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Systematic literature review: learning analytics framework for online education

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Abstract: Learning analytics (LA) has grown into a phenomenon with extensive applications in a variety of educational contexts. Diversity of applications such as LA framework and the need for a deeper comprehension of the practical implementation of the LA framework in the context of online education present a necessity. This article explores the practical implementation of LA in online education within four main phases phases associated in LA framework. This article examined significant outcomes, and the kind techniques that support each phase. By adhering to established guidelines and employing systematic literature review method, including problem formulation, search strategy, article selection, data extraction, and synthesis, this review provides helpful insights for refining the implementation of LA in educational settings. With 38 relevant publications, this article sheds light on the effectiveness and impact of LA phases particularly in online education.

Keywords: Learning analytics phases; learning analytics framework; online education

1. Introduction

Pandemic has accelerated technology advancement, which has had a considerable impact on the educational sector [1]. Since online education has become a new standard in teaching and learning implementation, the quantity of data produced is growing. As the quantity of data generated by online education continues to rise, the significance of learning analytics (LA) in extracting meaningful insights and informing instructional strategies grows [2]. The main objective of LA, which was founded on a data-driven approach to education, is to improve and optimize learning and its surroundings [3]. LA is rapidly becoming a phenomenon that has widespread applications in many different educational settings, ranging from pre-kindergarten all the way up to graduate school [4]. The use of LA was necessary for gaining an understanding of and progress in this educational process [5]. It is now considered that by utilizing data that can be accessed through an online platform, LA can provide valuable information for improving and advancing online education.

To acquire insights into student learning and guide educational decision-making, LA is the common process of gathering, analyzing, diagnosing, predicting, and interpreting data created by the learning process [2,6]. Recently, LA framework has emerged as a potential strategy to encourages the implementation of comprehensive LA practices [7-9]. Educators can enhance the overall quality of students' learning by aligning institutional procedures with the LA framework's principles. In addition to providing a high-level perspective that can guide the development of models, approaches, or methods, a LA framework can also include a clear definition of LA aims and objectives [8,10]. LA has been widely researched and many studies have proposed LA framework that cover various areas or contexts [11]. The LA framework provides a strong foundation to guide the implementation of proposed works. According to a review [12], LA framework consists of many components that may include analytics, visualization, feedback, performance, behavior, goals, and stakeholders where analytics are highly used in previous studies.

In LA framework, there are four phases that are valuable for improving teaching and learning includes descriptive, diagnostic, predictive and prescriptive analytics phase as shown in Figure 1 [13]. All phases are not mutually exclusive and designed upon the previous ones to provide a comprehensive understanding of data and guide decision-making in the educational context. The objective of descriptive analytics is to examine and summarise students' performance and engagement [14]. Meanwhile, diagnostic analytics is a specific branch that focuses on the analysis of student behavior data, including online activities and interactions with educational resources. The primary objective of this analytical approach is to provide educators and administrators with valuable insights into student performance issues or other challenges that may hinder academic achievement [15]. Predictive analytics is a specialized domain within the discipline of data analytics that involves the examination of past data through the application of statistical or machine learning techniques to make informed predictions about forthcoming events [16]. Prescriptive analytics is a form of data analytics to provide optimal recommendation [17].

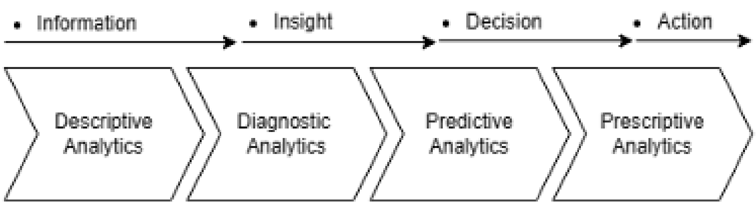


Figure 1. Phases in LA framework.

While all the four phases are useful, majority of existing research prioritizes specific phases, rather than focusing on all phases of LA to attain their specific objectives. Understanding the focus of all the phases is of utmost importance to gain insights into specific challenges and methodologies and applications associated with each phase, allowing for a more targeted and informed approach to further research and development. This knowledge is essential for refining and improving the implementation and utilization of LA in educational settings. This review purpose is to explore the practical implementation of LA within the context of online education, encompassing all phases in LA. By doing so, this study aims to uncover novel insights into the effectiveness and impact of each phase and provide valuable guidance for refining LA practices in educational settings in future. This review's objectives are twofold:

1. To determine the focus of the LA phases in the LA framework and their significant outcomes; and
2. To identify the techniques used to support the LA phases and their significant outcomes.

2. Related work

Besides that, LA framework is a standardized approach for collecting, analyzing, and utilizing data related to learning activities to improve educational outcomes [18]. The LA framework has been widely researched and proposed to cover various areas or contexts [11]. LA framework has been the subject of several systematic literature reviews in this area [2,6,11,19]. A systematic literature review (SLR) has been conducted by [6] identified and acknowledged LA as the following revolution of educational technology. The SLR comprehend the advantages and difficulties of LA in education. 36 selected articles revealed that ethics, privacy, theoretical foundations, and data quality are significant obstacles. Nevertheless, the utilization of LA has also exhibited potential benefits, including heightened student engagement, improved learning outcomes, identification of individuals at risk, immediate feedback, and individualized learning experiences. Implementing LA in education necessitates addressing ethical, pedagogical, and technical concerns, despite its potential.

While [11] examined the differences between the existing LA frameworks in terms of their traits and which components are commonly shared by the existing LA frameworks. The research study found that most of LA frameworks identified as conceptual or empirical frameworks and were created to be transferable across disciplines. The review [11] also shows the previous framework provides analytics that focus mostly on retention, students' support, and learning pedagogy. The other systematic review [2] aims to furnish readers with crucial details pertaining to the application of the LA framework in the field of online education. The main objective of this study is to ascertain the alignment of the LA framework with the many categories of analytics data relevant to students in online learning settings. The findings indicate that most of LA framework focuses on either monitoring or analysis and prediction, as well as intervention. The most utilized data categories in this context are learning behavior data and learning level data.

Other SLR [19] conducted a comprehensive analysis of the current advancements in the field of LA within the context of massive open online courses (MOOCs). This study highlights the importance of implementing systematic approaches, conducting evaluations, and utilizing conceptual frameworks to assist educators in developing LA-based feedback for MOOCs. The objective is to establish a connection between pedagogical principles and data-driven methodologies. Additionally, the research conducted in this study brings attention to the insufficiency of empirical investigations and the limited focus on pedagogy within the realm of feedback practices.

All the current SLRs, which are included in Table 1, offer helpful reviews that can be used as a reliable source of data for this study. Even so, their discussion was restricted to the methods that were utilized in providing and carrying out the LA framework because of the previous reviews. In addition, the studies offer a muddled question on which LA phases, the present LA framework priorities, and which LA phases contributed the most. It is important to discover the overall learning aspect to provide better, higher quality and relevant learning programs, there are other focus areas of LA framework that need to be covered.

Table 1. LA framework related work summary.

Publication Ref./year	Review Objectives	Review Output	Range Years Publication	Total Selection of Articles
[2]/2022	Determine the orientation of the LA framework and the type of analytics student-data	Most LA frameworks use learningbehaviour and level data for monitoring, analysis, prediction, and intervention.	2012-2020	34 articles
[6]/2018	SLR comprehend the benefitsand challenges of LA in education	revealed that ethics, privacy, theoretical foundations, and data quality are significant obstacles of LA framework.	2011-2017	36 articles
[11]/2022	Reviewed how existing LA systems differ and which components they share.	The survey revealed most LA frameworks were conceptual or empirical and cross-disciplinary, theymore focused on retention, student. support, and learning pedagogy.	2011-2021	46 articles
[19]/2023	Reviewed the news and latest information of LA in massive open online course (MOOCs).	This study underlines the necessity for systematisation, assessment, and conceptual tools to assist MOOC instructors develop LA-based feedback	2010-2022	38 articles

3. Research methodology

A well-defined, “unanswered but answerable” research question is essential for a successful SLR [20]. A SLR is a rigorous and systematic approach used to find, select, and evaluate published research. This process ensures transparency and allows for an auditable technique to choose the collection of articles that are included [21]. The guidelines constructed by [22] are followed to guide this SLR. There are five processes involved in completing this review.

1. Problem formulation is the process of creating research questions based on the stated goals of the study. The goal of this review is met by the research questions that are developed. This SLR address the following research questions (RQ):
    a) RQ 1: What are the outcomes that are related to each phase of the LA framework, and what is their primary focus (descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics)?
    b) RQ 2: What methods are used to support the various phases of the LA framework (descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics), and how do these methods assist the various phases?
    c) RQ 3: What the benefits and challenges of LA framework associated with different phases, observed in online education?
2. A search strategy that can be determined by locationg the keywords in the pertinent web databases of the search engine. “Learning analytics framework”, “learning analytics technique”, “learning analytics approaches”, “learning analytics phases” and “online learning” or “online education” are the keywords used to extract sources pertinent to the study.
3. The selection of articles based on inclusion and exclusion criteria. The publication must be written in English or Malay, its full text must be accessible, it must address the subject of the study, and it must have been published between 2014 and 2023 (10 years).
4. The processing of important data and attributes.
5. The analysis of data and result reporting.

A total of 38 publications are extracted as the relevant selected studies for this research. This SLR intends to comprehend and review the practical application of LA framework in online education, with a particular focus on the LA framework’s contributions and the types of supporting techniques that assist in achieving the objectives.

4. Finding and Discussion

Table 2 presents the outcomes of coding the 38 chosen publication on LA frameworks, which serves as the foundation for addressing RQ 1,2 and 3. Table 2 also presents the classification of the framework objectives, type of framework, prioritized phases, category of methodologies employed, and framework implementation as indicated in the second column until the last column, respectively. The published references are recorded in the first column, while any matches within the designated coding scheme are denoted by the letter "x". Due to spatial constraints, Table 2 does not include the column specifying in the types and kind of statistical, machine learning, or other techniques employed, which will be elaborated upon in subsequent discussions.

Table 2. LA framework schemes.

Publication Ref.	LA framework Objectives	Type of Framework		LA framework phases priorities				Techniques Used			LA framework Implementation
		Conceptual	Empirical	Descriptive	Diagnostic	Predictive	Prescriptive	Statistic	ML[1]	Other	
[23]	Improve students' engagement and motivation		x			x		x			MOOCs
[24]	Improve students' performance		x				x			x	MOOCs
[25]	Enhance learning process		x		x		x	x		x	Serious Game Platform
[26]	Improve Curriculum Development		x	x				x			Online Platform
[27]	Improve personalized learning platform		x	x	x	x	x	x		x	Adaptive Learning System
[28]	Improve students' performance		x		x		x		x	x	Personalized Platform
[29]	Improve communication	x			x			x			Dashboard
[30]	Improve learning effectiveness	x			x		x	x		x	Serious Game Platform
[31]	Aid design and UI	x			x			x			MOOCs
[32]	Improve students' performance	x				x	x		x	x	Virtual World
[33]	Assist educators design learning	x		x	x			x			Web Application
[34]	Improve students' self-evaluation	x			x			x			Online Platform
[35]	Improve learning practices	x			x			x			Dashboard
[36]	Guide systematic design learning	x			x		x	x		x	Online Platform
[37]	Enhance students' engagement	x		x	x			x		x	Dashboard
[38]	Enhance learning design	x			x			x			Online Platform
[39]	Enhance learning experience	x	x	x				x			Web-based Platfrom
[40]	Provide guidelines	x		x						x	Not Mentioned
[41]	Improve students' retention	x		x						x	Not Mentioned
[42]	Provide guidelines	x	x	x	x			x	x		Automated System

[1] Machine Learning

Table 2. *Cont.*

Publication Ref.	LA framework Objectives	Type of Framework		LA framework phases priorities				Techniques Used			LA framework Implementation
		Conceptual	Empirical	Descriptive	Diagnostic	Predictive	Prescriptive	Statistic	ML[2]	Other	
[43]	Improve learning design	x	x		x			x			Not Mentioned
[44]	Improve Data Management		x			x			x		IoT Application
[45]	Analyze students' performance		x		x				x		Computer-based system
[46]	Improve students' learning		x		x			x			Adaptive Learning System
[47]	Provide evaluation method	x		x				x			Moodle Platform
[48]	Understand Student Thinking	x		x				x			Not Mentioned
[49]	Assess students' engagement and academic performance		x	x				x			Learning management system
[50]	Analyze activities	x		x						x	Online Platform
[51]	Motivate self-regulated learning	x	x	x	x	x	x	x	x	x	MOOCs
[52]	Predict learning outcomes	x				x			x		Not Mentioned
[53]	Predict student engagement	x				x		x			THEOLt
[54]	Predict Students' completion degree		x			x		x			WEKA
[55]	Predict student core competency	x				x		x		x	Not Mentioned
[56]	Identify the validity and accuracy of data	x				x			x		Not mentioned
[57]	Improved students' learning	x	x			x			x		MOOCs
[58]	Improved predict performance	x				x			x		Online Platform
[59]	Provide guidelines	x				x			x		Online Platform
[60]	Predict academic performance	x	x			x			x		Online Platform

4.1. Finding and discussion of RQ1

RQ1: What are the outcomes that are related to each phase of the LA framework, and what is their primary focus (descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics)?

Based on the Table 2, LA frameworks' phases have distinct focal points. Majority of LA frameworks were developed by prioritising at least one of phases includes descriptive analytics (n = 13), diagnostic analytics (n = 17), predictive analytics (n = 14) and prescriptive analytics (n = 8). Throughout the analysis, it is revealed that, descriptive analytics (DeA) enables educators to comprehend the current condition of learning by shedding light on a variety of facets, including engagement [37,49] and academic performance [27,49]. While diagnostic analytics (DiA) assists educators in identifying the variables that influence the

[2] Machine Learning

performance [25,27,30,45,46]and learning outcomes [31,33-35,42,43,51]of their students. By identifying specific areas in which students may be having trouble, educators gain insight into individual learning requirements and are able to provide individualized interventions or support. DiA enables educators to customize instruction and employ effective teaching strategies based on identified specific needs of each student.

Predictive analytics (PdA) uses historical data to predict future events or behaviors. PdA enables educators to predict students' performance [25,27,30,32] potential dropouts [23] and predict the learning outcome [52,55] in thecontext of education. By identifying early warning signs, educators can intervene in a timely manner and provide proactive assistance to improve learning outcomes. Meanwhile, prescriptive analytics (PsA) provides actionable recommendations or interventions. PsA facilitates the design and implementation of targeted interventions, personalized learning experiences, and adaptive learning paths. This phase assists in optimizing curriculum development to meet the diverse requirements of learners such as academic performance [24,27,32].

Noting that the phases are not mutually exclusive and are designed to build upon one another, providing a comprehensive understanding of data and guiding decision-making in the educational context, is essential because all phases are associated with a better learning enhancement outcome for students. However, when researchers' priorities certain phases to achieve specific objectives and meet specific requirements, they may need to consider neglecting the preceding phase in favor of the phase they have chosen to priorities.

For instance, if researchers' priorities DeA DiA and PsA to personalize learning and provide customized educational experiences, they may place greater emphasis on these phases of analytics. Collecting and analyzing data to obtain insight into student performance and engagement would constitute DeA. DiA would delve deeper into identifying the underlying causes of learning difficulties and areas where students require additional support. Finally, PsA would use the insights gained to devise targeted interventions and individualized learning pathways for each student.

By prioritizing these phases of analytics, researchers can ensure that relevant data and information are accessible and accurate. Then, they can use this information to inform decision-making and personalize the learning experience for each student. This strategic approach enables a more efficient allocation of resources, with a focus on specific periods that contribute directly to the achievement of personalized learning objectives.

While all phases of the educational process are interconnected, researchers can priorities particular phases according to their objectives. This prioritization may necessitate ignoring the preceding phase to concentrate on the selected phase. Thus, researchers can utilize descriptive, diagnostic, and prescriptive analytics to personalize learning, provide individualized educational experiences, and allocate resources more efficiently. This strategic approach ultimately results in a more efficient and individualized learning environment for students.

4.2. Finding and discussion of RQ2

RQ2: What methods are used to support the various phases of the LA framework (descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics), and how do these methods assist the various phases?

Various phases of analytics in the context of education play a crucial role in leveraging data to improve student learning experiences. A study done by [51] suggested to build a framework that can lead to better decisions that can turn positive value towards students' learning enhancement. The study proposed specific methodology for each phase which is believed can help in making LA more valuable and effective in the educational context. Figure 3 shows the LA methodology designed by [51]. Data visualisation and descriptive statistics are used for DeA. Data visualisation permits the graphical representation of data, facilitating the identification of patterns and tendencies. In descriptive statistics, data are summarised and analysed using measures such as mean, median, and standard deviation to obtain insight into the characteristics of the data. Statistical analysis and data mining techniques are utilised in DiA. Statistical analysis is the application of statistical methods to data for the purpose of identifying relationships and correlations. To diagnose learning difficulties and obstacles, data mining techniques focus on discovering patterns and extracting meaningful information from large datasets. ML techniques are the foundation of PdA. Using historical data, machine learning algorithms are trained to recognise patterns and predict future outcomes. These algorithms use data to construct predictive models of students' performance and behaviour. Simulation and optimisation techniques are employed by PsA. Educators can evaluate the potential impact of various scenarios and interventions by simulating them in a virtual environment. By maximising or minimising specific criteria, such as resource allocation or learning outcomes, optimisation techniques seek to identify the optimal solution.

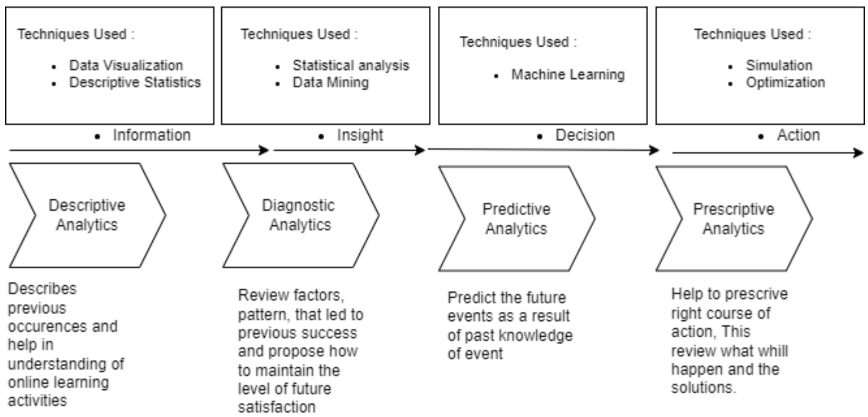


Figure 2. LA methodology [51].

Based on the Table 2, it is evident that the different phases of LA frameworks employ distinct techniques to support their respective objectives. In addition, various of techniques can be applied to deliver the phases well. Figure 2 shows the enhancement of LA methodology adopted from [51] based on analysis of 38 articles.

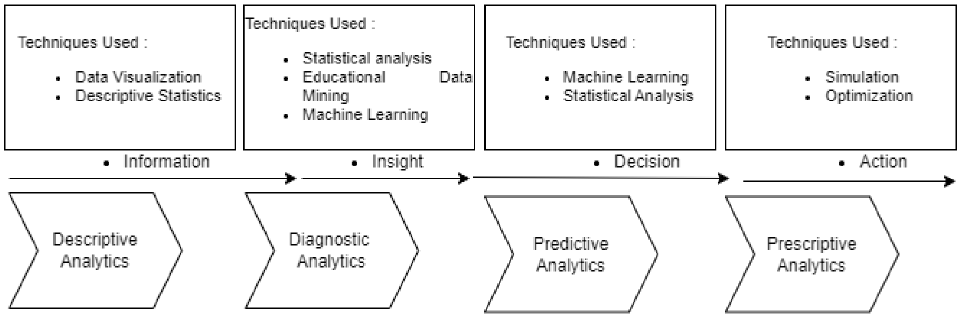
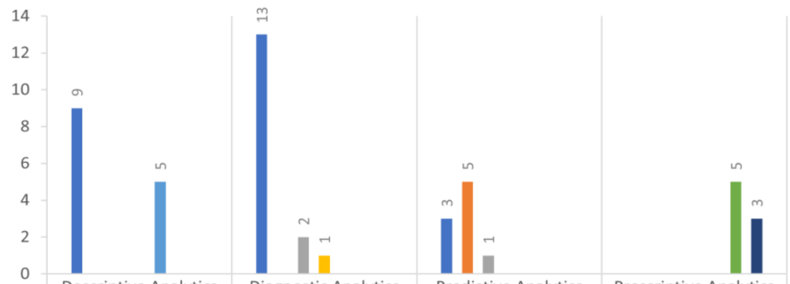


Figure 3. Adopted LA methodology [51].

To the extent of that, this article also analysis the commonly used for each phase. Figure 4 shows the graph trend of the techniques used for each phase.

- Descriptive Analytics (DeA). Techniques such as statistical analysis and data visualisations are commonly utilized to perform DeA. By analyzing and summarizing data using statistical methods, patterns, trends, and correlations can be identified, leading to informed decision- making regarding instructional design and resource allocation.
- Diagnostic Analytics (DiA). DiA focuses on understanding and diagnosing students' learning difficulties and challenges. The techniques employed in this phase include statistical analysis and machine learning algorithm. Machine learning (ML) and statistical analysis involves conducting experiments and gathering empirical evidence to uncover the factors that impact students' learning outcomes.
- Predictive Analytics (PdA). PdA techniques are crucial for predicting students' future performance and behavior. The techniques used in this phase include statistical analysis and ML. Statistical analysis and ML algorithms are employed to develop predictive models that leverage historical data to anticipate students' learning outcomes.
- Prescriptive Analytics (PsA). PsA aims to provide actionable recommendations to optimize students' learning experiences. Techniques such as simulations and learning optimization are employed in this phase to provide personalized and data-driven guidance to educators and students, facilitating informed decision-making and improving overall learning outcomes.



	Descriptive Analytics	Diagnostic Analytics	Predictive Analytics	Prescriptive Analytics
Statistical Analysis	9	13	3	
Machine Learning (Supervised)			5	
Machine Learning (Unsupervised)		2	1	
Machine Learning (Reinforcement)		1		
Visualisation	5			
Optimization				5
Simulation				3

Figure 4. Graph trend of technique used.

4.3. Finding and discussion of RQ3

RQ3: What the challenges or benefits of LA observed in online education?

LA framework's benefits in online education are noteworthy. Students who are at risk of academic difficulties or disengagement can be offered timely intervention and support. The insights provided by LA facilitate continuous development in instructional practices, curriculum design, and learning resources. In the end, LA enables evidence- based curriculum design, pedagogical approaches, and resource allocation, resulting in improved student outcomes in online education. Each phase of the LA framework contributes uniquely to the improvement of students' learning.

- Descriptive Analytics (DeA). DeA can offer educators a comprehensive overview of how students interact with online learning environments. Educators can identify trends, strength and shortcomings in instructional practices, curriculum designs, and learning resources by understanding the behavioral patterns of students. This data enables the continuous development and refinement of instructional strategies, resulting in more effective online instruction.
- Diagnostic Analytics (DiA). DiA digs deeply into the data to diagnose the factors that influence student learning outcomes. By analyzing multiple data points, such as assessment results, interaction records, and student feedback, DiA enables educators to identify specific areas in which students may be underperforming, allowing for targeted interventions and individualized support. Educators can provide expeditious support and prevent additional learning setbacks if they address these obstacles promptly.
- Predictive Analytics (PdA). PdA helps educators anticipate potential challenges or opportunities for individual students or groups by analyzing patterns and trends in student data. PdA aides in identifying students who could benefit from advanced coursework or additional learning resources, thereby ensuring a personalized and customized learning experience.

- Prescriptive Analytics (PsA). PsA provides actionable recommendations and interventions based on the insights obtained during the preceding phases. PsA enables educators to optimize the learning experience, resulting in enhanced outcomes for students in online education.

While the LA framework provides substantial benefits for online education, it also poses certain challenges. Data accessibility and availability are significant obstacles, as procuring relevant and trustworthy data from online platforms and ensuring data privacy [10] and security can be difficult. To effectively utilize analytics for decision- making, it is necessary to interpret complex data and develop data literacy skills. Moreover, implementing LA solutions at scale across multiple online learning environments and platforms necessitates addressing system integration.

5. Conclusions

Overall, the findings emphasize the significance of the various phases of the LA framework in enhancing learning experiences and facilitating educational decision-making. Each phase's techniques and benefits contribute to individualized instruction, targeted interventions, and evidence-based practices. Even though obstacles exist, addressing them can result in a more effective implementation of learning analytics in online education and enhanced student outcomes. RQ1 reveals that each phase of the LA framework has a unique emphasis. Diagnostic analytics (DiA) identifies the variables that impact student performance and learning outcomes. Prescriptive analytics (PsA) provides actionable recommendations or interventions, whereas predictive analytics (PdA) enables the prediction of future events or behaviors. Each phase contributes to significant enhancements of student learning. Based on their objectives to personalize learning and provide individualized educational experiences, researchers can prioritize phases.

RQ2 presents different techniques are used to support the various phases of the LA framework. Diagnostic analytics entails statistical analysis and machine learning algorithms, whereas descriptive analytics employs statistical analysis and data visualizations. Predictive analytics utilizes statistical analysis and machine learning, whereas prescriptive analytics employs simulations and optimization techniques learned through machine learning. These techniques allow educators and researchers to obtain valuable insights, make well-informed decisions, and optimize students' educational experiences. RQ3 disclose that each phase of the LA framework enhances learning and instructional practices. The LA framework provides advantages such as personalized instruction, opportune intervention for at-risk students, continuous development of instructional practices, and decision-making based on evidence. However, data accessibility, quality, privacy, and security present obstacles. Implementing LA at scale in online learning environments necessitates resolving system integration and technical infrastructure obstacles. Despite these challenges, the benefits of the LA framework in online education are substantial, resulting in enhanced student outcomes.

In the future study, there will be a further investigation conducted regarding the details of the techniques that were employed. The investigation will include further details on the significance of the techniques that were applied on each phase. The investigation will provide light on the significance of these strategies as well as their efficacy in advancing online education and improving student learning outcomes.

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Conflicts of interest

The authors declare no conflict of interest.

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