INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH in PROGRESSIVE EDUCATION & DEVELOPMENT
OPEN ACCESS JOURNAL
Vol 11, Issue 2, (2022) E-ISSN: 2226-6348

Implementation of Learning Analytics in Primary and Secondary School: A Systematic Literature Review

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To Link this Article: http://dx.doi.org/10.6007/IJARPED/v11-i2/13136 DOI:10.6007/IJARPED/v11-i2/13136

Published Online: 09 June 2022

Abstract
Increased adoption of educational technologies, the emergence of digital classroom concepts, and the interest in big data innovations have led to a growing awareness of the potential implementation of learning analytics to support learning development in educational institutions. However, most studies have focused on the implementation of learning analytics in higher education. As a result, research evidence and studies on actual and ongoing implementation in pre-higher education are still scarce. Therefore, there is a need to understand better the implementation of learning analytics at primary and secondary from the current learning analytics literature. This systematic literature review (SLR) aimed to identify learning analytics research that focuses on implementing learning analytics at pre-higher education levels, including in pre-school, primary, or secondary school. This SLR was carried out based on the SALSA framework to determine the protocol, search, appraisal, synthesis, analysis, and reporting approaches. The findings of the SLR support the arguments that the implementation of learning analytics in school is still in its infancy, where the implementation has been observed mostly in developed countries. Most of the Implementation is aimed at descriptive analytics, focusing on the purpose of monitoring, analysis, and feedback. The literature review has shown a lack of research on the implementation of learning analytics at the primary and secondary education levels.
Keywords: Systematic Literature Review, Learning Analytics, Pre-Higher Education, Learning Data.

Introduction

The Covid-19 pandemic has undoubtedly changed how people live. The pandemic has caused school closure around the world which has caused a sudden shift in the educational landscape. Teaching and learning have shifted from the physical platform to virtual online teaching and learning (Li & Lalani, 2020). Consequently, education stakeholders, especially teachers, face difficulties conducting assessments and making decisions about student learning. Visible and tangible evidence of student learning activities collected during face-to-face lessons is no more attainable during the pandemic. Therefore, there is an urgent need for the education ecosystem to implement a new approach, for instance, using effective technology, to address the limitation in providing continuity and sustainability of education.

Over the past decade, innovation in digital learning technologies has contributed to the massive volume of data in educational institution repositories. Online educational data carries insightful information about learning activities such as students' digital footprint, log frequency, time spent, number of learning resources accessed, and online test scores. These data can be manipulated to increase student learning experience and improve the quality of education (Ebbeler et al., 2017).

Thus, there is a growing emergence of educational research and projects regarding the potential of learning institutions, enterprises, and educators to leverage educational data in improving teaching and learning. Such endeavors in research and innovation have led to the birth of a new business intelligence field known as learning analytics. Learning analytics focus on teaching and learning data measurement, collection, analysis, and report to optimize students' learning and the surrounding environments (SOLAR, 2011).

Three aspects have fueled the rapid development of the learning analytics domain: first, the velocity of a large volume of educational data; second, the rise of online learning; and third, national concerns regarding educational progress (Ferguson, 2012). Implementing learning analytics expands the potential of learning strategies and academic success that meet the needs of each student in a personalized and data-oriented way (Sousa et al., 2021). Learning analytics implementation supports decision making in different aspects ranging from school improvement to increasing instructional achievement and progress (Mandinach & Gummer, 2016).

The adoption of learning analytics has gained importance in supporting teachers and students in instructional settings, especially in the digital learning environment. To constitute high-impact educational experiences, understanding the process and optimizing teaching and learning performance have become crucial yet challenging tasks in educational systems. Hence, implementing learning analytics provides better information about teachers' and students' activities, learning behavior patterns, and gaps in instructional practices (Pardimin et al., 2018). Many works have been done to tackle learning issues using learning analytics, such as student retention, at-risk student, performance prediction, learning patterns, learning styles, and many more.

Implementation of Learning Analytics

Learning analytics implementation can be defined as introducing learning analytics in an educational environment or using learning analytics in instructional practice (Wise & Vytasek, 2017). The word implementation is preferable instead to adoption, application, and intervention to broaden the learning analytics use as a sustainable activity assimilated into school teaching and learning across the instructional ecosystem from the start to the end.

Implementation of learning analytics is not a new practice in primary and secondary school, particularly for teachers. They always deal with data to get information about the teaching and learning process, especially in evaluating academic performance and preparing the overall education progress report. However, cutting edge technologies that apply advanced analytics techniques and tools are more promising to analyze a large volume of data extracted from digital online learning platforms. Therefore, as more analytics systems and tools become prevalent and accessible, these technologies can be used to leverage the large scale of data use in education, ranging from learning data collection, student learning process analysis, learning performance prediction, and making interventions to raise learning outcomes (Mokhtar et al., 2019).

The objectives, key players, data types, system, tools, technique, process, and feedback must be defined and outlined clearly when implementing learning analytics (Wise & Vytasek, 2017). Having a reference model is helpful to drive and ground the foundation of learning analytics implementation. Therefore, this SLR utilizes the learning analytics reference model proposed by Chatti et al (2014) as the groundwork for the scope and limitations. As shown in Figure 1, the implementation of learning analytics consists of four dimensions:

A. Dimension 1: What- What type of data is collected and used for analysis? What is the source of data? What kind of analytics is applied?
B. Dimension 2: Who- Who is the target of analytics? Who conducts the analysis?
C. Dimension 3: Why- What are the educational goals of the implementation of learning analytics?
D. Dimension 4: How? How does learning analytics being introduced in the teaching and learning environment? How are data being collected? What is the analysis technique that could be used? How is the result being conveyed?

Figure 1: Model of Learning Analytics Implementation by Chatti et al. (2014)

The model illustrates a systematic framework of learning analytics and its related concepts that support this SLR in pre-higher education level analytics implementation. It addresses the various challenges as understanding the technical, practical, and pedagogical issues surrounding learning analytics evolves (Chatti et al., 2014).

Previous Systematic Literature Review Studies

SLR is a “systematic, explicit, and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work made by researchers, scholars, and practitioners” (Booth et al., 2014). Many SLRs have been conducted since the emergence of learning analytics in 2011. These SLRs revolve around the challenges to measure, collect, analyze, and present learning data in the development phase of learning analytics technology in ways that become more useful to education stakeholders. There is a lack of studies that explored the implementation of learning analytics in teaching and learning practices.

A study by Avella et al (2016) provided an overview of the methods, benefits, and challenges of using learning analytics in higher education and Khan et al. (2017) highlighted the applications, issues and challenges, existing solutions and future directions in the context of big data. Meanwhile, Hu et al (2017) investigated the methodologies to predict student learning outcomes for certain circumstances, contributing to the development of a learning analytics system. The same work was investigated by (Herodotou et al., 2019). Using Technology Acceptance and Academic Resistance models, the study examined the impact of providing distance learning teachers in higher education institutions with learning analytics data to predict students' performance and empower teachers to identify and assist at-risk students.

Most of the SLR research in learning analytics focuses on the implementation in higher education. For instance, Blumenstein (2020) evaluated the effect sizes reported in key studies investigating effective learning approaches in measuring student learning gain to enhance higher education pedagogy and delivery. Ifenthaler and Yau (2020) reported empirical evidence demonstrating how learning analytics have successfully facilitated study success in continuing and completing students' university courses. Pargman and Mcgrath (2021) conducted research on ethical issues in higher education that have been empirically approached in the learning analytics literature.

In line with the increasing adoption of educational technologies and the emergence of future classroom concepts in primary and secondary education, there is a higher awareness of the potentials implementation of learning analytics to support students learning progress (Kovanovic et al., 2019). However, it could be observed that there is little research discussing and examining the implementation of learning analytics at the pre-higher education level. At the researcher's disposal, only one SLR research has been conducted recently on the implementation of learning analytics in high school, which is done by (Sousa et al., 2021). The SLR studied the adoption of learning analytics in high schools and concluded that learning analytics applications in these institutions focus on small-scale initiatives rather than institutional adoption. Therefore, it is argued that studies on learning analytics mainly focused on higher or tertiary education settings (Kovanovic et al., 2021). As Ferguson et al (2016) observed, the full potential and expectations of adopting learning analytics in the education system have not been realized. Furthermore, evidence on the actual implementation is still limited and scarce even though the early adopters of learning analytics are already leading research and development.

Learning analytics does not have the same level of adoption in other lower educational contexts, such as primary and secondary education, despite some promising results. This is due to the maturity level of adopting data analysis tools in these institutions (Sousa et al., 2021), the availability of facilitating conditions, and technical expertise in data analytics. There is an urgent need to increase studies regarding learning analytics implementation in pre-higher education. Hence, the Society of Learning Analytics Researchers (SOLAR), for its journal in recent years (SOLAR, 2020), has called for papers on learning analytics in primary and secondary schools. This proves that there is still insufficient endeavor has been taken to implement learning analytics in pre-higher education. By leveraging learning data and utilizing the appropriate techniques of big data analytics, students' performance in primary and secondary schools can be diagnosed and predicted.

The objective of this SLR was conducted:

- to identify learning analytics research that focuses on implementing learning analytics at the pre-higher educational level, specifically at the k-12 level.
- to addresses who can access analytic data, the tools used, their purposes, and how the analytics feedback occurs in the educational processes.

The model proposed by Chatti et al (2014) will be used to address the implementation. Based on this context, the following questions (RQ) were addressed:

RQ1 - What is the state of learning analytics implementation?
RQ2 - What are the educational goals behind the implementation of learning analytics?
RQ3 - How does learning analytics being implemented to achieve the objectives?
RQ4 - What are the significant results of learning analytics implementation in school?

The rest of this paper is organized as follows: the methodology of the SLR is explained in the Section 4 Methodology. Then, the results of the synthesis and analysis of the literature review data are presented and discussed in the Section 5 Results and Discussion. Lastly, the concluding remarks are demonstrated in the Section 6 Conclusion.

Methodology

The review protocols for this SLR are based on the SALSA framework proposed by (Booth et al., 2014). The SALSA framework comprises 5 phases- protocol, search, appraisal, synthesis, and analysis. The details of each phase are explained as follows:

A. Protocol

The first phase of SALSA is the 'protocol' phase, where the scope of SLR is determined and outlined. The PICOC framework is a widely known strategy for framing a research question, and therefore, it was used to determine the review scope in this study, as shown in Table 1 below:

Table 1
PICOC Protocol Outlines

P	Population	School teachers, students
I	Intervention	Analytics tools, learning data type, learning platform, analytics techniques, learning dashboard
C	Comparison	Similarities and differences in implementation at the pre-higher education and higher education level.
O	Outcomes	Details on the implementation of learning analytics in school, specifically the state of learning analytics implementation, objectives, design, and findings.
C	Context	School level (K-12)

B. Search

After determining the scope of SLR, the next phase is the 'Search' phase. During this phase, the sources of relevant information to the study are searched. First, the sources for search databases and search engines are listed, and the search string is then defined using the context identified in PICOC. After that, the search string is keyed into each database to retrieve the sources. The result of this protocol is as follows:

a. Database: Scopus, Lens.org, Mendeley, ScienceDirect, Association of Computer Machinery (ACM), Journal of Learning Analytics (JLA)
b. Search String: "Learning analytics" AND (schools OR K-12 OR primary OR secondary)
c. Retrieved Sources:

Vol. 11, No. 2, 2022, E-ISSN: 2226-6348 © 2022

The number of sources retrieved from each database is listed below:

Table 2
Search String and Number of Sources Retrieved from Each Database

Search String	Database	Date	No of Sources
TITLE-ABS-KEY ("Learning analytics" AND (schools OR K-12 OR primary OR secondary))	Scopus	13/11//2021	816
"Learning analytics" AND (schools OR K-12 OR primary OR secondary)	Mendeley	13/11//2021	68
"Learning analytics" AND (schools OR K-12 OR primary OR secondary)	Sciencedirect	13/11//2021	1012
Scholarly Works (2,371) = "Learning analytics" AND (schools OR K-12 OR primary OR secondary)	Lens.org	13/11//2021	2371
"Learning analytics" AND (schools OR K-12 OR primary OR secondary)	ACM	13/11//2021	1742
Manual searching in every journal volume	JLA	13/11//2021	4669

C. Appraisal

In this phase, the sources retrieved from the identified database and engines are evaluated to identify papers relevant to the research questions. The sources were evaluated during the appraisal to determine whether they fulfil the inclusion and exclusion criteria as listed in Table 3:

Table 3
Sources inclusion and exclusion criteria

Type	ID	Criterion
Inclusion	I1	Present discussion about LA implementation in school
	I2	Present discussion about LA implementation in K-12
	I3	Present discussion about LA implementation in primary education
	I4	Present discussion about LA implementation in secondary education
Exclusion	E1	Published before 2016
	E2	Open access; abstract only, no full text
	E3	Subject: education, computer science
	E4	Does not meet any of the inclusion criteria
	E5	Duplicates

The results of the appraisal are shown in Table 4 below:

Table 4
Sources Evaluation Result

Database	Search Result	E1	E2	E3	E4	E5
Scopus	816	684	188	62	12	
Mendeley	68	48	11	11	6	
ScienceDirect	1012	846	204	15	0	
Lens.org	2371	1181	1139	121	10	
ACM	1742	1272	30	26	6	
JLA	178	178	178	21	13	
Total	**6187**	**2117**	**1542**	**241**	**47**	**24**

There were 24 studies identified and selected based on the evaluation and appraisal criteria. An overview of each study selected, including the title, author, year, and country, is shown in Table 5 below:

D. Synthesis

The synthesis phase involves extracting and classifying relevant data from the selected studies to derive knowledge and findings that will answer the research questions. Thematic synthesis was used in this phase. The selected studies are read and re-read to scan and extract relevant data based on the scope highlighted in PICOC to map the themes for analysis. Based on research questions, the themes are state-of-art (school level, types of data, system, tools, platforms), analytics educational goals, types of analytics, implementation design, and findings. Data related to each theme was extracted into an Excel sheet for data processing.

E. Analysis

The analysis phase encompasses the previous phase's evaluation and data processing of the synthesized data. It involves four (4) steps: identification and extraction, analysis of themes (thematic analysis), result discussion, and conclusion. The process of analysis was conducted manually using Microsoft Excel. The result of this phase will be presented and discussed in detail in the next section.

Results and Discussion

As mentioned earlier, 24 studies were identified and included in the SLR. It is found that the implementation of learning analytics has been documented mostly in developed countries like USA, Netherland, Spain, Singapore and Australia. Most of these studies were published recently (in 2020 and 2021). These findings support the claim that the implementation of learning analytics in school (K-12, primary, secondary) is still in the infancy stage (Picciano, 2012), and it has been largely done in developed countries (Abdusyakur, 2015). Based on the study’s titles, the main areas of concern for implementing learning analytics are data visualization and the use of dashboards in teaching and learning. In this light, dashboards in learning analytics are crucial. They provide teachers with quick and accurate information about students’ learning process and progress and help teachers monitor students’ collaborative learning activities. It offers indirect support, especially for technology-enhanced learning in the classroom (Leeuwen et al., 2019). The following are the results of the synthesis and analysis presented and discussed according to the research questions of the study:

A. The state of Learning Analytics Implementation (RQ1)

The state of implementation refers to the current implementation of learning analytics in terms of school level, data, platforms utilized, and type of analytics. Based on the reference model for learning analytics implementation (Chatti et al., 2014) addresses the dimensions of 'what' and 'who' in learning analytics implementation. The details of the state of Learning analytics implementation as discussed in selected studies are presented in Table 5.

Table 5
State of Learning Analytics Implementation

Study	School Level	Data	Platforms	Type of Analytics
1	Grade 6	trace log	iRemix	Descriptive
2	K-12	trace log	WiREAD	Descriptive
3	Grade 7 - 12	visual	Chem Tutor	Descriptive
4	K-12	practical measures	Edsight (Dashboard)	Descriptive
5	Grade 8	score	Inq-Blotter (Dashboard)	Descriptive
6	K-12	trace log	C2STEM environment	Descriptive
7	K-12	trace log	MathTutor	Descriptive
8	Primary and secondary	trace log	Go-Lab	Descriptive
9	Middle	trace log	Cristal Island (GBLE)	Descriptive
10	Secondary	trace log	Lego Mindstorms EV3	Descriptive
11	Grade 4	score	Snappet	Descriptive
12	K-12	score	Snappet, Dashboard	Descriptive
13	Secondary	score	Got it Language	Descriptive
14	All level	trace log	LMS (no name)	Descriptive
15	Primary	trace log	Indoor Sensing	Descriptive
16	Secondary	trace log	WiREAD	Descriptive
17	Primary	trace log	MathTutor	Descriptive
18	K-12	trace log	LUMILO	Descriptive
19	All level	trace log	open textbooksystem	Descriptive
20	Secondary	student data	METAL LA	Descriptive
21	High	trace log, score	Alice	Descriptive
22	Primary and high	trace log	School Network	Descriptive
23	All level	score	Game Based Learning	Descriptive
24	Secondary	student data	Dashboard	Descriptive

From the table, it can be deduced that the implementation of learning analytics in pre-higher education occurs in all grades. Most of the data collected and used for analytics were extracted from the learning platforms, like students' trace logs and scores. The distribution of data is summarized in Table 6. As can be noticed from the table also, there are wide-range of learning digital platforms that have been used for learning and analytics. These platforms categories are learning systems (iRemix, open-textbook, WiREAD, Go Lab, Snappet, C2STEM), intelligent tutoring systems (Chem Tutor, Math Tutor), Game-based Learning Systems (Cristal Island), visualization tools (Edsight, Inq-Blotter), programming applications (Alice, Lego Mindstorm Software), and physical electronic devices (LUMILO, indoor sensing system, Lego Mindstorm robotics kit). It was observed that all of the analytics are descriptive, often used to gain information and identify patterns and meaning. Descriptive analytics usually answers the question, “What happened?” (or What is happening?). It is characterized by traditional business intelligence (BI) and visualizations such as tables, charts, graphs etc. (Gartner, 2022).

Table 6
Distribution of collected data types

Data Types	Percentage (%)
Trace log	65
Score	26
Practical Measure	4
Visual	4

B. Educational Goals (RQ2)

Table 7 presents several examples of educational goals behind the learning analytics implementation in school as extracted from the selected studies. According to (Chatti et al., 2014), several themes can be mapped to address why learning analytics is implemented in schools. These themes include monitoring, analysis, prediction, intervention, tutoring, mentoring, assessment, feedback, adaptation, personalization, recommendation, awareness, and reflection. As summarized in Table 8, half of the studies reported that the goals of learning analytics are within the monitoring/analysis theme, and about 45% fall under the assessment/feedback theme. In comparison, 8% have a reflection theme.

Table 7
Examples of Educational Goals

Study	Educational Goals
1	to understand student learning activity from trace log data (looking at evidence of 21st-century learning activities in an online environment)
2	to understand student learning experience and progress in the WiREAD dashboard
3	to understand how students construct concepts within social contexts when working with physical and virtual representation modes.
4	To support the work of teachers by providing a space of reflection about particular aspects of instruction.
5	To alert teachers on students' performance in science inquiry practices (difficulties, inquiry practices, activities completed)
6	to understand student collaborative learning processes in physics (problem-solving, computational modelling)
7	to provide information about students' collaboration in learning math, to alert teachers about deviating groups of students and their situation

Table 8
Themes identified from Learning Analytics Educational Goal

Goals Theme	Percentage (%)
Monitoring/Analysis	50
Assessment/Feedback	42
Awareness/Reflection	8

According to Chatti et al (2014), for monitoring/analysis-themed educational goals, students' learning engagement was tracked and reported to support decision-making by the teacher or the school institution. The teacher's evaluation of the learning process aims to improve the learning environment continuously. Thus, examining how students use different kinds of learning systems, tools and platforms and analyzing students' achievement and progress is useful for detecting patterns, understanding meaning, and deciding the future design of the learning activities. Furthermore, assessment/feedback-themed educational goals provide constructive feedback to students and teachers/mentors to improve learning efficiency and effectiveness. Constructive feedback provides useful data-based information about students' interests and the learning context (Chatti et al., 2014).

C. Implementation Design (RQ3)

Implementation design addresses the technique and how learning analytics is introduced and conducted in instructional settings to achieve educational goals. The design depends on the systems, tools, and platforms utilized in the implementation. Different methods and techniques can be applied for data collection and analysis to gain information and identify hidden patterns in student data.

Regarding data collection and data analysis on learning analytics implementation, two modes can be deduced from the selected studies:

I. Embedded mode
   Data collection and analysis are embedded within the learning platforms in this mode. There are built-in functionalities within some learning platforms that collect data and/or run analysis simultaneously as students engage with the learning systems and platforms. Learning platforms with these features include iRemix, Inq-Blotter, WiREAD etc.

II. Standalone mode
   In this mode, data collection and/or data analysis tools are not embedded within the learning systems, learning tools, or learning platforms. Data collection and analysis are conducted outside of learning systems, learning tools, or learning platforms functionalities. Data collection and analysis are done using external tools, such as Google Form, MS-Excel, SPSS, Tableau, R etc.

Table 9 below summarizes the mode of data collection and data analysis in the selected studies:

Table 9
Mode of data collection and data analysis

	Data Collection	Data Analysis
Embedded System	73%	32%
Standalone System	27%	68%

According to Chatti et al (2014), there are four frequently used techniques in learning analytics implementation, namely statistics, information visualization, data mining, and social network analysis. As summarized in Table 10, the distribution of techniques used in the selected studies is as follows:

Table 10
Analytics technique

Technique	Percentage (%)
Statistics	41
Visualization	35
Data Mining	12
Social Network Analysis	9
Natural Language Processing	3

D. Implementation Findings (RQ4)

This section reviews the results, evidence, and conclusions deduced from the studies on the implementation of learning analytics. This section will answer the research question regarding the implementation of learning analytics in school. These studies concluded that the implementation of learning analytics during instructional activities positively impacts students and teachers.

Impacts on Students

The implementation of learning analytics in instructional settings improved student learning performance. For example, visualization activities via the WiREAD dashboard help enhance students' English language and literacy performance. Students' engagement in online social reading and discussion spaces in WiREAD fosters greater self-awareness, reflective, and self-regulatory learning dispositions (Tan et al., 2017). Additionally, a majority of students have shown significant improvement in their science inquiry practices using Inq-Blotter with teachers' guidelines (Dickler et al., 2021). The results also indicate that students immersed in learning analytics enhanced-technology settings have shown significant progress in arithmetic skills compared to those still taught in the paper & pencil setting (Molenaar et al., 2017).

The implementation of learning analytics also contributes to higher learning motivation and engagement, especially in promoting self-directed, social online collaboration and blended learning. For instance, the study on the use of iRemix found that students can identify themselves pursuing possible future technological work opportunities in creative industries. It has increased the potential for self-directed learning and social learning online (Martin et al., 2016). The C2STEM modules provide students with the opportunities to a) explore resource-intensive processes, such as trial and error, to more systematic processes, such as debugging model errors by leveraging data tools, and b) learn from each other using socially shared regulation and productive collaboration (Emara et al., 2021). A study by Campen et al (2021) showed that educational technologies that combine standalone and embedded learning analytics help support blended learning by balancing teacher-led instructions with class-paced and individually-paced practices.

Teachers

The studies also posited that learning analytics in instructional settings, such as visualization tools, support teachers' decision making (Macarini et al., 2020) and identify student-student and student-teacher interaction patterns in the classroom (Ponciano et al., 2020). It is also suggested that using learning analytics dashboards affects how teachers provide feedback concerning the type of feedback provided and how different types of feedback are channeled to students (Knoop-van Campen et al., 2021). Furthermore, alerting dashboard could inform teacher support of students' science inquiry practice competencies and the value of in-depth analyses of the implementation of new technological genres in classrooms (Dickler et al., 2021).

Similarly, Campos et al. (2021) found that emotional, analytical, and intentional responses inform teachers' sense-making of the dashboard. In this light, teachers will respond differently to data visualization in the dashboard based on the different roles they play in schools. It was also concluded that general teacher characteristics (gender, age, teaching experience, technology experience or self-reported technology proficiency) did not explain the variation in the teacher dashboard used in the awareness, interpretation, and enactment phases (Leeuwen et al., 2021).

Nonetheless, it is equally important to mention that the study's findings have emphasized the crucial roles of teachers in blended learning. In both physical and virtual learning modes, teachers play a crucial instructor role in encouraging students to elaborate on connections between concept representations Technology-based support cannot "replace" teachers' support, at least not when students have little prior knowledge about the concepts and representations (Rau, 2017).

Conclusion

This paper presents the results of an SLR on the selected studies regarding the implementation of learning analytics in primary and secondary schools. The goal is to examine the current implementation of learning analytics in teaching and learning. The SLR identified the state of implementation, educational goals, implementation design and analytics techniques. The findings from the SLR are discussed below.

The findings of the SLR support the arguments of previous studies, which are: 1) the implementation of learning analytics at the pre-higher education level is still at the early stage, 2) learning analytics is most applied in developed countries, and 3) there is a lack of research on the implementation of learning analytics at the primary and secondary level.

Moreover, different learning platforms have been developed and used in instructional settings to facilitate learning analytics. These platforms include social learning systems, intelligent tutoring systems, game-based or programming-based learning systems, etc. However, the result showed that learning analytics in primary and secondary school only reached the descriptive level, the first stage of data analytics. More complex data analytics such as diagnostic, predictive, and prescriptive analytics have yet to be implemented. This explains why the educational goals theme in the selected studies encompasses monitoring, analysis, assessment, feedback, and reflection. The theme regarding educational goals like prediction, intervention, adaptation, personalization, and recommendation, as mentioned by Chatti et al (2014), has yet to be implemented in learning analytics at the pre-higher education level.

Third, in terms of design and technique, it was found that studies have used many data collection tools which are embedded within the architecture of learning platforms. This indicates that learning analytics is already considered crucial for developing learning platforms' functionalities. However, data analysis and visualization for the collected learning data were still conducted in standalone systems. Having data collection, analysis, and visualization functionalities embedded as part of learning systems facilitates the implementation of learning analytics in school. It avoids the implementation barriers such as time constraints, lack of skills, perceived difficulty to use, heavy workload, and insufficient facilitation conditions.

Fourth, from the SLR, it can be concluded that the implementation of learning analytics in teaching and learning benefits primary and secondary school students and teachers. Findings showed that learning analytics improved student progress and performance in learning. It improved student engagement in online learning activities and fostered self-awareness, reflection, motivation, collaboration, and self-regulatory. The implementation of dashboards also supports teachers' teaching practices and decision making. It affected the ways teachers provided feedback and informed them about student learning inquiry.

The potential of implementing learning analytics in teaching and learning for primary and secondary schools is exciting and promising. Having clear insights about different types of learning systems, variety of implementation state-of-art, various features, learning goals, and possible outcomes is crucial in planning and designing classroom instruction. Improving teachers' concerns, school facilitating conditions, and learning systems analytics features are suggested to ensure the successful and sustainable adoption of data-based assessment, evaluation and decision making in teaching and learning. Therefore, it is recommended that teachers require courses, training, and workshops to learn more about learning analytics implementation in the school. Future research on the design and planning of learning analytics in the instructional process is required to improve teaching practices and increase student learning potential in the digital environment.

Limitations

The main limitation of this study is embodied in the search process that only focused on studies that contain the specific database mentioned in the SLR methodology. This could potentially exclude research from other databases describing the better implementation of learning analytics in primary and secondary schools.

Secondly, a few papers had limited information about the study's objectives, which led to several coding of some studies with labels such as “no available” in some of the categories analyzed in the SLR. However, these papers were still selected because of little relevant information to at least one research question.

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