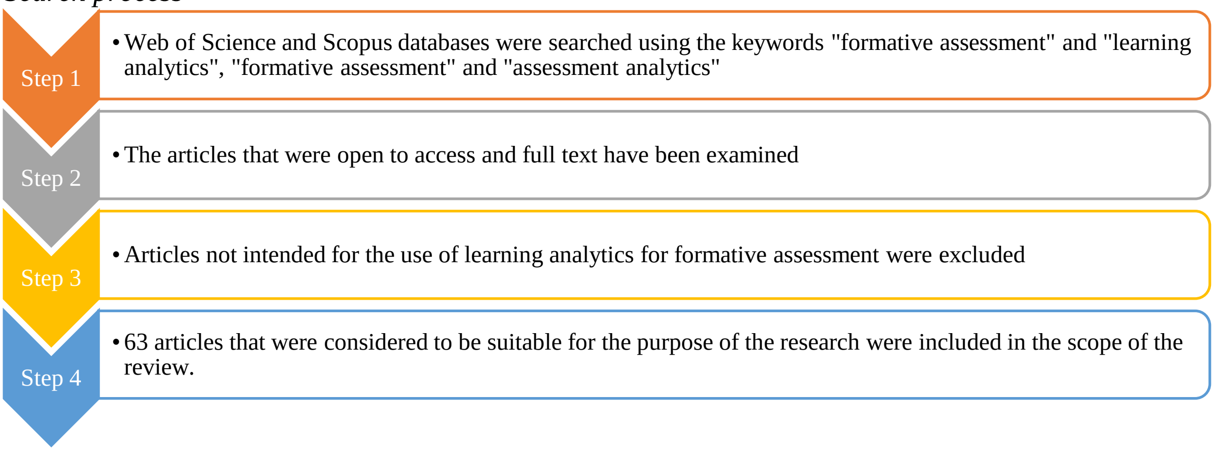
Search and Selection: Criteria and Processes

Multiple rounds of search were conducted. Web of Sciences and Scopus databases were identified and selected as the source databases to find related research publications on LA in FA, using the following keywords: “formative assessment” and “learning analytics”, “formative assessment” and “assessment analytics”.

The article search process in the databases was carried out by searching the keywords throughout the entire paper. In the Web of Science database, 90 articles were found using the keywords "formative assessment" and "learning analytics" and three additional articles were found using the keywords "formative assessment" and "assessment analytics". In the Scopus database, 796 articles were found using the keywords "formative assessment" and "learning analytics" and 24 articles were found using the keywords "formative assessment" and "assessment analytics". Duplicates in the multiple search results were excluded. Retrieved articles were further screened by the researchers, in terms of suitability for the purpose of the study. As a result, 63 articles were included in the systematic review. The search process is shown in Figure 1.

Figure 1

Search process



Considering the aims of this review, 63 articles were selected for further analysis. Multiple analyses were conducted, including selected bibliometrics (Okubo, 1997; Thelwall, 2008), a categorical meta-trends analysis (e.g., Hung & Zhang, 2012; Thelwall, 2008; Zhang & Aslan, 2021), and inductive content analysis (e.g., Gao et al., 2012; Mogil et al., 2009; Zhang & Aslan, 2021).

In order to find answers to the research questions, criteria were determined, and a form was created in the Microsoft Excel program according to these criteria, and the data obtained by examining 63 articles were processed into this form. Graphics and visuals have been prepared to make the data more understandable. Microsoft Excel and VOSviewer programs were used for these processes.

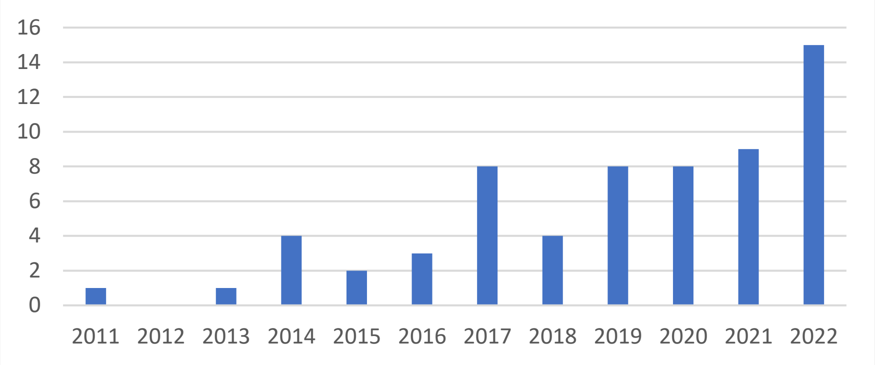
Findings

Descriptive Bibliometrics of the reviewed articles

LA in FA Research Article by Year

Figure 2

The Distribution of the articles by publication years

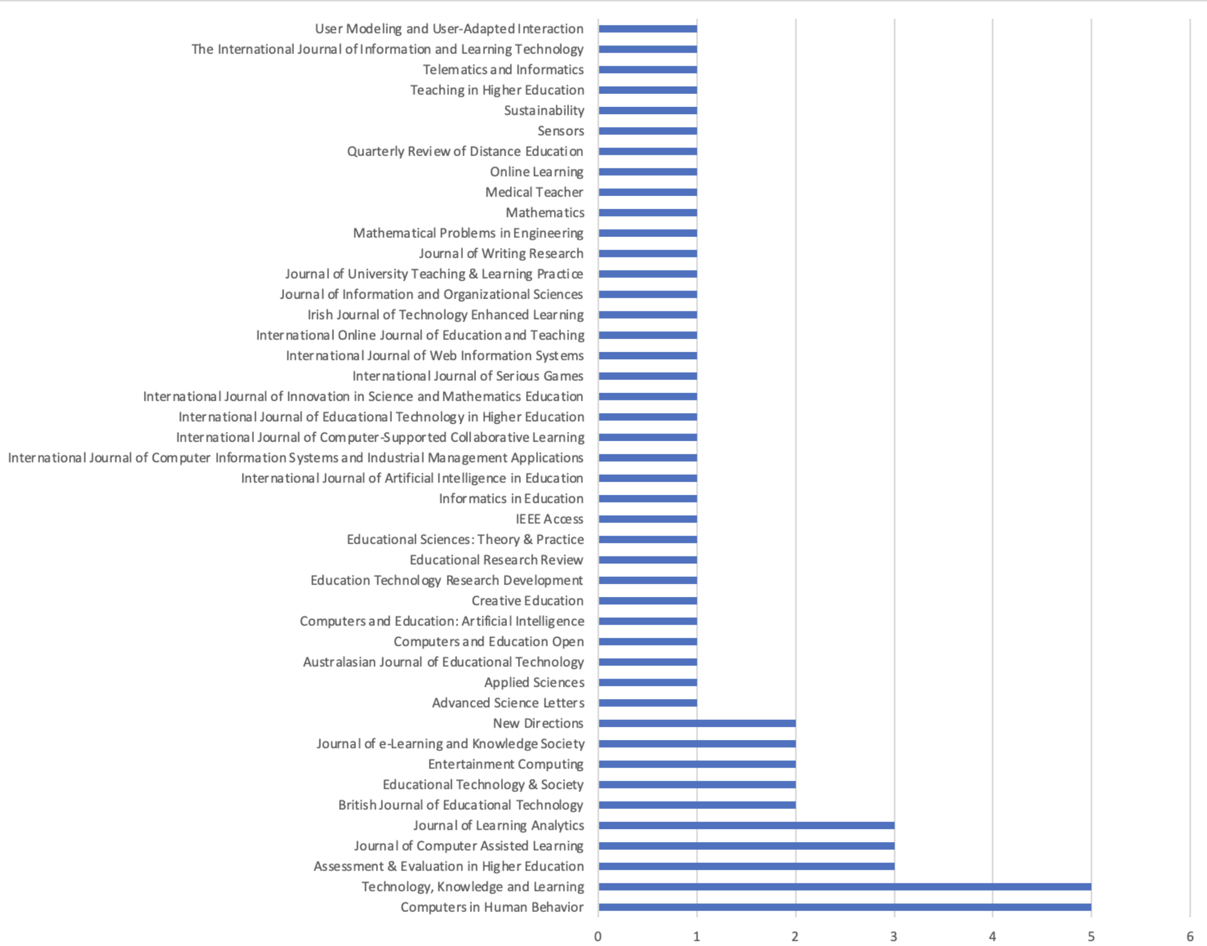


As illustrated in Figure 2, the first eligible research article in this review was published in 2011. Since then, in 12 years, the number of related research articles has increased from one in 2011 to 15 in 2022.

Journals publishing LA in FA research articles

Figure 3

The distribution of the articles according to journals

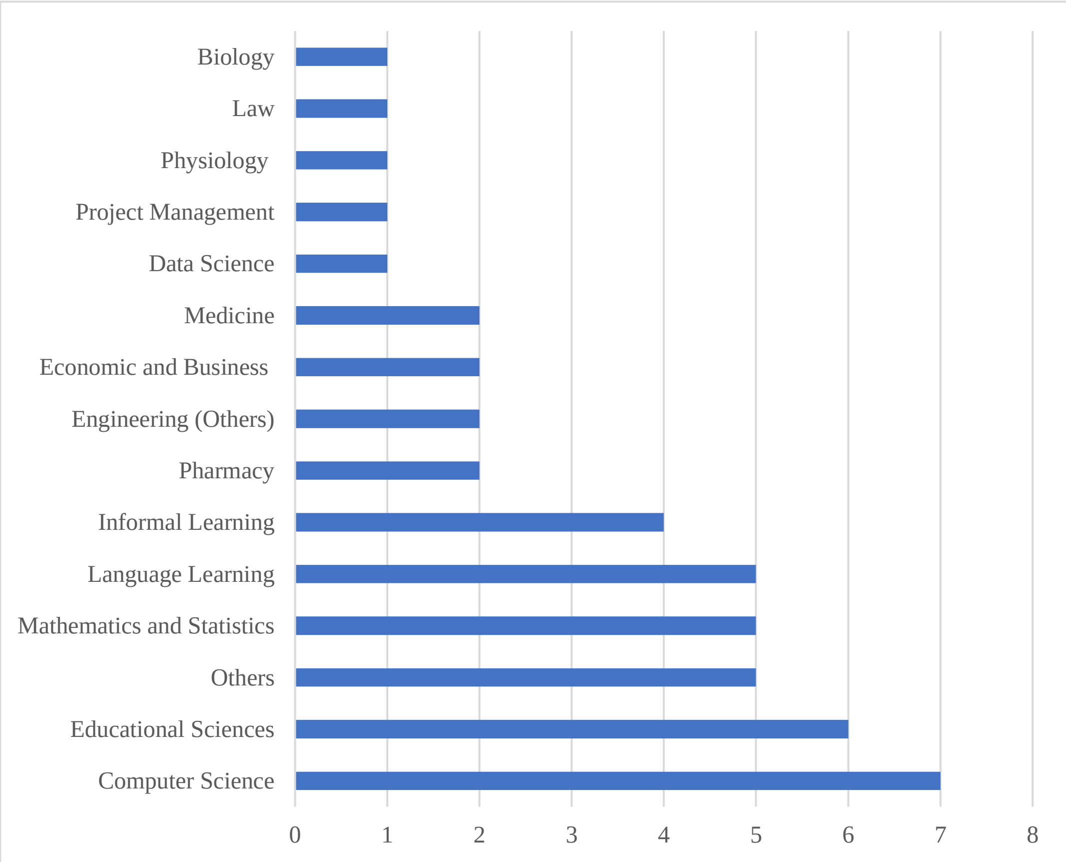


A total of 44 journals have published articles on LA in FA. Most of these journals have only published one or two of such studies so far, while the following journals have published a few more, *Computers in Human Behavior* (n=5), *Technology, Knowledge and Learning* (n=5), *Assessment & Evaluation in Higher Education* (n=3), *Journal of Computer Assisted Learning* (n=3), *Journal of Learning Analytics* (n=3).

LA in FA Research Article by discipline

Figure 4

The distribution of the articles according to the educational fields

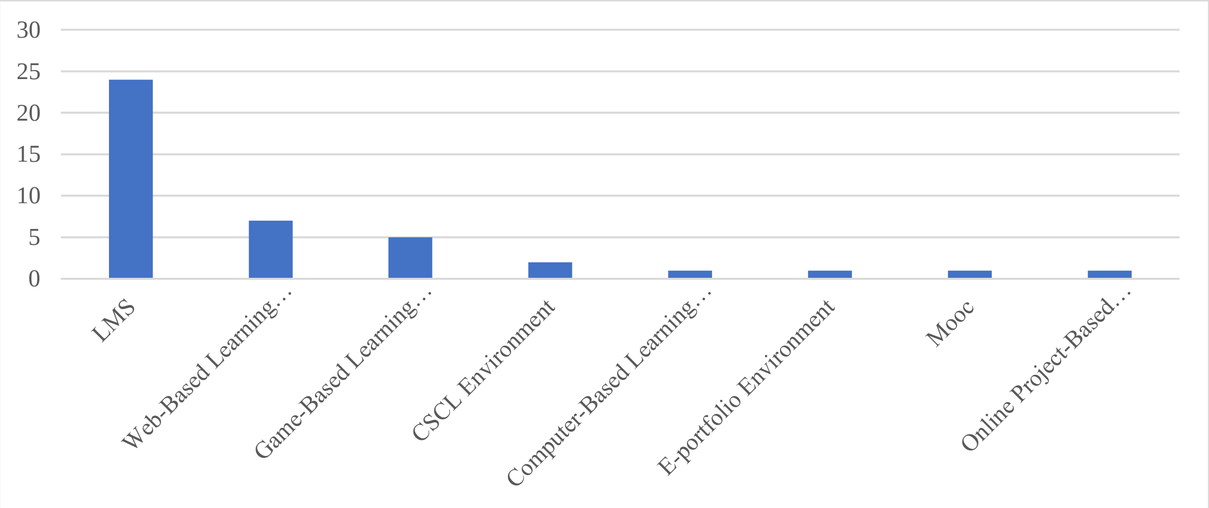


As seen in Figure 4, the articles on the use of learning analytics in formative assessment are mostly prepared on computer science (n=7), educational science (n=6), mathematics and statistics(n=5), and foreign language learning (n=5). Some studies have been conducted to include more than one discipline (e.g., Knight et al., 2020) or not to include any discipline (e.g., Barana et al., 2019). Therefore, the number of disciplines in which the research is conducted may differ in this respect.

LA in FA Research by technological learning environment

Figure 5

The distribution of the articles according to the learning environment

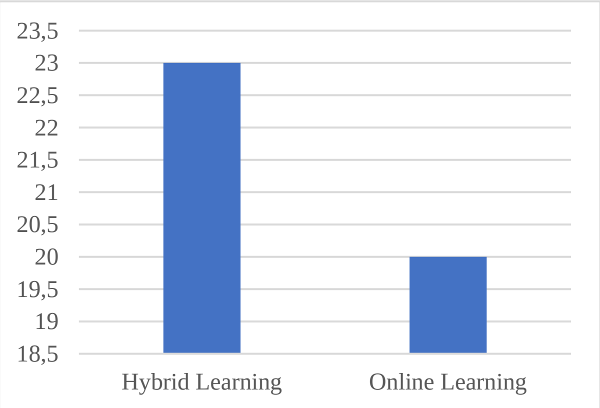


As seen in Figure 5, the studies on the use of learning analytics in formative assessment were mostly carried out using LMS. In addition to LMS, it is seen that web-based learning environments, game-based learning environments and CSCL environments were also used in the studies. The descriptions of the learning environments expressed in Figure 5 are as follows: Learning Management Systems (LMS) are utilized for educational purposes, exemplified by platforms like Moodle. Web-based learning environments encompass dynamic or static web pages designed for educational purposes. Computer Supported Collaborative Learning (CSCL) environments are utilized for computer-supported collaborative learning activities. Computer-based learning environments operate without an internet connection. E-portfolio environments allow students to create e-portfolios, upload content, and share them with their peers. Massive Open Online Course (MOOC) environments offer a wide range of courses to a large number of participants such as Khan Academy. Online project-based learning environments allow students to plan, collaborate and structure project products online.

LA in FA Research by delivery mode

Figure 6

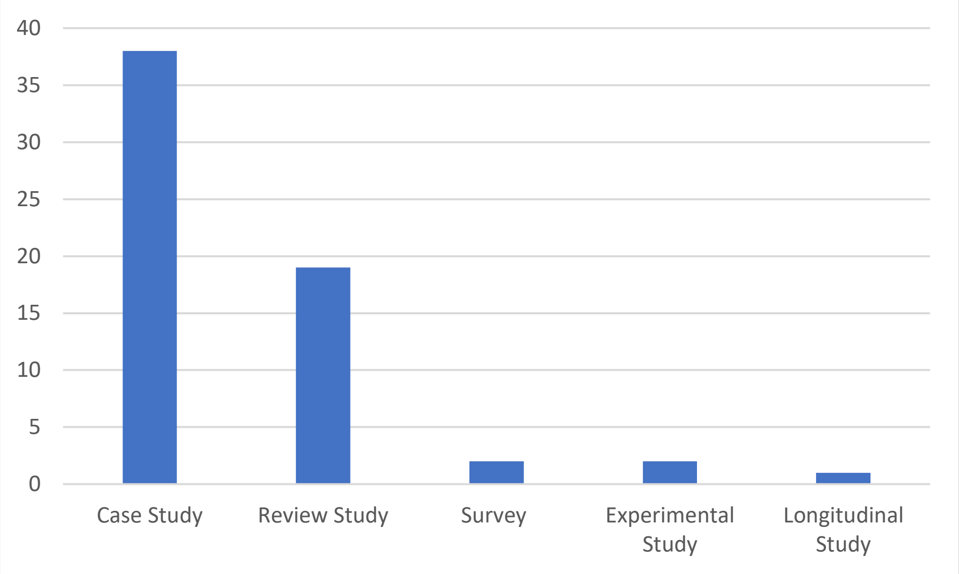
The distribution of the articles according to delivery modes



As seen in Figure 6, the studies on the use of learning analytics in formative assessment were mostly carried out in the modes of Hybrid Learning (n=23) and Online Learning (n=20).

Methodologies
Methodologies used in LA in FA research

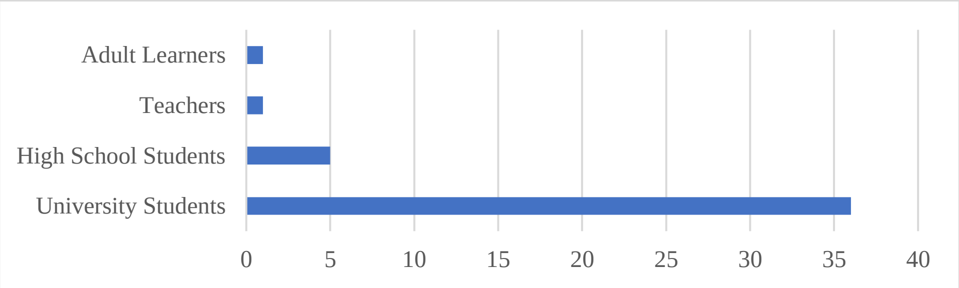
Figure 7
The distribution of the articles according to the research method



As seen in Figure 7, the case study method was mostly used in studies on the use of learning analytics in formative assessment, with 38 out of 63 studies. In addition, there were also studies conducted using the methods of Review Study (n=19), Survey (n=2), Experimental Study (n=2) and Longitudinal Study (n=1).

LA in FA research participants

Figure 8
The distribution of the articles according to the types of participants



As seen in Figure 8, studies on the use of learning analytics in formative assessment were mostly conducted with university students (n=36). In addition, there were also studies conducted on high school students (n=5), teachers (n=1), and adults (n=1), albeit a small number.

Discussion

Since the first LA in FA study was published in a Web of Science journal in 2011, the number of such publications has increased tremendously in the past decade. The 63 articles analyzed in this review represent the current state of research on LA in FA, through a range of disciplines, journals, research methods, learning environments, and delivery modes.

LA in FA has been applied in various fields, including computer science (e.g., Yan et al., 2021), law (e.g., Knight et al., 2020), education (e.g., Merikko et al., 2022), engineering (e.g., Gasevic et al., 2017), pharmacy (e.g., Liu et al., 2021) and many more. Thus, journals that have published such studies are diverse as well. A total of 44 journals have published research on LA in FA since 2011. The following journals including *Computers in Human Behavior*, *Technology, Knowledge and Learning*, *Assessment & Evaluation in Higher Education, Journal of Computer Assisted Learning* and the *Journal of Learning Analytics* have published a few more such studies than other Web of Science journals.

A wide range of applications of LA in FA was reported in these studies. For instance, LA is used to monitor the learning progress and learner engagement (e.g., Koc, 2017; O'Dowd, 2022; Nguyen et al., 2016), identify learners at risk (e.g., Choi et al., 2018), generate adaptive testing (e.g., Yilmaz et al., 2021), provide feedback for instructors and learners (e.g., Banihashem et al., 2022; Krull & Leijen, 2015), predict academic performance (e.g., Bulut et al., 2023; Martin & Ndoye, 2016), detect learning strategies (e.g., Gasevic et al., 2017), facilitate peer assessment (e.g., Er et al., 2021) and provide early warning for potential dropouts (e.g. Choi et al., 2018).

Most of the studies were conducted in either fully online or a hybrid delivery mode, which generate rich digital data ready for LA. More specifically, the research on LA in FA was implemented in learning management systems (LMS), web-based, game-based or CSCL learning environments. LA in FA was employed in higher education (e.g., O'Dowd, 2022) and high schools (e.g., Gomez et al., 2021). Thus, varied participants were recruited in related research, including teachers (e.g., Admiraal et al., 2020), high school students (e.g., Tempelaar et al., 2015), college students (e.g., Karaoglan Yilmaz, & Yilmaz, 2020), and adult learners (e.g., Serrano-Laguna et al., 2014) to explore the effects and user experiences of LA in FA.

A few different research methods are employed in these studies. Case study is the most often applied method in LA in FA studies, which allows deeply contextualized analysis of the practice. At the same time, the methodological limitation of such methods may also significantly limit the generalizability of the research findings. It is noteworthy though, that a small number of longitudinal (e.g., Martinez-Maldonado, 2019) and experimental (e.g., Tan et al., 2017) studies are also available.

LA techniques used in these studies include data mining, predictive modeling, and visualizations. The types of data analyzed in the studies include clickstream, log, and assessment data. The impact of LA in FA has been examined in terms of student learning outcomes, student engagement, and instructor feedback.

The review has found that LA in FA increases the capacity of digital learning by providing timely and actionable feedback to students and instructors. These studies investigate LA in FA for different purposes, such as generating feedback for students, providing feedback for instructors, creating student profiling, facilitating peer assessment, monitoring student performance, detecting learning strategies, offering automatic instant corrections, and more.

LA has become an essential area of education research. These reviewed studies provide further evidence for the educational benefits of LA in FA. LA provides instructors with data-driven insights into student learning (Karaoglan Yilmaz & Yilmaz, 2020). By leveraging LA, instructors can make informed choices about best supporting their students' learning progress. It can enhance student learning and engagement by providing personalized feedback and support while supporting instructor decision-making and promoting metacognitive development (Harindranathan & Folkestad, 2019). Besides, it can assist in identifying students who may be at risk of falling behind or encountering difficulties. By analyzing data related to behavior, participation, and student performance, instructors are able to intervene in advance and provide additional support to these students during the FA process. This proactive approach allows for timely interventions and can prevent academic setbacks.

The surge of AI technologies calls for creative ways to transform education and extend the educational landscape for more equitable and accessible education (Üstün, 2021; Zhang & Aslan, 2021). With the emergence of learning engineering as a new, interdisciplinary field (Zhang & Zhu, 2022), LA in FA becomes even more important as educators, educational technologies and educational researchers collaborate to transform digital learning. While LA focuses on the analysis of data to improve teaching and learning, learning engineering is concerned with the design, development and research of effective learning systems and technologies (Zhang & Zhu, 2022). LA in FA research can inform learning engineering by providing insights into student learning behaviors, preferences, and needs (Zhang & Zhu, 2022). LA makes it possible to provide immediate feedback to both students and instructors during the FA process. Through data analysis, instructors are able to identify areas where students may be struggling or excelling and provide relevant and constructive feedback to guide their learning (Ustun et al., 2022). Students can also receive personalized feedback during the FA process and LA-based feedback enables them to understand their strengths and weaknesses and make necessary improvements.

LA can help teachers tailor instruction to individual student needs. By analyzing learner-generated data, LA can identify patterns and trends (Hung & Zhang, 2008) that can be used to optimize learning design and delivery. By analyzing student data, instructors can identify knowledge gaps, learning styles, and preferences, allowing them to adapt their teaching strategies accordingly. For example, LA can be used to identify which instructional strategies are most effective for different types of learners, or which types of learning content are most engaging. This personalized approach enhances the effectiveness of FA by addressing specific student needs and promoting a more profound understanding. On the other hand, learning engineering can inform LA for FA by providing guidance on the design and development of effective LA tools (Zhang & Zhu, 2022). By designing tools that are tailored to the needs of learners and instructors, learning engineering can help to ensure that LA is actionable and scalable. For example, learning engineering can help to design LA tools that provide personalized feedback to learners (Ustun et al., 2022).

For LA to be used effectively, it is crucial to integrate it into learning environments. Cavus Ezin and Yilmaz (2022) indicate that LA must be integrated into the learning environments to benefit from the potential of LA in both online and hybrid learning. While different strategies and approaches can be followed, integration can be planned with the following steps by considering the educational goals of LA in general: a) Setting learning goals, b) Monitoring the learning process, c) Personalizing the learning experience, and d) Improving the learning experience.

a) Setting learning goals: LA can help instructors to set students' learning goals. Instructors can use student performance data to determine which areas students struggle or excel in. This information can assist them in setting goals and choosing appropriate activities to support students' learning. They should clarify the goals of lessons and what they want students to learn. These goals will help determine which data types and metrics to use for LA. For example, time-related results can be obtained from log data to increase students' attendance time in online courses. It is also essential to determine which data will be analyzed by LA. Various methods can be used to collect data such as exam grades, assignment performance, online interactions, and class attendance. LMS log data, surveys, quizzes, and other digital tools are some of the tools that can be used to collect data. LA can help instructors better understand students' learning and teach them more effectively. This tool can contribute to developing students' self-efficacy, and students who have developed self-efficacy increase their active participation in the lesson and feel their learning is more exciting and effective (Karaoglan-Yilmaz et al., 2023).

b) Monitoring the learning process: LA can be used to monitor students' learning progress. Instructors can use student performance data to track how students' learning progresses over time. This information can help instructors identify their needs and offer them sufficient support. Appropriate tools can be used to analyze the collected data. At this stage, the most frequently used data mining algorithms are decision trees, support vector machines, Naive Bayes, artificial neural networks, and regression methods (Tosunoğlu et al., 2021). At this stage, LA tools (dashboards, etc.) or data analysis software (R, Python, etc.) can be used to visualize data, identify trends, and understand student performance. Students' progress, strengths and weaknesses, interactions, and other important factors should be considered when analyzing data in this process.

c) Personalizing the learning experience: LA can be used to personalize students' learning experiences. Instructors can use student performance data to select activities that suit students' interests and needs. Hence, students' learning can be made more engaging and effective. Individualized feedback can be provided to students using the information obtained with LA. Suggestions can be made for students to improve their weaknesses while appreciating their strengths. This feedback can help them make their learning process more effective.

d) Improving the learning experience: LA can be used to improve the learning experience. Using student performance data, instructors can improve their teaching methods and materials. This can make students' learning more effective. Each item mentioned above regarding the integration of LA into the learning process constitutes a stage of the formative evaluation process. Therefore, through the formative assessment process, LA enables data collection, reporting on the acquired information, and facilitating interventions based on these reports. This way, LA can effectively support the advancement of the learning process. The learning process can be adjusted based on the information LA provides. For instance, if LA results show that students have difficulty understanding a particular subject, they may devote more time to it or offer them additional learning materials. Interactive activities or discussions can be organized to increase student interest and participation.

The above processes can be followed in integrating LA into the lessons. One of the essential points to be considered in this process is data privacy and ethical processes (Çetintav et al., 2022). Since LA results contain students' personal data, it is essential to pay attention to ethical processes in obtaining and using this data. LA results of a student should not be shared with other students in the class in a way that makes it identifiable to whom they belong.

Limitations of this review

This review is limited in its scope, as defined and specified in the method section. The selection of the source database and the specific search engines used in this review have also contributed to its methodological limitation. Research publications that do not include the selected keywords/terms as a descriptor in their title, abstract, or keyword list, as well as those not indexed in the source database are not included in this review.

Suggestions for future reviews

Future reviews may extend the search scope to include other reputable databases, specialized journals, or peer-reviewed conference proceedings. In addition, applying different search strategies, keywords, selection criteria, and exclusion criteria may retrieve more relevant research publications for a broader review.

Conclusion

Research has explored some of the powerful potentials of LA in renovating FA practices in digital learning. Dynamic LA empowers educators by providing critical insights into students' learning progress (e.g., Koc, 2017; O'Dowd, 2022; Nguyen et al., 2016), identifying struggling students (e.g., Choi et al., 2018; Saqr et al., 2017), and generating adaptive materials accordingly (e.g., Yilmaz et al., 2021). Thus, effective implementation of LA in FA could result in increased learner engagement, improved learning outcomes, boosted teaching efficiency, and better retention rates. The potential benefits of LA for FA make it a worthwhile investment for educational institutions, together with technology advancement.

Through a systematic review of empirical studies published in Web of Science and Scopus databases, this article portrays the trends of LA in FA research in the recent decade, since the first study was published in 2011. It has also explored the learning environments, delivery modes, disciplines, and participants of these studies, to develop a macro, as well as a micro-view of LA in FA research. The findings provide a preliminary foundation for more, historical, or meta-analyses of the increasing body of research literature on LA in FA.

To build a deeper understanding of the benefits as well as the challenges and issues of using LA in FA in digital education, more research is necessary. Different research methods are essential, and a larger number of participants are required for research on the scalable practice of LA in FA.

Declarations

Author Contribution: All authors equally contributed to conceptualization, methodology, analysis, writing, reviewing & editing, and visualization.

Conflict of Interest: No potential conflict of interest was reported by the authors.

Ethical Approval: Ethical rules were followed in this research. Ethical approval is not required, because data from WoS and Scopus was used in this research.

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript

Consent to Publish: Written consent was sought from each author to publish the manuscript.

Competing Interests: The authors have no relevant financial or non-financial interests to disclose.

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