

Learning analytics and tech-tools: Insights of the practical implications for stakeholders' perspectives



Malissa Maria

Mahmud¹

Nor Fazlin Mohd

Ramli^{2*}

Siti Fauziana Zakaria³

Rusreena Rusli⁴

Mohammad Radzi

Manap⁵

Shiau Foong Wong⁶

^{1,6} Sunway University, Malaysia.

¹Email: malissam@sunway.edu.my

²Email: jamcevv@sunway.edu.my

^{3,4,5} University Teknologi MARA, Malaysia.

²Email: norfa707@uitm.edu.my

³Email: sitifauziana@uitm.edu.my

⁴Email: rusreena@uitm.edu.my

⁵Email: moham830@uitm.edu.my



(+ Corresponding author)

ABSTRACT

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The aim of the current study is to perform a systematic review of the literature to determine how learning analytics and technological tools used in education relate to one another. The review looked at 30 samples from 15 (n=15) academic databases, and found that the recent learning analytics research typically used web-based applications, Web 2.0 tools, dashboard and visualization tools, and eye-tracking devices. These technological tools, such as learning management systems and social networking websites, are widely employed in order to facilitate online learning and communication as well as to analyze and visualize data for informed decision-making. One of the practical implications of this research for learning analytics stakeholders, such as educators, policymakers, and researchers, is the ability to use these technologies tools to enhance teaching and learning. By utilizing these tools, policymakers can learn information that can be applied to the development of strategies and policies relating to the integration of technology in education. Researchers can utilize these tools to generate data that will aid in the study of teaching and learning, which will lead to the development of new teaching strategies and technological advancements. Stakeholders must establish appropriate policies and practices, be aware of the potential risks and limitations associated with their usage, and work to ensure that these tools are used in the classroom in an ethical and efficient manner. This study shows, in general, how effectively these technological tools can enhance teaching and learning when used in educational settings.

Contribution/ Originality: Learning analytics can be a key instrument to support the success of individual learners. The advantages associated with incorporating learning analytics are shown in this study. This study highlights the potential of learning analytics to ensure its effective application in educational settings.

1. INTRODUCTION

Learning analytics is a process for understanding and improving learning experiences by using data and analytics. Due to the prevalence of learning technologies, it is widely accepted and regularly used in education. According to Viberg, Hatakka, Bälter, and Mavroudi (2018); Romero and Ventura (2020) and Ifenthaler and Yau (2020) learning analytics are important because they may promote the development of evidence-based practices and

aid in identifying key factors that influence learning, such as motivation and attitudes. Learning analytics can dramatically improve the effectiveness and efficiency of learning environments in addition to enhancing the success of individual students.

Learning analytics is the measurement, collecting, analysis, and reporting of data about learners and their circumstances to understand and improve learning and the environments in which it takes place. It is a web analytics solution for education that focuses on learner profiling, which is the process of compiling and examining detail of individual student interactions with online learning activities. Academics and administrators have recently become interested in learning analytics since it is a potent tool. Due to the ability to collect and make student data available for study, online learning has grown significantly during the 1990s, especially in higher education. By changing the ways we support learning processes, learning analytics can enhance learning practises. By analysing the data, educators can better understand how students engage with technological tools like e-learning platforms to learn. Learning analytics offers a deeper knowledge of the learning process by utilising digital technologies to record and analyse data on students' interactions with educational tools and platforms. Beyond the classroom, learning analytics' practical applications offer insightful information to many different education stakeholders. Learning analytics offers a variety of data from students to staff to administrators that can guide decision-making and enhance educational outcomes. Stakeholders may improve the learning experience by using data-driven decisions by developing a thorough understanding of students' learning habits, identifying areas for development, and more. Multidisciplinary research fields like social network analysis, user modelling, and cognitive science are all used in the subject of learning analytics. With an expanding amount of literature and study, it has developed as a distinct subject. Since the first Learning Analytics and Knowledge Conference in 2011 (Joksimović, Kovanović, & Dawson, 2019) the area of learning analytics has developed, addressing both technological problems with data collection and analysis and socio-technical problems with acceptance and ethics. Understanding how learning analytics can be used to address the various demands of the educational community depends on stakeholders' perspectives on the topic (Gray et al., 2022). Learning analytics can give students personalised feedback, highlight areas for development, and improve their overall learning experience. Learning analytics can help teachers and administrators plan curricula, spot children who may be at risk, and allocate resources more effectively. We can obtain a thorough grasp of how learning analytics can be used to give beneficial insights for stakeholders by looking at the insights of students and staff.

According to research, learning analytics can, for instance, assist educators and learning professionals in identifying opportunities for improvement in the learning environment (Troussas, Krouska, & Virvou, 2020) personalizing learning to individual learners (Lee, Huh, Lin, & Reigeluth, 2018) enhancing learning outcomes (Viberg et al., 2018) and improving efficiency (Mangaroska & Giannakos, 2018). Additionally, learning analytics can offer insightful data that can inform decision-making at the individual and institutional levels, assisting educators and learning professionals in making decisions regarding methods of instruction, the allocation of resources, and other important issues. According to one study, using learning analytics can help educators in identifying and optimizing the most efficient teaching and learning techniques, enhancing the efficiency of the educational process (Ryan, Gašević, & Henderson, 2019). In order to increase the effectiveness and efficiency of learning environments and support the success of individual learners, learning analytics can be a key instrument. Some of the advantages associated with incorporating learning analytics in the context of teaching and learning are shown in Figure 1. Despite the widespread use of learning analytics, there are not many theoretical frameworks in the field that can help researchers in explaining discrepancies, avoiding misunderstandings, and taking into account the various contextual factors like instructional, sociological, and psychological factors that impact learning (Er, Dimitriadis, & Gašević, 2021; Hernández-Leo, Martínez-Maldonado, Pardo, Muñoz-Cristóbal, & Rodríguez-Triana, 2019). This highlights the need for further research and development in the area of learning analytics to ensure its responsible and effective application.

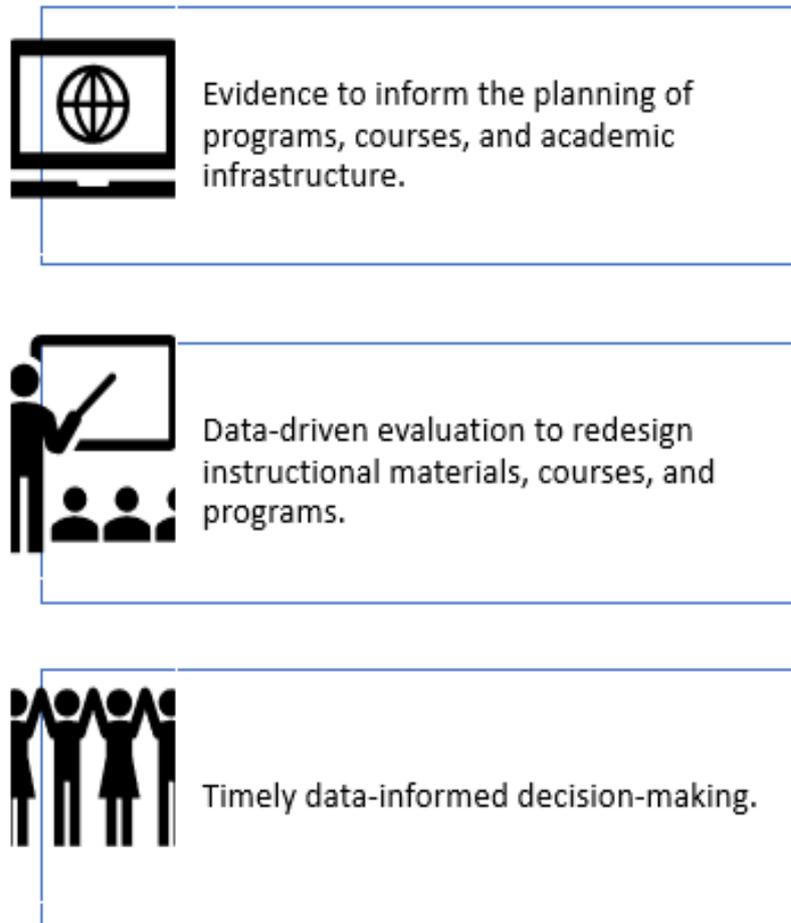


Figure 1. Benefits of learning analytics.

The selection of key indicators affects how well learning analytics are implemented. It is crucial to consider the particular objectives and needs of the learning environment as well as the learners engaged when selecting indicators. Some of the most common indicators used in learning analytics are engagement, performance, attitude, behavior, and outcomes (Lytras, Aljohani, Visvizi, Ordonez De Pablos, & Gasevic, 2018; Tsai et al., 2020; Yau & Ifenthaler, 2020). These indicators can provide educators and learning professionals with helpful information regarding the effectiveness of their teaching and learning strategies with students. A variety of data sources and analytical techniques should be used to measure and analyze the key indicators that are most relevant to the learning environment and learners in order to employ learning analytics effectively (Wong, Li, & Cheung, 2022). By tailoring their teaching and learning strategies to the needs of individual learners, educators and professionals in education can identify areas for improvement. The key learning analytics indicators and corresponding measurements are shown in Figure 2. The figure demonstrates how indications including time spent on task, participation in online discussions, and assignment completion may be used to gauge engagement. Grades, test scores, and completion rates are a few examples of indicators that can be used to evaluate performance. Indicators like motivation, satisfaction, and self-efficacy can be used to gauge attitude. Behavior can be measured using indicators like participation, the quantity of times a student visits a particular web page, and the number of times they click on a particular resource. Indicators like learning increases, retention rates, and data on the extent to which learning is being applied by students can all be used to measure outcomes. The effective implementation of learning analytics depends on the selection of key indicators.

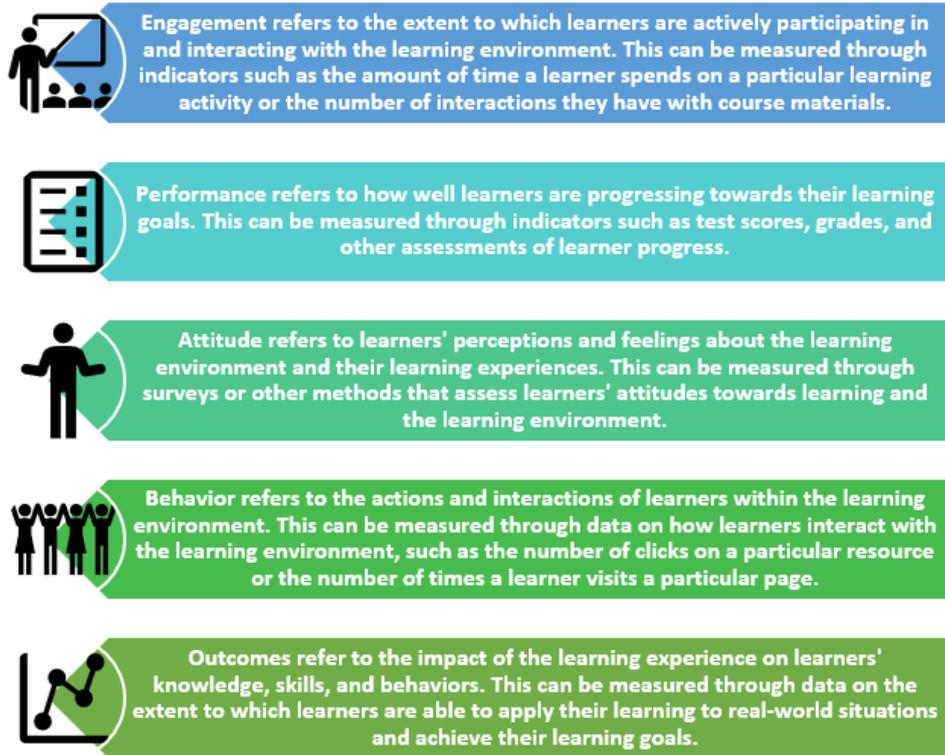


Figure 2. The key indicators for learning analytics.

The aim of this research is to carry out a comprehensive literature review with the intention of investigating the relationship between learning analytics and learning design. The study seeks to provide insights that go beyond particular research findings in each discipline and a more comprehensive understanding of these fields. Despite learning analytics being a relatively new topic of research, there has been enough scholarly work to support systematic reviews that can inform stakeholders about current trends and practices (see Figure 3: Google Trends search in Learning Analytics). Research is needed, though, to better understand how learning analytics might offer practical design insights to various stakeholder groups. This study aims to close this research gap by offering new insights into this area of study by undertaking a comprehensive literature review that investigates the relationship between learning analytics and the technology tools used. An important understanding of the relationship between learning analytics and learning design is provided by the literature review conducted for this study. The review highlights how important it is to use learning analytics to inform decisions on instructional designs and improve learning outcomes. The study outlines the key stakeholders engaged with applying learning analytics, such as staff members, decision-makers, and students. The review also emphasizes the requirement for practical design insights that might guide decisions made both institutionally and individually. Recent research on learning analytics has focused heavily on the use of technological tools, including learning management systems, social networking sites, dashboard and visualization tools, and eye-tracking devices. By providing useful data that can inform decision-making and improve learning outcomes, these tools have the potential to enhance teaching and learning.

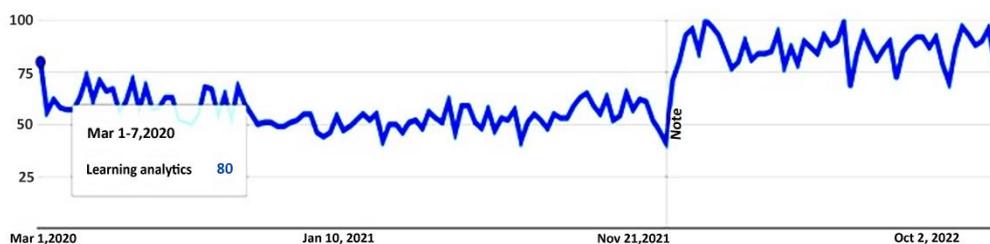


Figure 3. Google trends search for learning analytics during the pre-pandemic and post-pandemic.

2. METHODOLOGY

2.1. Searching the Database

Several steps went into the process of selecting the studies to be included in this review. The authors conducted literature searches and reviewed the titles and abstracts of the resulting studies. Those that might be pertinent underwent additional eligibility assessment. For the purpose of ensuring the quality of the selected studies, the authors solely included empirical, peer-reviewed papers. The risk of bias in each study was evaluated by looking at elements including measurement bias and sampling bias. By selecting studies that met particular inclusion criteria and by employing a standardized approach to assess the quality of the studies, the authors aimed to minimize bias. The PRISMA flow diagram (Figure 4), which was adapted from Page et al. (2021) shows the visual representation of the sample's identification process.

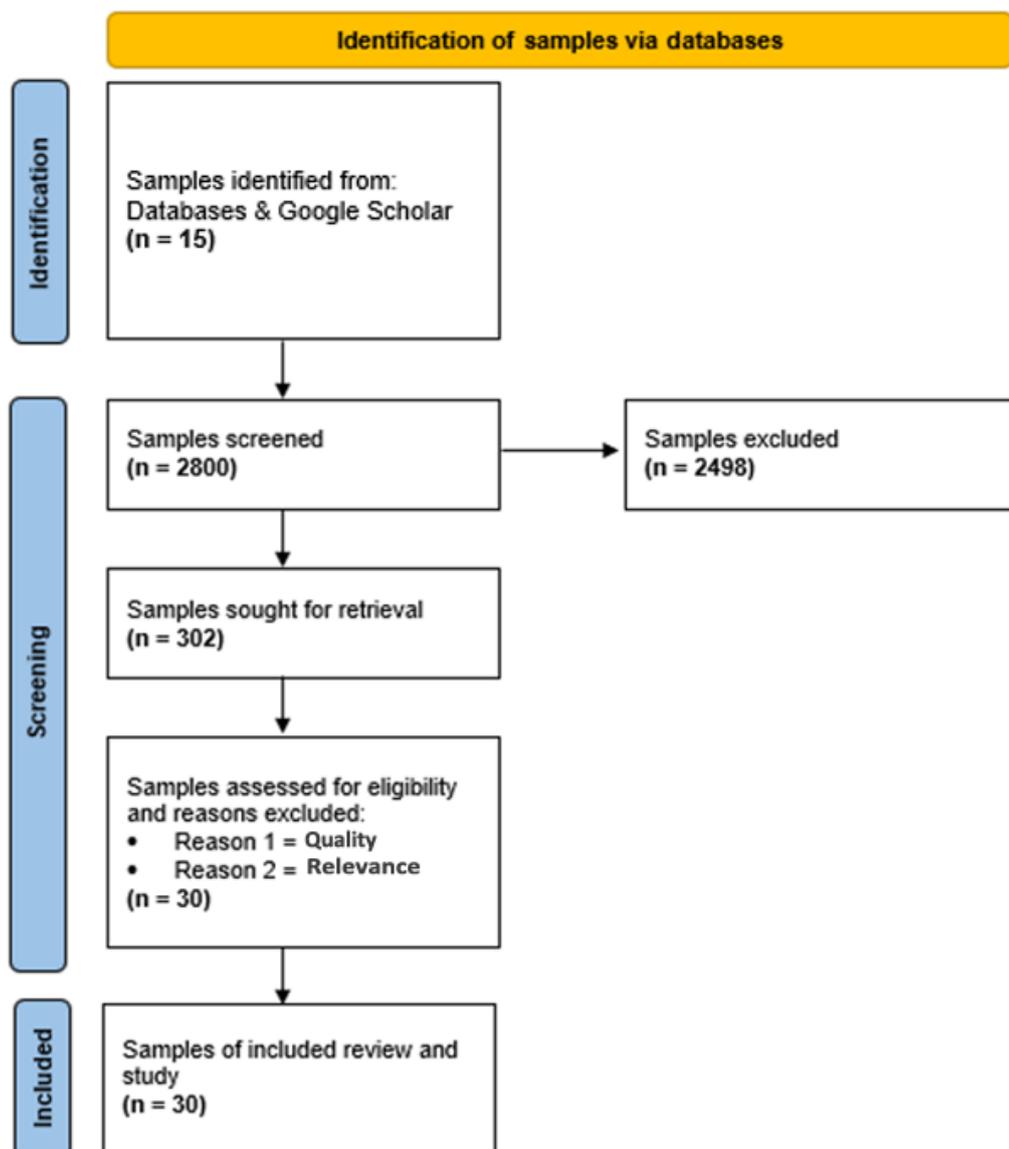


Figure 4. The PRISMA flow diagram.

The diagram displays the number of studies that were identified, screened, assessed to be eligible, and included in the review. At each stage of the process, the diagram also displays reasons for excluding studies. The authors searched two additional databases, SAGE and ERIC, in addition to five major electronic databases for Technology Enhanced Learning (TEL), including ACM DL, IEEE Explore, Springer-Link, Science Direct, and Wiley, to

identify relevant research papers. The authors also looked through research papers in educational technology journals listed in Google metrics under "Educational Technology" subcategory, including Computers & Education, British Journal of Educational Technology, The Internet and Higher Education, Journal of Educational Technology & Society, Journal of Computer Assisted Learning, Educational Technology Research and Development, International Journal of Computer-Supported Collaborative Learning, IEEE Transactions on Learning Technologies, and the International Conference of Learning Analytics and Knowledge. A search on Google Scholar was also conducted to find potentially relevant literature that may not be indexed in common academic databases. Finally, the authors used the "snowball technique" by searching the reference sections of each selected paper to find additional relevant papers.

The initial search yielded 2800 potential samples, wherein the terms such as "analytics" and "design" and "learning" were used in the search string (Prieto, Holenko Dlab, Gutiérrez, Abdulwahed, & Balid, 2011). Figure 5 illustrates the three steps of the search strategies, wherein these samples were subsequently analyzed based on the following inclusion criteria:

1. Clear research problem.
2. Clear statement of research aims.
3. Sufficient description of the research context.
4. Relevant research design.
5. Relevant research methods was the
6. Rigorous data analysis
7. Clear deliberations of research findings
8. Clear reiterations of practical value

The relevance and quality of the studies identified in the search were evaluated using the inclusion criteria. To ensure the validity and reliability of the findings, the authors of this study specifically sought out studies that satisfied these requirements. Based on the inclusion criteria, a detailed evaluation of the selected studies was performed. To determine which studies should be included in the review, the authors reviewed the research problem, research objectives, research context, research design, methods of research, data analysis, discussion of the research findings, and reiterations of the practical value in each study.

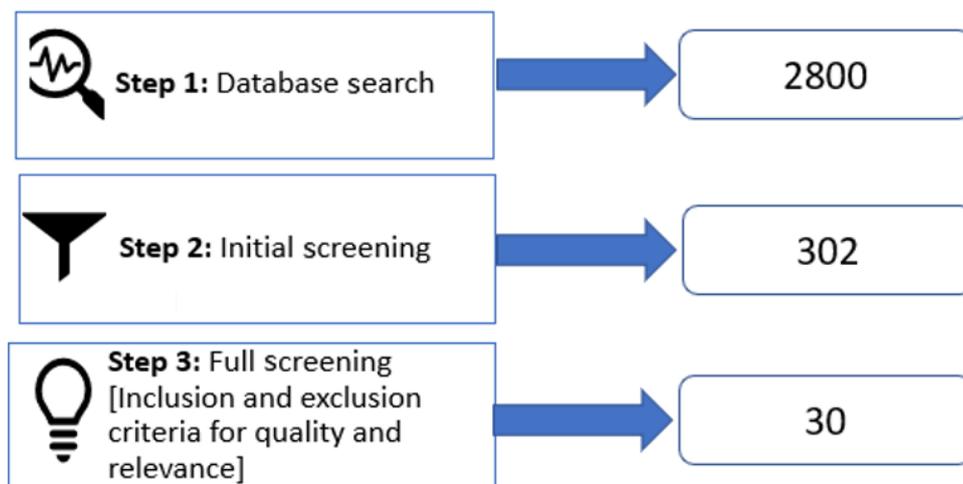


Figure 5. Search strategies.

Of the 302 samples retained, the full text was reviewed for quality and relevance, using the following criteria adapted from Critical Appraisal Skills Programme, and by principles of good practice for conducting empirical research in software engineering (Kitchenham et al., 2002). The authors of this study aimed to select high-quality empirical studies that met these criteria to ensure the reliability and validity of the findings. At this juncture, thirty

(30) samples were successfully included in the systematic literature review. The studies included in the review were sourced from various academic databases and journals, ensuring a comprehensive and diverse range of literature for the systematic literature review. The authors of this study conducted a thorough assessment of each study to ensure that it met the inclusion criteria and provided valuable insights into the relationship between learning analytics and learning design.

Table 1. Frequency of tech-tool.

Tech-tool	Frequency
Web-based applications	8
Web 2.0 tools	6
Dashboard and visualization tools	5
Eye tracking devices	4
Learning analytics tool	3
Mobile	2
Conventional tool	2

3. FINDINGS AND DISCUSSION

Table 1 shows the frequency of technology tools used in the 30 included samples. Web-based applications, which are educational software or platforms that utilize the Internet, were the most frequently used technology tools, with a frequency of 8. This finding is consistent with the current trend in blended learning studies, as many institutions are adopting web-based applications to respond to the challenges of ubiquitous technology use. Presently, there are many web-based applications accessible that can be utilised for teaching and learning purposes. Bradley (2021) encapsulated that web-based applications such as Learning Management Systems (LMS) is able cater to the needs of the students' learning styles, as well as to augment the quality of teaching (2021). In a similar vein, LMS allow users to design and organize their learning experiences to meet specific goals and objectives (Rabiman, Nurtanto, & Kholifah, 2020). To complement face-to-face instruction, latest web management tools like Moodle are included into the teaching and learning contexts. A well-liked open-source learning management system called Moodle enables educators develop and manage online courses and resources. As it enables students to engage in a range of educational activities and communicate with their instructors and peers, it is a helpful tool for online learning. It offers several features like videos, discussion forums, chat, materials, and quizzes that enhance the online learning experience. These features provide more interactive and dynamic learning experience for students by enabling them to engage with a variety of educational resources.

With a frequency of 6, Web 2.0 tools come in second place on the list of frequently utilized technology tools in learning analytics research. The second generation of the World Wide Web, known as Web 2.0, is defined by the usage of web-based applications and services that facilitate interactive and group-based content creation and communication. Social networking sites, blogs, wikis, video sharing platforms, podcasts, collaborative software, and online forums are examples of these technologies, also referred to as Web 2.0 tools. They are frequently employed in educational settings to promote collaboration, communication, and easy access to a variety of online learning resources. Studies by Kaur and Kauts (2018) and Abdelazim, Ajmi, and AlBusaidi (2021) have shown that the use of Web 2.0 tools in education can increase student engagement and improve learning outcomes. As a result, in order to encourage interactive and collaborative learning experiences, educators and policymakers may think about integrating Web 2.0 tools into their teaching practices and policies. However, there are risks associated with using Web 2.0 tools, such as the possibility of distraction and improper use, which emphasizes the need for careful thought and the establishment of appropriate policies and guidelines.

Next is the dashboard and visualization tools, and they were present in all 5 of the included examples. Dashboard and visualization tools are software applications that allow users to monitor and analyze data, frequently using interactive graphs, charts, and maps. Real-time updates and alerts may be included in these tools, which can

be tailored to display relevant data. They are designed to support users in making sense of sizable and complex data sets and making informed decisions using this data. When it comes to assisting students in comprehending trends, patterns, and relationships within the data as well as effectively communicating this information to others, visualization tools can be especially helpful (Szymkowiak, Melović, Dabić, Jeganathan, & Kundi, 2021). Students can receive feedback in a more participatory and engaging manner by using visualization tools. Teachers can use graphs or charts to demonstrate to students how they are doing in comparison to their peers or how they have improved over time, for instance. Additionally, by allowing students to share and discuss data and insights in real-time, these tools can be used to promote student collaboration, resulting in improved learning outcomes and decision-making (Jalalitar & Wang, 2022).

The eye-tracking devices with a frequency count of four come next. The employment of sensors in eye-tracking technology allows for the tracking and measurement of eye movement. These tools can be used in educational context to examine how students interpret and process visual information, such as that found in instructional materials, videos, and digital resources. Educators can discover areas that might be difficult for students to understand and make the required adjustments to improve the efficacy of their teaching methods by examining how students interact with the learning materials (Beach & McConnel, 2019). Examining reading comprehension is one potential educational use for eye-tracking technology. Researchers who monitor students' eye movements can determine which passages of a text they spend more time reading, which can reveal which parts of the text may be more challenging for kids (Kao, Chiang, & Foulsham, 2019). This information can be used to guide instruction and design materials that better support reading comprehension. Using eye-tracking technology, researchers may examine how students interact with multimedia resources including videos and interactive simulations (Wang, Lin, Han, & Spector, 2020). The most interesting parts of a video or simulation can be identified by measuring eye movements; this information can then be used to improve the design of multimedia learning tools. Overall, eye-tracking tools have the potential to offer insightful data about how students take in and process visual information. This knowledge can then be used to inform the design of learning resources and instructional materials that are more effective to promoting learning.

From the included samples, the authors obtained three learning analytics tools. Tools for analytics gather and analyze data on student learning in order to monitor progress, identify areas of strength and weakness, and guide instruction. Learning management systems (LMS), platforms for adaptive learning, and learning analytics dashboards are some of these tools. Teachers can create and manage online courses and materials using LMSs, which are web-based applications that frequently incorporate analytics features for monitoring student progress and giving feedback. Adaptive learning platforms typically incorporate analytics features to monitor progress and adjust instruction, and they use artificial intelligence to customize learning experiences for individual students (Alam, 2022; Arsovic & Stefanovic, 2020). Teachers can monitor their students' development and performance in real-time using learning analytics dashboards, web-based applications that frequently include interactive graphs and charts.

The frequency count for mobile is 2. To support learning and instruction, mobile education tools are applications that can be accessed on a mobile device, such as a smartphone or tablet. These tools can be utilized by teachers to develop and deliver curriculum, evaluate student progress, and give feedback, as well as by students to access course materials, complete assignments, and engage with peers (Bernacki, Greene, & Crompton, 2020). The accessibility of mobile educational materials is one of their key advantages. As long as they have an internet connection, students can utilize these tools to access learning resources and complete assignments from anywhere, at any time. Students who do not have access to a computer or who need to finish coursework on the fly may find this to be of great use. A student who is absent from class due to illness, for instance, can still access the course materials and finish the tasks by using a mobile education tool. Mobile educational tools can be modified to meet the requirements and preferences of certain students, resulting in a more personalized learning experience (Almaiah et

al., 2022). In addition, mobile educational tools can help students and teachers collaborate and communicate more effectively (Chen & Tsai, 2021). Many mobile educational tools provide chat, video conferencing, and discussion forum features that can help to make learning more dynamic and interesting.

Finally, conventional tool yielded 2 counts from the included samples. Conventional teaching and learning tools are physical or digital resources that have been traditionally used in education settings. Physical resources like textbooks, lectures, and handouts as well as digital resources like PowerPoint presentations, videos, and online readings may be included in these tools. Conventional teaching and learning tools are frequently combined with more interactive and collaborative teaching approaches, such as group projects and discussion. While these tools may be useful in some situations, it is crucial for educators to take into account their potential drawbacks and use a variety of teaching strategies to engage and support students' diverse needs, especially those of 21st century learners (Mahmud, Wong, Wong, Ismail, & Ramachandiran, 2022).

4. CONCLUSION

The aim of the systematic literature analysis in this study was to investigate the relationship between learning analytics and the technology tools used in education. A number of key findings were drawn from the analysis of 30 samples from 15 academic databases. According to the review, dashboard and visualization tools, Web 2.0 tools, eye-tracking devices, and web-based applications have all been extensively used in contemporary learning analytics research. These technological tools are frequently used to support online communication and learning, as well as to analyze and visualize data for informed decision-making. Common web-based applications for designing and managing online courses and materials, monitoring student progress, and giving feedback include learning management systems and social networking websites. By providing a forum for discussion and collaboration between students and teachers as well as access to a wide range of online learning resources, these tools have enhanced teaching and learning. Dashboard and visualization tools have been used to track and evaluate student learning data, including engagement and progress, allowing educators to make informed decisions based on this data. Eye-tracking devices, in particular, have been utilized to understand how students process and perceive visual information, enabling educators to identify challenges and adapt their teaching methods accordingly. The practical implications of this research for learning analytics stakeholders, including educators, policymakers, and researchers, are significant. These technology tools have the potential to enhance teaching and learning in various ways.

Learning management systems and web-based applications can streamline the delivery of educational content and facilitate personalized learning experiences. Web 2.0 tools can foster communication and collaboration among students and teachers, promoting active engagement and knowledge sharing. Dashboard and visualization tools can be utilized to monitor and analyze data on student learning, such as progress and engagement, and to make informed decisions based on this data. With the aid of eye-tracking devices, educators may examine how pupils interpret and process visual data as well as identify student difficulties, allowing them to modify their teaching strategies. In addition, using these technological tools can help policymakers learn things that can help them establish strategies and policies for integrating technology into education. These resources can be used by researchers to gather information that will help with the study of teaching and learning and will result in the development of new educational technologies and approaches. However, stakeholders must understand the potential risks and limitations related to the use of these tools. Ethical considerations and appropriate policies and strategies should be established to ensure their effective and responsible use in the classroom. In conclusion, this systematic literature review provides valuable insights into the relationship between learning analytics and the technology tools utilized in education. The findings highlight the prevalence of web-based applications, Web 2.0 tools, dashboard and visualization tools, and eye-tracking devices in recent research on learning analytics. These technology tools offer practical implications for stakeholders, including educators, policymakers, and researchers, by enhancing teaching and learning experiences, informing decision-making, and driving educational innovation.

By leveraging these tools effectively and responsibly, stakeholders can harness the full potential of learning analytics to improve the effectiveness and efficiency of teaching and learning in educational settings.

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