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Review

A Systematic Review of the Role of Learning Analytics in Supporting Personalized Learning

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Abstract: Personalized learning is becoming more important in today's diverse classrooms. It is a strategy that tailors instruction to each student's abilities and interests. The benefits of personalized learning include students' enhanced motivation and academic success. The average teacher-to-student ratio in classes is 1:15.3, making it challenging for teachers to identify each student's areas of strength (or weakness). Learning analytics (LA), which has recently revolutionized education by making it possible to gather and analyze vast volumes of student data to enhance the learning process, has the potential to fill the need for personalized learning environments. The convergence of these two fields has, therefore, become an important area for research. The purpose of this study is to conduct a systematic review to understand the ways in which LA can support personalized learning as well as the challenges involved. A total of 40 articles were included in the final review of this study, and the findings demonstrated that LA could support personalized instruction at the individual, group, and structural levels with or without teacher intervention. It can do so by (1) gathering feedback on students' development, skill level, learning preferences, and emotions; (2) classifying students; (3) building feedback loops with continuously personalized resources; (4) predicting performance; and (5) offering real-time insights and visualizations of classroom dynamics. As revealed in the findings, the prominent challenges of LA in supporting personalized learning were the accuracy of insights, opportunity costs, and concerns of fairness and privacy. The study could serve as the basis for future research on personalizing learning with LA.

Keywords: learning analytics; personalized learning; systematic review; methods; challenges; learning technologies

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1. Introduction

Personalized learning is an educational strategy that adjusts pace, content, and instruction based on each student's particular needs, interests, and aptitude to meet the demands [1]. The advantages of this strategy lie in its capacity to meet the various demands of students and improve their engagement and performance. Personalized learning creates a deeper comprehension of subjects, boosts motivation, and enhances student accomplishment by recognizing and accommodating individual variations [2]. Additionally, it can encourage students to take charge of their learning and pursue independent study [3]. By offering specialized support to students who might need extra help or have difficulties, personalized learning can also aid in bridging educational disparities [4]. Students gain from personalized learning since it considers their individual needs and characteristics for assignments, tests, and learning. This contrasts with the conventional "one-size-fits-all" approach to education, which, as studies have shown, hinders teacher from identifying and meeting the needs and talents of every student [5]. Personalized learning is becoming more and more common in schools and universities today due to the plethora of advantages mentioned above [6,7].

At the same time, amidst the fervor surrounding personalized learning, there exists a nuanced discourse that questions the universal benefits attributed to this educational paradigm. Critics argue that the emphasis on performance within personalized learning may jeopardize students' psychological well-being by potentially compromising their sense of autonomy and relatedness. Self-determination theory [8] states that students require feelings of competence, autonomy, and relatedness for optimal well-being. The risk emerges when an excessive emphasis on numbers overshadows the intrinsic value of the learning process. Students may be driven to pursue performance goals solely to satisfy teachers, neglecting the essential aspect of understanding the learning process itself [9,10]. Moreover, the primacy of personalised learning pathways might inadvertently sideline the crucial social aspects of learning. Classroom studies emphasize the value of collaborative work, teamwork skills, and communication, elements often overshadowed in the current landscape of personalized learning systems. The absence of verbal interaction and insufficient attention to students' need for relatedness in these systems poses a potential limitation, challenging the assumption that personalized learning inherently encompasses all aspects of a dynamic learning experience [11]. Therefore, these works underscore the need for a nuanced understanding of the conditions under which personalized learning can thrive and the potential pitfalls that may impede its success.

The effective implementation of personalized learning includes (1) a meticulous gathering of data on each student's progress levels, strengths, and weaknesses in different topics, (2) the customization of learning materials and quizzes based on the needs of each student, and (3) customized feedback for each student. Given that today's curriculum does not only involve individual exams but also group projects, there are even more areas for personalized guidance from teachers. Hence, personalized learning requires a lot of time and manpower. However, the average percentage of a teacher's work hours spent in the classroom is only 46% [12], and the average teacher-to-student ratio in classes is 1:15.3 [13], which means that there is a lack of time and manpower to monitor each student and effectively personalize their learning. Therefore, it is possible that teachers will not be able to monitor and identify every student's behavior, traits, and preferences on their own. Additionally, because of time restrictions, teachers frequently use a one-size-fits-all strategy whereby they teach a large class of students at once. These restrictions can cause a few gaps where teachers may not be able to provide differentiated instruction based on each student's strengths and learning pace and may not be able to give timely and thorough feedback to every student. This can affect students' learning because they may not be aware of where and how to improve. A system that can evaluate student data, provide feedback, aid in differentiated instruction, and assist teachers in making instructional decisions in the classroom is required to close these gaps. LA is a promising solution that can accomplish the aforementioned.

In this regard, LA can be very useful as it allows for a quick assessment of students' strengths and weaknesses, progress tracking, automatic customization of learning materials and quizzes, and automatic feedback. Sometimes, teachers' feedback can be more subjective and based on their impressions and experiences with each student. LA can help such feedback be more objective by providing data-driven insights to the teachers. In addition, LA can even measure students' participation and performance in group work and assist in providing necessary feedback.

LA measures, collects, analyzes, and interprets data on students and their contexts to enhance student learning outcomes [14]. In the past ten years, LA has made significant contributions to the area of education by gathering vast amounts of data to better understand various facets of learning, including student engagement, behavior, and performance. Based on these findings, LA has now been able to quickly provide feedback and support to students and teachers [15]. By encouraging self-regulation, reinforcing their learning, and developing positive habits that will enhance their learning experiences, LA has also been able to empower students as they move forward in their educational journey [16].

It is noteworthy that the roots of data-driven approaches in education trace back to the 1980s and 1990s when Intelligent Tutoring Systems emerged as pioneering systems aimed at providing personalized instruction [17,18]. These early systems laid the groundwork for the development of more sophisticated LA methodologies [19].

LA supports the objective of personalized learning as it has the advantage of being able to track all online student behavior and automatically develop or adjust online resources. The use of LA for creating learning activities and raising student engagement has been the subject of a sizable body of study, but relatively few studies have examined how LA might enable personalized learning [15]. This study seeks to close the gap by analyzing the ways in which LA can promote personalized learning and the challenges involved with its implementation.

2. Methodology

A systematic literature review was conducted to address the current research gaps. The main steps carried out in this study include (1) problem definition, (2) creation of criteria, (3) data gathering and analysis, and (4) discussion. There are significant knowledge gaps between theory and practice in the emerging field of LA, particularly when it comes to how it relates to personalized instruction. The methods and challenges of LA must be understood to use it to assist personalized learning. Thus, the following research questions were formed:

RQ1: How can LA be leveraged to support personalized learning?
RQ2: What are the challenges in leveraging LA in personalized learning?

In this study, journal articles, books, and published dissertations published in Scopus and ProQuest were included. Five inclusion criteria and exclusion criteria were considered, as shown in Table 1, to only gather studies that were pertinent. Other literature evaluations on LA and the Critical Appraisal Skills Programme (CASP) [20,21] served as a guide for these criterion selections.

Table 1. Inclusion and exclusion criteria.

Inclusion	Exclusion
Empirical studies	Non-empirical studies
Studies that address educational practices	Studies that do not address educational practices
Studies with full text	Studies without full text
Studies that were published after 2015	Studies that were published before 2015
Studies there were published in English	Studies there were not published in English

In addition to the inclusion/exclusion standards, four quality standards were also taken into account to further filter the chosen studies and guarantee a high grade (Table 2).

Table 2. Quality assessment.

Quality Test (QT)	Question
QT1	Does the study have results related to the research questions?
QT2	Is there a clear statement of the research problem?
QT3	Does the study clearly determine the research methods?
QT4	Is there a clear statement of findings?

The first three keywords that were required to appear in the pertinent studies were "learning," "analytics," and "personalization" in the search string. To further limit the scope, the word "challenges" was also used. The terms "learning" and "analytics," however, were combined as "learning analytics" because using them separately produced numerous articles that were not relevant. To obtain more relevant results, the terms "learning analytics" and "challenges" were also combined. The final search term was, therefore, "Learning Analytics" or "LA" AND "Learning Analysis Challenges" AND "Personalization" AND "Student Learning". Figure 1 summarizes the process of article selection.

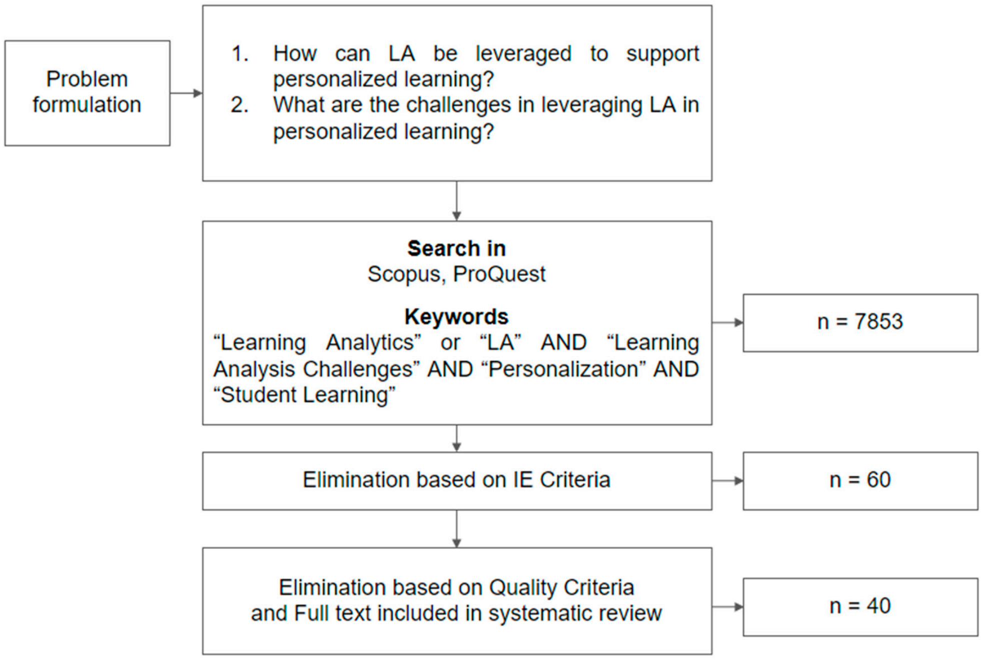

Figure 1. Main steps of the systematic review.

3. Findings and Discussion

In total, 40 articles were included in this study's final review. Four of the articles that were used in addressing RQ1 were also utilized to answer RQ2. Results from the analysis were reported in this section to address the research questions. The review of 28 articles focuses on the use of LA to support personalized learning at individual, classroom/group, and structural levels. Extracted analytics presents data for interpretation, while embedded analytics eliminates teacher interactions by automatically recommending tasks, resources, and opportunities based on a student's skill level. LA can track student progress, identify students' unique approaches to problem-solving, and provide real-time feedback on student performance. Teachers can use LA to categorize students based on ability levels, assess course materials, and forecast learning. LA can also evaluate previous student behavior and performance to predict future academic success. Social network data and student profiles can also be used to forecast future performance. Overall, LA can be used to provide personalised support in the classroom, allowing teachers to better understand and support their students.

The review of 16 articles reveals that the key challenges in leveraging LA for personalized learning include accuracy, privacy concerns, fairness concerns, and opportunity cost. The accuracy of LA results may be affected by factors such as student absence, which could lead to low engagement on platforms that leverage LA. Privacy concerns are another significant barrier to the implementation of LA in education. Students prefer anonymity in LA elements. Fairness is another challenge, as LA algorithms may contain biases, such as racial and gender stereotypes, which can negatively affect students' experiences and engagement. Opportunity cost is another challenge associated with LA in classrooms. High usage of digital tools may discourage creativity and detract from students' ability to learn, communicate, and interact physically.

Figure 2 illustrates the total number of articles obtained for this study between 2015 and early 2023 based on the year of publication. The distribution of articles based on RQs is shown in Figure 3. The number of articles published shifted between 2015 and 2016, as LA was only starting to gain traction. However, in 2017, there was an increase in the number of articles published as a result of the shift in technology trends in education, likely as a result of the use of Learning Management System (LMS) as a personalized tool to support students. Studies on LA reached a record level in 2020. It is assumed that the sharp growth resulted from the COVID-19 pandemic at the time, which caused teaching and learning to be largely moved over to online, and personalized instruction is crucial for online learning. LA trends will continue to gain popularity in the future given its many benefits [22]. Hence, it is crucial for future research to explore LA in personalized learning and evaluate its effectiveness in enhancing students' performance.

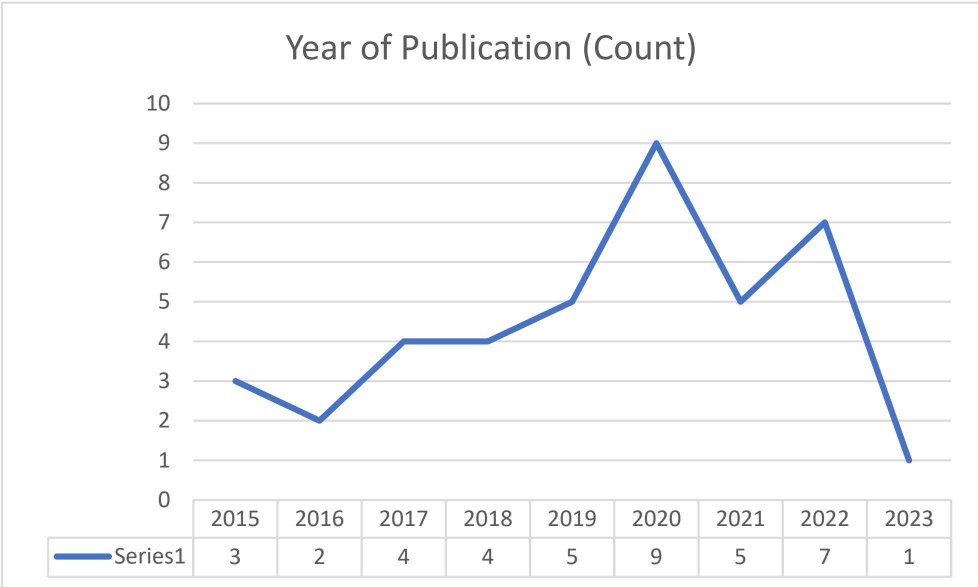

Figure 2. Year of publication for selected articles.

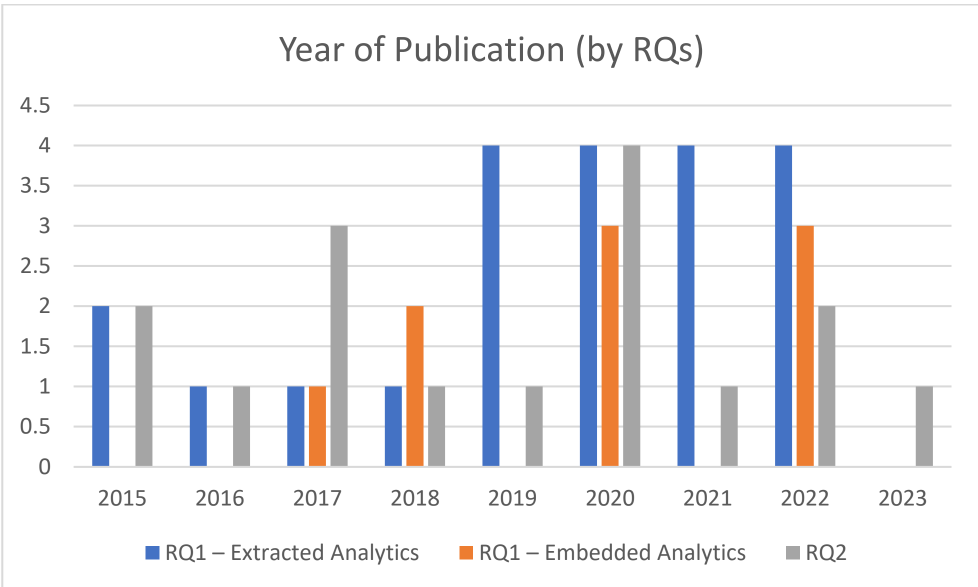

Figure 3. Year of publication (by RQs).

The articles included in the final review are organized by nation in Figure 4. The selected articles, which identified personalizing learning with LA, came from a total of 21 different nations. Studies on applying LA to support personalized learning have been carried out repeatedly in Western nations like the US, the UK, Australia, and Norway. Asian nations like Singapore, South Korea, and Japan also demonstrated interest in examining how LA is leveraged in personalized student learning. Accordingly, since it presents a variety of results on the use of LA in personalizing students' learning, it is critical for future studies to ensure diversity of demographic backgrounds. Students and teachers can do this by putting into practice the strategies and tools recommended in the research that use different forms of sampling and demographic backgrounds to improve the quality of the learning process in personalized learning contexts.

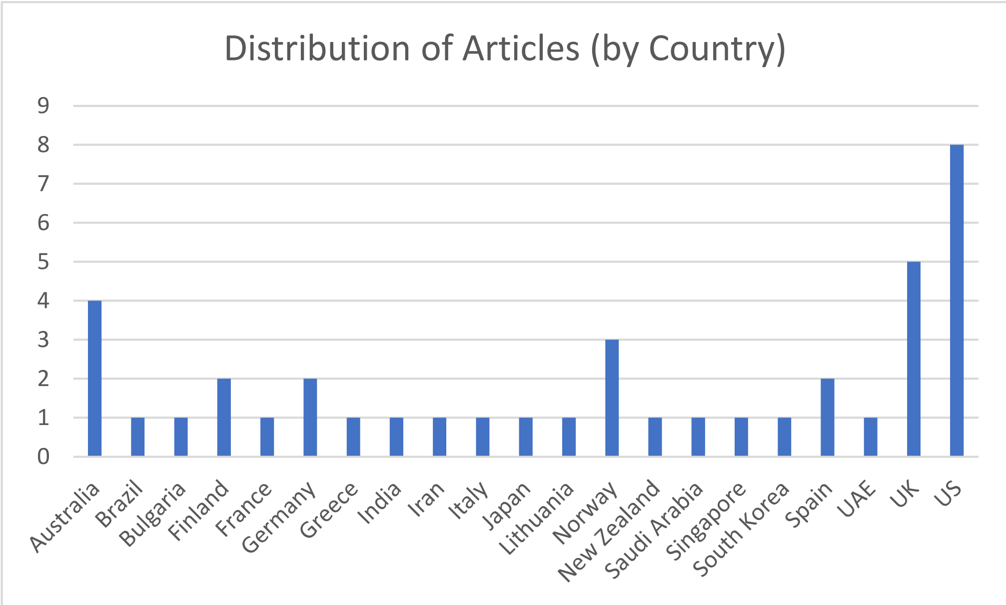

Figure 4. Distribution for selected articles by country.

3.1. The Way That LA Supports Personalized Learning (RQ1)

A total of 28 articles were reviewed to address RQ1. LA can be leveraged to support personalized learning in two ways: extracted analytics and embedded analytics. The approach known as extracted analytics presents data for interpretation so that teachers and students can obtain an understanding of the learning process and its outcomes, hence facilitating the personalization of teaching and learning in the classroom. Meanwhile, embedded analytics eliminates the requirement for teacher interactions by using data to automatically recommend tasks, resources, and opportunities based on a student's skill level [23].

3.1.1. Extracted Analytics

Through extracted analytics at the individual, classroom/group, and structural levels, LA can be leveraged to promote personalized learning. The included articles for extracted analytics are shown in Table 3.

Table 3. Types of extracted analytics in personalized learning.

Extracted Analytics	Articles	Count
Individual Level	[15,23–34]	13
Classroom/Group Level	[23,24,35–37]	5
Structural Level	[38–42]	5

- Individual Level

At the individual level in the context of LA, the focus is on the unique characteristics, progress, and behaviors of each student. Extracted analytics are utilized to provide personalized support and insights tailored to individual students' needs and learning styles.

For example, Ruipérez-Valiente et al. [24] revealed that LA could aid in tracking and visualizing each student's progress as they worked through puzzles. Additionally, it could identify which problems and corresponding concepts individual students found the most and least challenging. This can help provide each student with personalized support. Most significantly, LA might tell teachers whether a student has been actively trying to solve the problems or is simply speculating by examining how students engage with the puzzles. Decisions on pedagogy in the classroom can be guided by such knowledge. According to Sousa and Mello [23], LA could be used to track student progress in real-time on platforms like Khan Academy and Google Classroom.

With LA, teachers are able to view real-time feedback regarding students' performance as reported by Vahdat et al. [25]. This will assist teachers in identifying students who require assistance. According to Kleinman et al. [26], LA can be used to track students' behaviors while they attempt to solve problems and can provide data on both the quantity and sequence of those actions. The latter could be used to identify each student's unique approaches to problem-solving and identify the precise ideas that each student finds challenging. Teachers could utilize this data to identify the areas where their students need to improve and create lessons that are specifically geared toward those needs.

Kurilovas [27] found that teachers may utilize LA to categorize their students according to their ability levels, identify those who require more assistance, assess which course materials benefited various student groups the most, and forecast their learning. Additionally, it was mentioned that LA could classify students thoroughly based on the various ways they learn and process information. The data might then be used by teachers to develop various material kinds for differentiated education with their students. LA could also evaluate the behavior and performance of previous students to forecast academic success in the future [28–33].

Teachers could utilize this information to compare test results with actual student performance and provide tailored feedback. Social network data and student profiles can also be utilized to forecast future performance and determine how long each student can stay engaged in a course in addition to prior student performance [34]. According to Mangaroska et al. [15], LA that incorporated student data from several educational platforms improved the ability to forecast performance for specific students. Overall, teachers can use the data produced by LA to provide students with personalised support in the classroom. Table 4 summarizes the data (what) and methods (how) used in the selected study for leveraging LA to support personalized learning in the context of individual level.

Table 4. Data and methods used to support personalized learning with extracted analytics (individual level).

Article	Data	Methods
[15]	Examples, challenges, and coding exercises	A cross-platform architecture that incorporates and makes use of analytics was used to gather rich, real-world data from connected learning spaces, harmonize it, and present it visually as a tool for students and teachers. This could then increase teachers' and students' awareness of their own behavior and the settings in which learning takes place.
[23]	Educational data generated from digital tools (Google Classroom and Khan Academy)	Learning Analytics Dashboard (LAD) was created using information gathered from online resources like Khan Academy and Google Classroom. LAD assists teachers in locating, tracking, and suggesting solutions to address the learning gaps of their students. The data produced by student usage of digital tools can be utilized to track, evaluate, forecast, intervene, suggest, and enhance the effectiveness of teaching and learning.

Table 4. *Cont.*

Article	Data	Methods
[24]	Students' interactions with the game (how many puzzles they solve, how long they spend in the game world, and the events that each student creates)	Through a visualization dashboard, teachers access real-time analytics about how their students are interacting with the Shadowspect game. The dashboard assists teachers in keeping tabs on the general operation of the classroom as well as the progress of individual students, identifying problem areas, and giving each student tailored feedback. The dashboard also assists teachers in changing their instructional approaches, which can result in more efficient and personalised learning opportunities for students.
[25]	Programme for International Student Assessment (PISA) data and student population	LA and Educational Data Mining were applied to collect empirical data on the various variables that can impact learning and to apply computational methods to characterize, identify, and comprehend the preconditions of effective learning. This facilitates the customization and adaptation of technology enhanced learning systems to enhance instructional design and pedagogical decisions depending on the needs of students.
[26]	Data were collected from a learning game called Parallel that was equipped to record students' actions at a fine-grained action-to-action level as they completed a task or problem.	Human-in-the-loop method was used to sequence analysis to enhance personalized learning with LA. By visualizing the results of a clustering algorithm, this method enables stakeholders to better comprehend the data and the methodology. A deeper understanding of the algorithm's interpretation of the sequences is also made possible by the displayed output, which can be utilized to modify the algorithm's settings. The findings indicate that clustered sequences that more closely resemble an expert's assessment of the data are produced when stakeholders are given the opportunity to examine the displayed sequences and iteratively modify the algorithm. In the end, this strategy can support the identification of underperforming students and the creation of suitable and efficient personalized learning settings.
[27]	Data on students' behaviors in learning environments	Decision-making models were used to assess the applicability, acceptance, and use of personalized learning units in virtual learning environments. The methodology uses probabilistic appropriateness indices, the educational technology acceptance and satisfaction model, and multiple criteria decision analysis to determine whether learning components are appropriate for a given student's needs in accordance with their learning preferences.
[28]	The websites of the individual universities were used to compile the archival (secondary) data used in the study. The information was gathered from a sample of universities' websites, and the accuracy of the information was determined by the websites' content	Social networks adapting pedagogical practice (SNAPP) and Graphical Interactive Student Monitoring (GISMO) were used to gather information about students and their environments, providing both students and teachers the feedback. Students' motivation may rise due to the feedback's ability to control their work and make them aware of their progress.
[29]	FutureLearn MOOC platform data (unique IDs and time stamps with students, weekly-based step visits, completions, comments added, and attempted questions)	Student behaviors were utilized to forecast whether they would decide to enroll in a MOOC and receive course certification. This forecast can aid in planning future runs and determining their profitability. The analysis may also reveal what personalization options could be offered for students.
[30]	Usage data, participation data, response time-related measures, navigation logs	An adaptive platform was used to gather information on the contexts of the students. By contrasting the learning outcomes of students who received education using adaptive media with those who received traditional instruction, the efficacy of the adaptive intervention was determined. Students using the adaptive platform performed better academically than those receiving traditional education.

Table 4. *Cont.*

Article	Data	Methods
[31]	Student-related datasets, such as traditional questionnaire surveys, and student activity log data from LMS are examined as well as unstructured datasets like SNS activities, text data, and other transactional data	Data mining and machine learning algorithms were utilized to identify key features of students based on student data. A brand-new paradigm for research on student characterization that is driven by spatial data was provided to characterize students and forecast their outcomes.
[32]	Students' interactions with online activities	A predictive model was developed using a recursive partitioning technique that can recognize student sub-populations based on their anticipated exam results. This model employs indications that are directly drawn from the learning design to categorize students and give each subset of students tailored feedback. The methodology can assist teachers in creating personalised feedback for various student sub-populations and pedagogical interventions that are informed by data.
[33]	Student activities and the learning process throughout the course	Support vector machine (SVM), a machine learning method, was utilized to determine where students are falling behind and how the suggested strategy enables them to dynamically improve their performance. During adaptive e-learning, the SVM technique is used to determine the prior demographic data and dynamical inputs in terms of feedback, special assistance, and tailored recommendations to help students avoid failures and improve performance. The performance of students is enhanced by the provision of adaptive feedback, personalization, and customization of the responses in accordance with their preferences.
[34]	Educational data (students' profiles, historical performance, and demographics data) combined with external data gathered from social networks	The behavioral and attitudinal characteristics of students were examined to reveal significant factors affecting various aspects of each student's learning process. The contents can be modified to be presented, the order and level of difficulty of knowledge items, as well as the format, style, and pace of learning, to enhance knowledge understanding and reception retention for specific students at distinct learning stages. When a higher risk of failure is anticipated, early warnings and additional tutoring can be given.

- Classroom/Group Level

At the classroom/group level, in the context of LA, the analysis is focused on understanding and optimizing the collective dynamics, engagement, and performance of students within a specific classroom or group setting. Teachers can then leverage this information to tailor their teaching strategies, address common challenges, and provide targeted support to enhance the overall learning experience for the entire class.

For instance, at the classroom level, LA may assist in analyzing the status of the class during a task, with statistics including the percentage of students who started, submitted, and successfully completed each question [24]. Teachers might better understand how different classes might need assistance with various topics with the aid of such data. The authors also stated that LA may evaluate the difficulty level of each question by taking into account the amount of time spent, the proportion of tries that were successful, and other factors. In the event that students find a question more challenging than they should have, this can assist teachers in identifying any gaps they may have overlooked when teaching a concept.

LA can also identify common mistakes students make, which the teacher can subsequently correct with the class right away. Using a dynamic recommendation system that may suggest both individual and group learning activities to be employed in the classroom, based on students' profiles, Antonova and Bontchev [35] discovered that LA might benefit teachers. According to Wen and Song [36], LA can be used to depict both group and individual student engagement. Teachers can utilize this to determine which class activities are more interesting, effective, and interactive, and to make the best pedagogical choices.

Teachers can use this information to provide more personalized instruction to both groups and individuals.

LA might be used to monitor the caliber of group contributions, allowing teachers to identify areas that needed improvement and offer advice on how to do so for each group [23]. According to Saqr et al. [37], LA could be used to identify group dynamics, or how members of a group interact with one another. To do this, it can be useful to examine how students behave in cooperative groups, paying particular attention to their communication styles, contributions to group debates, and general participation. This could be used to determine the degree to which isolated or active students are, as well as which students are more active. Teachers can use this information to better understand the dynamics of the class and identify students who would need additional targeted guidance or encouragement.

Overall, teachers may utilize the information offered by LA to (1) select the emphasis for each class, (2) recognize any gaps in their explanation, (3) assign students the kind of work they will be most involved in, and (4) keep an eye on group projects and offer tailored support to different groups. Table 5 provides a summary of the data and methods used in the chosen study to employ LA to enhance personalized learning at the classroom/group level.

Table 5. Data and methods used to support personalized learning with extracted analytics (classroom/group level).

Article	Data	Methods
[23]	Educational data generated from digital tools (Google Classroom and Khan Academy)	Learning Analytics Dashboard (LAD) was created using information gathered from online resources like Khan Academy and Google Classroom. LAD assists teachers in locating, tracking, and suggesting solutions to address the learning gaps of their students. The data produced by student usage of digital tools can be utilized to track, evaluate, forecast, intervene, suggest, and enhance the effectiveness of teaching and learning.
[24]	Students' interactions with the game (how many puzzles they solve, how long they spend in the game world, and the events that each student creates)	Through a visualization dashboard, teachers access real-time analytics about how their students are interacting with the Shadowspect game. The dashboard assists teachers in keeping tabs on the general operation of the classroom as well as the progress of individual students, identifying problem areas, and giving each student tailored feedback. The dashboard also assists teachers in changing their instructional approaches, which can result in more efficient and personalised learning opportunities for students.
[35]	Smart devices data	Smart services were used where digital solutions that are user-centered, context-aware, automated, and data-enabled are provided through smart services. Customizable and flexible instructional labyrinth video games are created through the APOGEE platform. Teachers can more easily see the benefits of various learning methodologies, learning personalization, and dynamic adaptation. Smart services can help teachers keep track of students' progress toward learning objectives, individual and group development, and necessary corrections. Smart services can set up learning goals that better match students' changing interests and motivations, or they might indicate learning paths to overcome risks and problems.
[36]	Lesson plans, field notes from each post-lesson discussion, teacher interviews, screenshots of LA findings, and screenshots of student-generated artifacts	LA was used in collaborative language learning classrooms. The authors contend that LA can aid personalised instruction by giving language teachers helpful data regarding particular curricula or learning settings. When the learning design (LD) for language learning is based on social constructivist theories, LA can successfully inform pedagogical refinement. On the premise that the teacher has innovation-oriented beliefs and is enthusiastic about working with researchers and professional development, LA can also enhance teacher inquiry and LD.
[37]	Students' interaction in online problem-based learning	Social network analysis was leveraged to investigate how social dynamics and performance in online collaborative learning are affected by group size. This offers insightful data on how students learn and interact with one another to increase the efficiency of collaborative learning settings.

- Structural Level

The structural level refers to the broader institutional and organizational aspects of the educational system. It involves analyzing data and implementing personalized learning strategies at a systemic level, beyond individual classrooms or students. At this level, LA focuses on understanding and optimizing various structural elements of the educational environment.

For example, Llurba et al. [38] revealed that LA may be used to identify students' emotions at the structural level. Different emotions fluctuate greatly at different times of the day, and students who report feeling the most positive, neutral, and least negative emotions outperform the others. The ability to predict student emotions at different times of the day can greatly assist teachers and school administration in developing lesson plans that will maximize learning for students.

LA could also aid teachers in developing lesson plans, as reported by Troussas et al. [39]. By examining students' performance against a variety of curricular structures, teaching schedules, teaching techniques, and evaluation technologies, it could be able to identify areas where the educational process is lacking. This could be used to decide if and how the curriculum needs to be altered to better serve the needs of the students. According to Colasante et al. [40], LA could give students more flexibility in their lesson medium. Instead of requiring them to attend in-person lessons, LA could measure their learning outcomes and educate the schools and teachers on the best ways to implement the hybrid curriculum to enhance student learning.

LA could analyze the effectiveness of different learning tools and behaviors for the learning performance of individuals. For instance, a study conducted by Chen et al. [41] revealed a significant positive correlation between learning performance and the use of markers as a learning activity. As a result, teachers can decide which teaching methods to employ or which learning styles to promote in the classroom with such information. By looking at the questions that students attempted and struggled with, Coussement et al. [42] discovered that LA can be used to predict student dropout in online learning and even determine why they dropped out. Concentrating on the areas where students struggle and providing them with personalised support can help teachers and schools create student retention programs that are more effective. Overall, teachers can create more personalised lesson plans and timetables for the students in each batch using the data provided by LA. A summary of the data and methods used in the selected study to employ extracted analytics to improve personalized learning at the structural level can be found in Table 6.

Table 6. Data and methods used to support personalized learning with extracted analytics (structural level).

Article	Data	Methods
[38]	Data obtained from a camera	A camera for emotion recognition was utilized to track students' emotional states. The teacher's decision-making in the classroom, as well as maximizing attention to students, modifying their methods, or concentrating on a particular student, can all be improved with the use of this information.
[39]	Student performance, demographic, student behavior, and engagement data	A multi-module model that includes the identification of target content, curriculum enhancement, cognitive state and behavior prediction, and personalization was used. This model aids in better understanding learning and the settings in which it takes place. To deliver personalized learning routes and evaluation resources, the approach makes use of data about students and their environments. A hierarchical clustering was used to separate students' data into distinct clusters to enhance students' learning experiences, and students can be supported with appropriate instructional designs.
[40]	StudyFlex trial data (subjects designed and taught in a flexible hybrid format at a university)	A complex mechanism was incorporated into designs for capturing analytics to ascertain student involvement and learning behaviors as applied to understand that more complex metrics are needed because attendance data techniques are not the best way to gauge involvement in flexible hybrid formats. Longitudinal information was utilized to make institutions more amenable to future hybrid learning projects by enabling them to prepare ahead for issues like booking learning spaces, staffing, and timetabling.

Table 6. *Cont.*

Article	Data	Methods
[41]	Learning tests, survey responses, and learning logs	Personalized learning with LA was used in collaborative problem-solving to support key elements of STEM education, such as learning strategy and learning behaviors.
[42]	Student learning activities interactions, demographics, cognitive, academic, and behavioral engagement data	A logit leaf model (LLM) algorithm was employed to improve student dropout predictions and by identifying elements that can encourage students to continue their education. The authors employed five different types of indicators to accurately predict student dropout in a subscription-based online learning environment, including demographics, classroom features, and cognitive, intellectual, and behavioral forms of participation. The LLM algorithm performs better than any alternative method in striking a balance between comprehensibility and predictive performance. Additionally, in contrast to a conventional LLM visualization, the authors provided a new multilayer informative representation of the LLM that provides fresh benefits. By analyzing LLM segments, numerous insights for distinct student segments with different learning styles become apparent. These insights can be leveraged to tailor student retention strategies.

3.1.2. Embedded Analytics

LA can also be leveraged to support personalized learning through embedded analytics through (1) feedback collection; (2) the assessment and classification of students with similar profiles; and (3) the creation of a feedback loop. LA firstly enables the collection of information about students' ability levels and preferred learning styles. According to Moltudal et al. [43], LA can gather information and form insights about students' abilities both generally and specifically. The LA-enabled technology might be used to continually personalize and adapt the online curriculum and assessment questions to each student's skill level by feeding the program feedback loop with students' answers to math problems [43].

LA might be used to track how students use online course materials [44]. LA may automatically reorder the materials according to what students prioritized and gained the most from. Additionally, Niemala et al. [44] stated that LA could evaluate each student's performance and make recommendations for future work, including connections to helpful resources and activities. Additionally, if some students succeed after implementing the aforementioned advice, LA will automatically give the same advice to other students with a similar profile, creating a continuous feedback loop that continually customizes learning for students.

Additionally, LA could help to automatically classify each student and recommend personalized resources to level up, thus relieving teachers of the burden of differentiated instruction after teachers classify each homework question as easy, medium, or hard and add necessary resources for those who have cleared levels, as reported by Meacham et al. [45]. According to Roberts et al. [46], LA may automatically create a student-customizable dashboard depending on their current skill level, which would include further personalized readings as well as a reminder of any relevant scholarships and competitions based on their interests and areas of strength. Furthermore, LA was able to predict the cognitive states of students and offer personalized learning courses and exams depending on those states [39].

Aside from the above results when the insights from LA are fed into the feedback loop, there are also other benefits. Studies have reported that when the automatic and personalized insights from LA were shown to students, students were more engaged and found the insights useful for reflecting on their learning and progress [47–49]. Table 7 displays data and techniques applied in the selected study to enable personalized learning with embedded analytics.

Table 7. Data and methods used to support personalized learning with embedded analytics.

Article	Data	Methods
[39]	Student performance, demographic, student behavior, and engagement data	A multi-module model that includes the identification of target content, curriculum enhancement, cognitive state and behavior prediction, and personalization was used. This model aids in better understanding learning and the settings in which it takes place. To deliver personalized learning routes and evaluation resources, the approach makes use of data about students and their environments. A hierarchical clustering was used to separate students' data into distinct clusters to enhance students' learning experiences, and students can be supported with appropriate instructional designs.
[43]	Data about learning progress, performance, and behavior, as well as feedback from teachers	Adaptive learning technology (ALT) was integrated into classroom management and teachers' professionalism in a real-world primary education context. ALT is an inherent opportunity to enhance teacher-facilitated learning and to individually tailor the curriculum and learning experiences for each student.
[44]	Data from the LMS and Gitlab	LAOps, a cutting-edge course-scope analytics technology, was used to enhance personalised learning with learning analytics. Data from the LMS and Gitlab, which serves as a gateway for student submissions, are used in this program. After the data have been securely protected and moved to the cloud, models are trained, and analysis are carried out. Both teachers and students receive the results, which are then used to tailor and differentiate exercises based on students' ability levels.
[45]	Easy and medium quiz questions, weekly contents, and student profiles	An adaptive virtual learning environment (AdaptiveVLE) framework, leveraging the MPS JetBrains Domain-Specific Modeling Environment, was used by teachers to design adaptive VLEs that are customized for their needs and help develop a more general foundation for adaptive systems. The framework is made up of the following stages: data collection configuration by the teachers, application of the adaptive VLE, data processing, and learning path adaptation. The framework enables the teachers to configure the data collected and the way the data are processed without having any prior understanding of software development and/or the implementation specifics of data science techniques. This enables quick experimentation with various approaches.
[46]	Data from focus groups, content analysis of dashboard drawings made by students	Student dashboards were used to support personalized learning where students have access to information on extra resources, scholarships, personalized links to assignments they have already completed, and opportunities to catch up.

3.2. The Challenges of LA in Personalized Learning (RQ2)

A total of 16 articles were reviewed to address RQ2. The accuracy of LA insights, privacy concerns, concerns about fairness, and opportunity cost are the key challenges in employing LA to support personalized learning. Table 8 categorizes the article along with the type of challenges.

Table 8. Types of LA challenges in personalized learning.

Challenges	Articles	Count
Accuracy	[43,50]	2
Privacy	[25,39,46,51–54]	7
Fairness	[46,55–58]	5
Opportunity Cost	[43,59–61]	4

- Accuracy

LA results might not always be accurate [43]. Some students might become sick or be absent, which would result in a low level of engagement on platforms that leverage LA. Without sufficient time spent on these platforms, the system may not accurately grade the students, failing to offer them resources and assessments that are appropriately tailored to their ability level. Therefore, for more accuracy in personalizing, it is advised that LA be used in conjunction with other methods of tracking students' skill levels. Furthermore, Moltudal et al. [43] found that because students frequently do not have to write out their calculations while using online resources, they may simply guess their results, and not all LA technology may be able to pick them up. The personalization's correctness may be impacted by this. In addition, Wilson et al. [50] highlighted that LA might not always be reliable for projecting students' success. In this study, LA was used to identify trends in the way that students interacted with the course materials and other students. Following these exchanges, performance forecasts for the students were made. However, this study discovered that there was little connection between online interaction patterns and students' academic achievement. Therefore, it may be erroneous and thus unhelpful if these predictions provided by LA were used to take further measures to tailor to student learning.

- Privacy

Privacy issues pose a significant barrier to the implementation of LA in education [25,51]. This is due to the uncertainties and worries surrounding the gathering, exploitation, and dissemination of student personal information. Students wanted to know how they compared to the rest of the cohort, but Reimers and Neovesky [52] found that they disliked it if the comparison included personal information. Similar to this, Roberts et al. [46] found that students preferred that all LA elements that enabled comparisons be anonymous. These demonstrate the importance of data privacy to students. As mentioned by Rubel and Jones [53], before LA can be leveraged in education, it is important to determine whether personal data on students can be analyzed, who can view them, and how secure they are. Troussas et al. [39] also highlighted that it is crucial that researchers develop transparency in their processes of data collection, data use, and data sharing if LA is to be used in education. Through the aforementioned techniques, Wintrup [54] reported that student involvement in lessons may increase if privacy concerns are allayed.

- Fairness

Fairness is one of the main challenges in LA. Students valued personalised dashboards and learning materials, but most thought that all students should have access to them [46]. Giving specific materials only to some students may exacerbate the feeling of being profiled and may seem unfair. The study, therefore, suggested that all the information should remain accessible to everyone, even while students can receive tailored recommendations. Furthermore, as found by Uttamchandani and Quick [55], LA may contain the biases of the algorithm, including racial and gender stereotypes, and this may have a negative effect on students' experiences with and engagement in LA-enabled technology. We found that there are differing levels of algorithmic fairness among LA algorithms, and these variations can have negative effects. According to Riazy et al. [56] and Gartner et al. [57], flaws in the algorithm can make it difficult for LA to forecast students' outcomes, frequently underestimating the potential of particular student groupings. Similar findings were made by Bayer et al. [58], who discovered that minority groups are unfairly and biasedly analyzed by current LA performance prediction algorithms, which favor the majority group.

- Opportunity Cost

There is a considerable potential cost associated with the use of LA in classrooms [43]. High usage of digital tools in the classroom may discourage creativity and promote bad work habits, which would be detrimental to students' subject-specific talents. Additionally, employing digital tools during class time takes up time and space, detracting from students' ability to learn, communicate, and interact physically with topics. Similarly, Knight et al. [59] also stated that the use of LA in the classroom has the opportunity cost of preventing students from concentrating on and devoting much time to ideas other than those identified by LA, even if they may need assistance in those areas. According to Alamri et al. [60], students who spend too much time in online learning may miss out on face-to-face contact with peers and teachers and consequently feel lonely. Carlson [61] also stated that LA-enabled technology should only be used up to a certain point because it cannot replace the activities and interactions that promote holistic student development.

4. Conclusions

The need for an LA approach to personalized learning was first explored in this systematic literature review. Next, we discussed the challenges encountered in supporting personalised learning through LA. The findings show that LA can enable personalized learning primarily in two ways: extracted analytics and embedded analytics. We discovered that LA could offer insights using extracted analytics to direct teacher intervention at the individual, group, classroom, and structural levels. The emphasis of each class is defined by the teacher, blind spots in their instruction are identified and corrected, and personalised lesson plans and timetables are planned to enhance student learning results. These teacher interventions also involve providing focused aid for individuals or groups of students inside the classroom. We also found that LA can automatically adapt learning for students under embedded analytics by gathering feedback, evaluating and categorizing students who share comparable profiles, and establishing a feedback loop for ongoing customization. This is crucial because it can ease the pressure on teachers to organize and carry out differentiated education in the classroom.

Before students receive personalized learning, we recommend combining the insights and comments from LA with teacher observations as there is evidence showing that the automatic insights from LA may not always be accurate. As for privacy, a number of the articles mentioned above demonstrate how privacy worries can be allayed. For better outcomes in terms of student motivation and engagement with LA, we strongly advise developers to take these suggestions and student input into mind. Fairness and opportunity cost are still being researched as problems that need to be resolved. Meanwhile, as previously noted, before moving forward with personalization, we recommend combining the observations and recommendations of LA with teachers' input. This is so that any biases in the algorithm that can affect the feedback students receive can be checked by the input and observations of teachers.

The findings of this review paper provide insights into LA approaches and how LA be leveraged to support personalized learning and its challenges. In addition, some recommendations for future researchers were provided. However, there are some limitations to this study. Firstly, methodological choices, such as choosing a database and crafting search queries, could skew the results. Furthermore, there were times when some instances of the papers under review were misrepresented, which resulted in gaps in the information coding. It is important to note, nonetheless, that these information gaps were only somewhat present and were not anticipated to have a significant impact on the study's conclusions. A limited number of articles were reviewed. The selected articles were gathered from only journal articles, books, and published dissertations published in Scopus and ProQuest. Book chapters and other types of publications were not taken into consideration. Hence, future research may include relevant articles published in other databases. Another limitation is that the affordances and challenges of LA mentioned in many research papers heavily depend on the exact software or technology used, as well as the subject. For example, Moltudal et al. [43] reported that there were cases where teachers felt that students could have guessed their math answers in the MSØ software, and the LA could not have picked that up. Nevertheless, Ruipérez-Valiente et al. [24] found that with the use of another technology, Shadowspect, LA was able to differentiate between students mindfully trying to solve a puzzle versus arbitrarily guessing. Therefore, researchers may examine how LA can assist personalized learning for various courses in the future and delve more into the various technologies being employed to compare their affordances and limitations.

It is very important that efforts toward personalized learning are equitable and inclusive. Some studies analyzed in the paper have shown that LA models can contain biased algorithms, which may discriminate against minorities. Hence, future research can focus on developing LA models that effectively cater to diverse students, including those with different backgrounds, languages, and disabilities. It is crucial to ensure that personalized systems do not perpetuate bias and provide effective support for all students. In addition, most of the studies analyzed in this paper focus on short-term interventions and the consequences of using LA for learning. Further research could explore how personalized LA can support students over an extended period. This could involve investigating the impact of LA on students beyond formal education, such as the impact on long-term educational achievement, career success, and life satisfaction.

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