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A Systematic Literature Review of Articles on Learning Analytics

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Abstract: This study conducted a systematic literature review of articles on learning analytics published between 2004 and January 2024. A total of 1,064 articles, identified using the keyword "learning analytic*" in the Scopus database, were analyzed. The study integrated systematic literature review and bibliometric analysis approaches to explore academic developments in the field. It also employed t-SNE (T-distributed Stochastic Neighbor Embedding), text mining, and social network analysis techniques. The findings revealed a significant surge in learning analytics research in recent years, with the United States, Spain, Australia, and the United Kingdom as leading contributors. Prominent institutions included Monash University, the University of South Australia, and The Open University. Dragan Gašević and Bart Rienties emerged as the most prolific researchers in the field. Key subtopics within learning analytics research encompassed (1) its application in personalised learning processes, (2) data-driven decision-making, (3) ethical considerations in using personal data, (4) its role in formative assessment and evaluation, and (5) its potential influence on the future of online learning in higher education.

Keywords: learning analytics, big data, systematic literature review, bibliometric analysis, online learning

Highlights

What is already known about this topic:

- Learning analytics has gained popularity as a critical tool for data-driven insights.
- Prior research has demonstrated its role in facilitating personalized learning and identifying at-risk students.

What this paper contributes:

- This study provides a comprehensive analysis of learning analytics research trends from 2004 to January 2024.
- Key researchers, institutions, and emerging research themes in the field of learning analytics were identified.

Implications for theory, practice and/or policy:

- Establishing learning analytics laboratories or research units could advance both theory and practice in the field.
- Online learners are encouraged to use dashboards within learning management systems to monitor their progress effectively.

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Introduction

With the proliferation of online learning environments and the growing adoption of e-learning models, learning analytics has become a critical trend in higher education (Booth, 2012; Johnson et al., 2012; Sin & Muthu, 2015). Brown (2012) defines learning analytics as the systematic collection and analysis of large datasets from online sources to improve learning processes. Bozkurt and Sharma (2022) define learning analytics as a concept that measures student performance, facilitates comparisons, supports accurate diagnoses, enables predictions, and simplifies the analysis of large-scale educational data. According to Long and Siemens (2011), the primary goal of learning analytics is to enhance learning processes and environments through the collection, analysis, and reporting of data related to learners and their contexts. According to Gašević et al. (2017), learning analytics is a field developed to leverage the vast amount of data generated by the widespread use of technology in education. The development of learning analytics has brought together researchers and practitioners from various disciplines, including education, psychology, economics, statistics, data mining, and information visualization.

The benefits of learning analytics are multifaceted. It fosters student interaction, enhances time management and motivation, and develops self-regulated learning skills (Cansu Topallı & Fırat, 2023). Furthermore, it enables personalized and time-efficient assessments in large-scale classes, facilitating quicker feedback (Joksimović et al., 2019). Learning analytics also aids curriculum development, tracks student outcomes, supports personalized learning, and enhances post-education employment opportunities. However, challenges include issues related to data collection, evaluation, alignment with educational sciences, and ethical and privacy concerns (Avella et al., 2016).

Despite a growing body of literature reviews on learning analytics (e.g. Avella et al., 2016; Bozkurt & Sharma, 2022; Börekçi & Sarıtaş, 2023; Kıcıman et al, 2021; Mangaroska & Giannakos, 2019; Oliva-Cordova et al., 2021; Pineda & Cadavid, 2018; Sousa et al., 2021), there is a need for periodic updates to reflect the field's rapid evolution. This study systematically analyzes research conducted on learning analytics, addressing the following research questions:

1. What is the distribution of articles on learning analytics by year?
2. Which countries are most active in learning analytics research?
3. Which institutions are leading contributors to learning analytics research?
4. Who are the most published researchers in the field of learning analytics?
5. What themes emerge from the titles, abstracts, and keywords of articles on learning analytics?

Related Literature

Existing literature highlights a steady increase in studies on learning analytics over time (Bozkurt & Sharma, 2022; Börekçi & Sarıtaş, 2023; Oliva-Cordova et al., 2021; Pineda & Cadavid, 2018; Sousa et al., 2021). Moreover, studies have also explored intersections between learning analytics and other educational concepts. For example, the number of publications addressing the relationship between learning analytics and self-regulated learning (Çetintav & Karaoğlan Yılmaz, 2021) or smart learning environments (Papamitsiou & Economides, 2016) has significantly increased in recent years. Çetintav et al. (2022) conducted a review focusing on the overlap between educational data mining and learning analytics. They observed that the number of publications peaked in 2020, experienced a slight decline in 2021, and has been increasing again more recently. Overall, the literature reflects a continuous upward trend in studies on learning analytics.

Several studies have analyzed the countries contributing the most to learning analytics research. Çetintav and Karaoğlan Yılmaz (2021) found that learning analytics studies are predominantly conducted in Australia, the United States, and various European countries. Pineda and Cadavid (2018) noted that most studies were conducted in the United States, Spain, China, Germany, and India, with Europe being the leading continent in terms of contributions. Similarly, Çetintav et al. (2022) reported that Europe leads in publications, followed by North America. Conversely, Bozkurt and Sharma (2022) and Sousa et al. (2021) found that the United States leads in learning analytics research, while Oliva-Cordova et al. (2021) reported that the United Kingdom, China, and the United States were key contributors. Despite minor differences in findings, most studies consistently highlight the United States as a dominant contributor to the field.

Some studies have examined the institutions and researchers leading in learning analytics. Bozkurt and Sharma (2022) identified The Open University as the top institution, followed by Monash University. Prominent researchers in the field include Dragan Gašević, Hiroaki Ogata, Hendrik Drachsler, and Bart Rienties, whose contributions have shaped the trajectory of learning analytics research.

Keyword analysis has also been a focus of prior reviews. For instance, Kıcıman et al. (2021) found that "learning analytics" is the most commonly used keyword, followed by terms such as "online learning", "analytical learning", "learning", "higher education", and "MOOC". Börekçi and Sarıtaş (2023) identified frequently used keywords like keywords "learning analytics", "educational data mining", "open and distance learning", "learning management systems", "self-regulated learning", and "online learning environments". Similarly, Çetintav et al. (2022) noted that keywords such as "analytics", "ethics", "privacy", "data", "big data", "higher education", and "education" frequently appeared in publications. These patterns indicate recurring themes and priorities in the field.

Methodology

Research Design

This study employed a combination of systematic literature review and bibliometric analysis approaches to examine academic studies on learning analytics. Additionally, t-SNE analysis, text mining, and social network analysis methods were utilized to provide a comprehensive understanding of the data. The integration of these approaches allowed for an in-depth analysis of the research data, enhancing the validity and reliability of the study. The study employed a systematic literature review (Gough et al., 2012) and bibliometric analysis approaches (Donthu et al., 2021b) to develop a deeper and broader understanding of the field and to identify emerging research trends and patterns in the use of learning analytics. To enhance the depth and scope of the analysis, the study incorporated various data mining and analytical techniques (Fayyad et al., 2002), including t-SNE analysis (van der Maaten & Hinton, 2008), text mining (Feldman & Sanger, 2007), and social network analysis (Hansen et al., 2010). These techniques were applied to examine different dimensions of the dataset and provide a multifaceted perspective on the research questions. As this study synthesized findings from previously published literature, ethics committee approval was not required.

Research Data Set

The dataset comprised articles directly related to learning analytics. These articles were identified using the keyword "learning analytic*" in the Scopus database. The rationale for including publications with the term "learning analytic*" in the title is to establish a more focused and robust research foundation by identifying highly representative findings that accurately reflect research on learning analytics. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021) was adopted to guide the systematic review process.

Following the PRISMA protocol, the inclusion and exclusion criteria were as follows:

- **Search term:** "learning analytic*"
- **Database:** Scopus
- **Identification:** A total of 2,897 studies were initially identified.
- **Screening:** Studies published between 2004 and January 2024 were considered. Publications other than journal articles (e.g., book chapters, conference proceedings) were excluded,

resulting in the removal of 1,809 studies. Additionally, 24 studies published in languages other than English were excluded.

- **Final inclusion:** A total of 1,064 studies met the criteria and were included in the review.

The data were collected in January 2024. Scopus, as a leading database in education research, was selected to ensure access to high-quality and relevant publications. By focusing on the term "learning analytic*", the study aimed to create a robust research foundation and provide insights into the primary themes and trends within the field.

Data Collection Techniques and Analysis

Systematic literature review and bibliometric analysis methodologies were employed to analyze the studies on learning analytics. Systematic literature reviews provide answers to predefined research questions using explicit and reproducible methods to identify, evaluate, and synthesize evidence related to key concepts (Pollock & Berge, 2018). Such reviews can combine findings from diverse studies to uncover new perspectives or meaning (Snilstveit et al., 2012).

Bibliometric analysis was conducted to map the intellectual structure of the literature on learning analytics (Donthu et al., 2021a; Donthu et al., 2021b; Verma & Gustafsson, 2020). In particular, this study applied the t-SNE (T-distributed Stochastic Neighbor Embedding) method, a non-linear dimensionality reduction technique that preserves the overall structure of high-dimensional data (van der Maaten & Hinton, 2008). Titles of the analyzed studies were subjected to t-SNE analysis to identify focal points in the research. In addition, data mining (Fayyad et al., 2002) was employed to apply analytical techniques such as text mining (Feldman & Sanger, 2007) and social network analysis (Scott, 2017) to gain deeper insights into studies on learning analytics and address the research questions.

In summary, the methodology was designed to achieve a comprehensive understanding of learning analytics research by addressing the research questions, identifying recurring themes, and pinpointing gaps for future exploration. The integration of systematic review, bibliometric analysis, and advanced data analytics ensured a robust and holistic approach to the study.

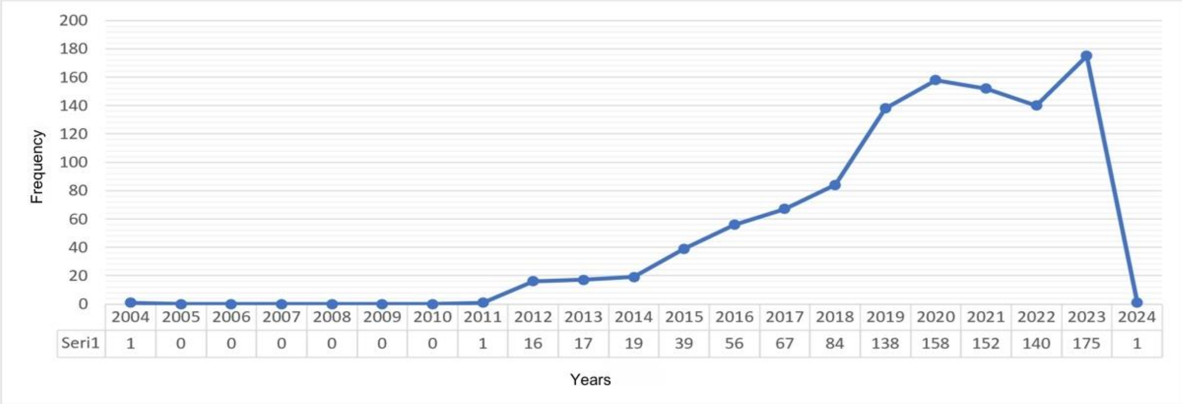
Findings and Discussion

Bibliometric Trends

This study analyzed 1,064 peer-reviewed articles published between 2004 and January 2024, covering a span of 20 years. These articles, identified through a Scopus search using the keyword "learning analytic*", were published in 319 refereed journals. Among these, 98 were single-authored, while 966 were multi-authored studies.

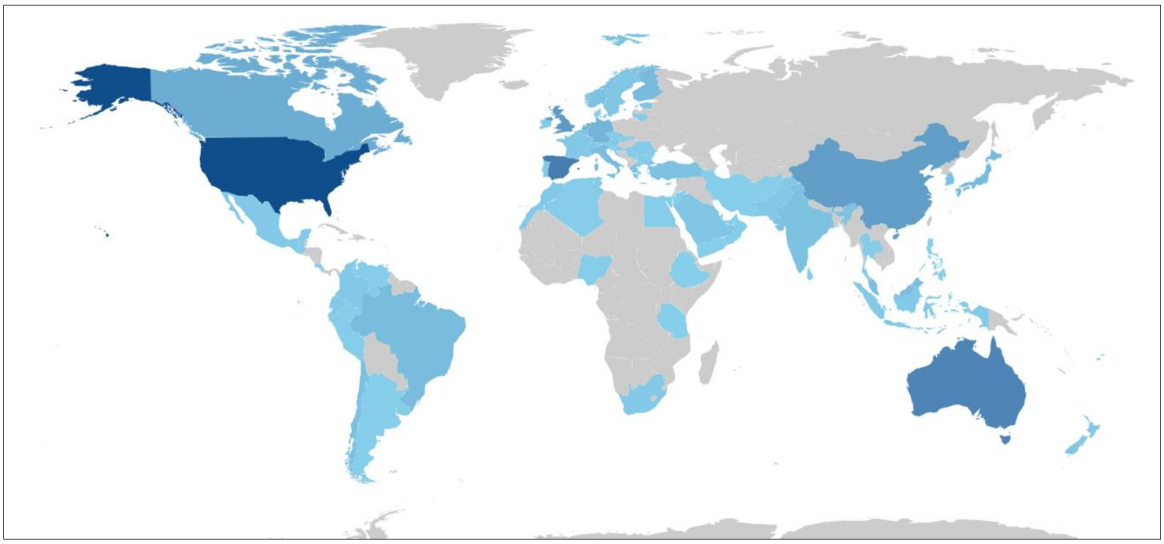
The annual distribution of learning analytics studies is presented in Figure 1. The first study in the dataset was published in 2004, with no further publications until 2011. From 2011 onwards, there was a marked increase in research output, likely influenced by the inaugural Learning Analytics & Knowledge (LAK) conference held in 2011 (LAK, 2011). Additionally, the Horizon Report of 2011 (Johnson et al., 2011) highlighted learning analytics as a long-term trend poised to gain prominence within four to five years. The growth in publications was further bolstered by advancements in big data, artificial intelligence, and other related technologies (Pelletier et al., 2011). In 2024, there appears to be a significant decrease, likely because the research data were collected in January of that year. Consistent with prior research, this study confirms that learning analytics has seen significant growth in recent years (Börekci & Sarıtaş, 2023; Çetintav & Karaoğlan Yılmaz, 2021; Çetintav et al., 2022; Oliva-Cordova et al., 2021; Pineda & Cadavid, 2018; Sousa et al., 2021).

Figure 1. Distribution of studies on learning analytics by year.



An analysis of the countries contributing to learning analytics research (Figure 2) reveals that the top contributors are the United States (n=647), Spain (n=392), Australia (n=353), the United Kingdom (n=249), China (n=233), Canada (n=159), the Netherlands (n=118), Germany (n=117), Japan (n=96), and Finland (n=92). The USA ranks first. When analyzed by continent, Europe and North America emerge as the leading contributors to the field of learning analytics. Numerous review studies in the field of learning analytics support this finding in the literature. For example, Ifenthaler and Yau (2020), Sousa et al. (2021), Pineda and Cadavid (2018), and Waheed et al. (2018) reported that most studies in learning analytics were conducted in the USA. Similarly, Oliva-Cordova et al. (2021) found that learning analytics studies were predominantly produced in the UK, China, and the USA. Çetintav et al. (2022) determined that most publications in the field of educational data mining and learning analytics originated in Europe, followed by North America. Additionally, Çetintav and Karaoğlan Yılmaz (2021) identified Australia, the USA, and European countries as having the highest number of publications in the field of learning analytics and self-regulated learning.

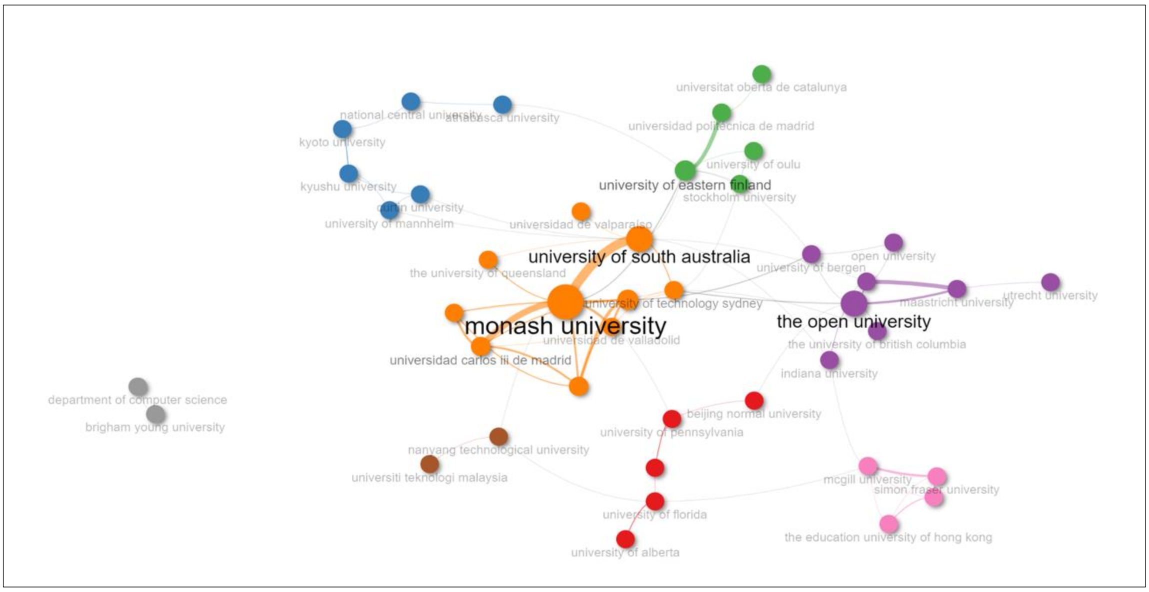
Figure 2. Distribution of leading countries in learning analytics research.



The prominence of the United States in learning analytics research may be attributed to substantial investments in education and research infrastructure. As big data technologies are central to learning analytics, financial resources play a critical role in enabling research and development. Developed nations with robust educational funding tend to lead in such technology-driven fields

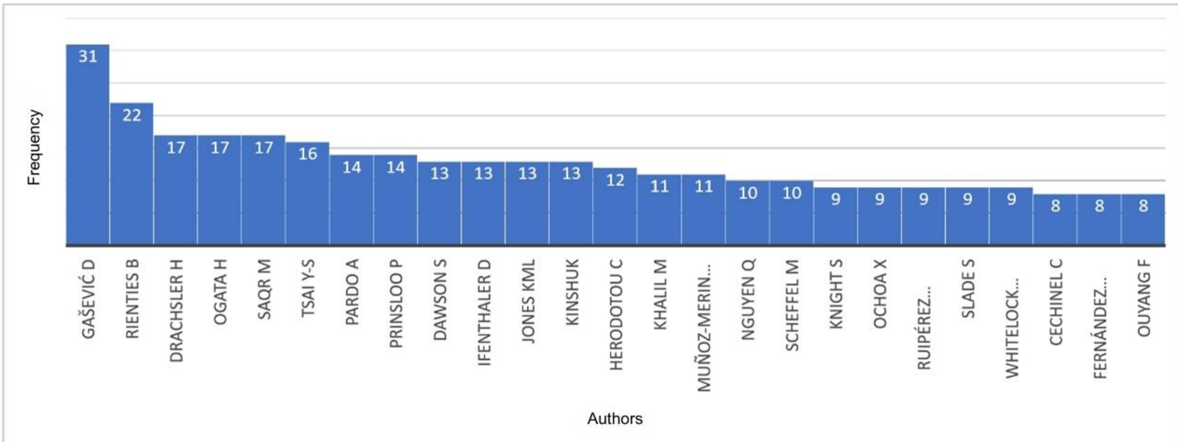
Institutional collaboration patterns indicate that Monash University, the University of South Australia, and The Open University in the United Kingdom play pivotal roles in advancing learning analytics research (Figure 3). These institutions appear to prioritize learning analytics, forming collaborative networks that contribute significantly to the field.

Figure 3. Collaboration networks of institutions in learning analytics.



The leading contributors to learning analytics research include Dragan Gašević, Bart Rienties, Hendrik Drachsler, Hiroaki Ogata, and Mohammed Saqr (Figure 4). These researchers often collaborate with teams and spearhead research efforts within dedicated laboratories or research centers (e.g., Gašević and Rienties).

Figure 4. Leading researchers in learning analytics.



Dragan Gašević, identified as the most prolific researcher, leads the Centre for Learning Analytics Monash (CoLAM) at Monash University in Australia. CoLAM is a world-renowned hub that trains students, professionals, and researchers while advancing the theoretical and practical applications of learning analytics (CoLAM, 2024). Bart Rienties, the second most prolific contributor, leads the Learning Analytics and Learning Design research program at the Open University in the UK, which focuses on enhancing blended and online learning environments (IET, 2024). This emphasis on specialized research centers and laboratories underscores the importance of institutional and team-based approaches in driving learning analytics research.

Thematic Patterns

To identify thematic patterns, the titles, abstracts, and keywords of the articles included in the research were analyzed and visualized, making the large volume of data more interpretable. Figure 5 presents the t-SNE analysis of the article titles, Figure 6 displays the text mining analysis of the article abstracts, and Figure 7 illustrates the social network analysis of the keywords used in the articles.

Figure 5. t-SNE analysis of article titles.

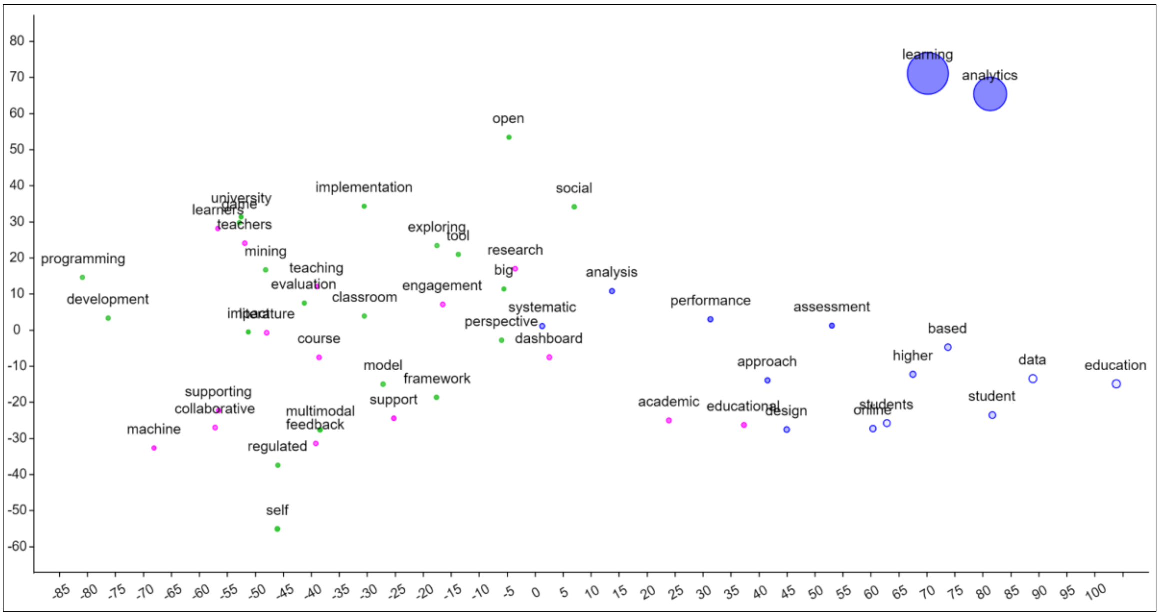


Figure 6. Text mining analysis of article abstracts.

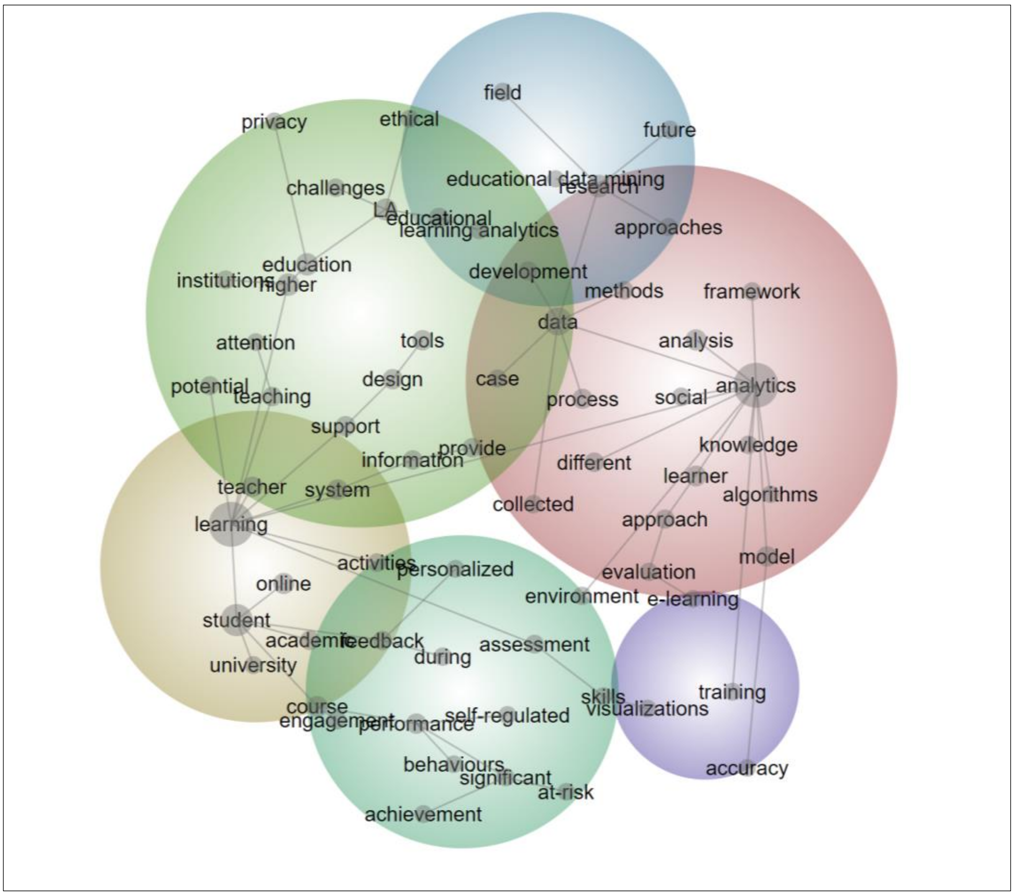
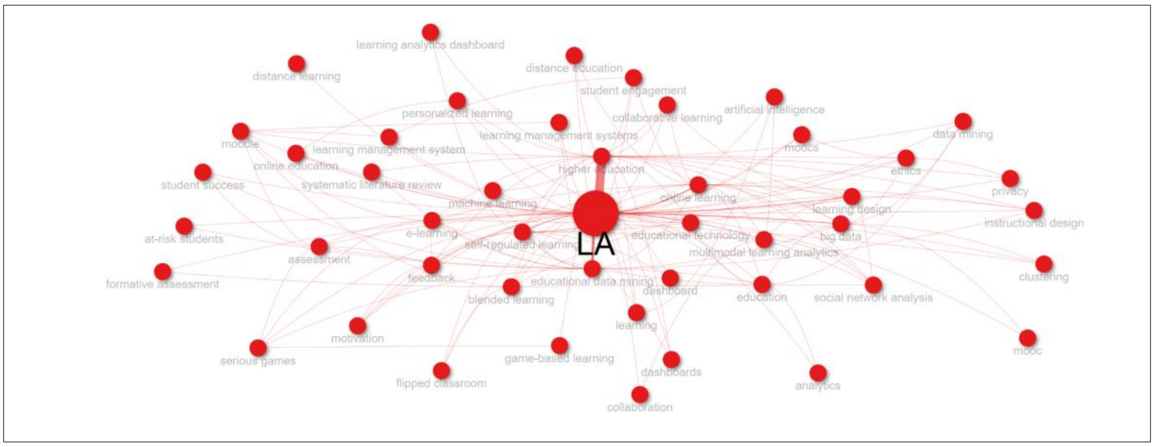


Figure 7. Social network analysis of article keywords.



Based on these analyses, five key research themes were identified: (1) The use of learning analytics in personalized learning processes, (2) data-driven decision-making processes in learning analytics, (3) ethical considerations and the use of personal data in learning analytics, (4) applications of learning analytics in formative assessment and evaluation, (5) the role of learning analytics in the future of online learning in higher education.

Use of learning analytics in personalized learning processes

The nodes identified in the t-SNE analysis (Figure 5: learning, analytics, self, regulated, dashboard), the paths determined through text mining (Figure 6: engagement, performance, self-regulated, learning, support, personalized, feedback, visualizations), and the nodes highlighted in the social network analysis (Figure 7: self-regulated learning, personalized learning, learning management systems, learning analytics dashboard) collectively indicate the significance of learning analytics in personalized learning processes. These findings suggest that learners with high levels of self-regulation and self-direction can benefit from personalized learning experiences. Dashboards, for instance, allow learners to track their progress within online learning environments, such as learning management systems, fostering increased motivation and engagement. For instructors, these dashboards are equally important as they facilitate the personalization of the learning experience by monitoring participant progress and providing tailored learning recommendations when necessary.

Through dashboards, learners can access personalized information such as daily performance summaries, comparisons of individual and group performance, and predictions of future success. Understanding which performance indicators students examine extensively and how they interact with these insights provides invaluable data for researchers and instructional designers. These emerging patterns, when analyzed, can lead to refined educational designs. The data extracted from learning analytics can thus be used to generate tables, graphs, word clouds, and dashboards that deliver actionable insights to all stakeholders, including learners, instructors, researchers, and administrators (Şahin & Yurdugül, 2020).

A comparative study on three different learning management systems revealed that students preferred platforms offering detailed learning analytics, including personalized analyses and tailored recommendations to enhance their learning (Ifenthaler, 2017). This highlights the growing need for learning analytics that are adaptable and personalized to specific learning management systems, facilitating the planning of future learning activities and the identification of effective current strategies (Klašnja-Milićević et al., 2020). Consequently, data-driven personalization through learning analytics emerges as a vital tool for shaping the future of learning environments.

Data-driven decision-making processes in learning analytics

Effective utilization of learning analytics requires the processing of vast amounts of data, commonly referred to as big data. This necessity is supported by findings from t-SNE analysis (Figure 5: big, data, based, approach, mining), text mining (Figure 6: educational data mining, data, process, method, development, analytics, algorithms, training, model), and social network analysis (Figure 7: educational data mining, machine learning, clustering, big data). These analyses highlight the continued emphasis on data-driven decision-making processes in learning analytics, underlining the critical role of big data in driving insights and shaping educational strategies.

The data generated through learning analytics has a profound impact on decision-making processes in education. Research demonstrates that learning analytics empowers both students and instructors by enabling evidence-based decisions that can enhance learning outcomes (Wise, 2019). For example, in higher education institutions, educators and administrators rely on big data to make informed decisions regarding student success, retention strategies, and curriculum design (Banihashem et al., 2018; Chacon et al., 2012; Long & Siemens, 2011; Niet et al., 2016). This data-driven approach facilitates the identification of at-risk students, the personalization of instructional strategies, and the optimization of teaching methods.

Moreover, leveraging big data enables academic administrators to support decision-making processes at all levels of institutional management. As highlighted in previous studies, effective use of learning analytics in higher education requires integrating its advantages into administrative decision-making, particularly regarding student performance, resource allocation, and institutional policies (Elgendy & Elragal, 2016; Shorfuzzaman et al., 2019). Today's technologies generate rich datasets that can be analyzed to monitor student performance, organize learning processes, and improve the quality of education.

Ethical considerations and the use of personal data in learning analytics

The use of learning analytics requires processing vast amounts of data, often derived from learners' digital footprints in online environments. These data points, while essential for generating meaningful insights, frequently include sensitive personal information. Consequently, the ethical use of personal data emerges as a significant concern in the implementation of learning analytics. This issue is substantiated by findings from t-SNE analysis (Figure 5: learning, analytics, machine, learning, data, mining), text mining (Figure 6: higher, education, privacy, learning, analytics, challenges, ethical, methods, data, process, collected), and social network analysis (Figure 7: big data, data mining, privacy, ethics). Collectively, these analyses highlight privacy and ethical concerns as central themes in learning analytics research.

Higher education institutions must address privacy issues arising from the use of learning analytics. They should clearly define all steps, including who can access specific data, as well as where, how, and for how long the data will be stored (Ifenthaler & Schumacher, 2016). Pardo and Siemens (2014) emphasize that learning analytics environments and analyses must be reliable. Research has shown that when more information about learning processes is required, researchers often need access to additional data. To address this, many researchers (Pardo & Siemens, 2014; Slade & Prinsloo, 2013) have proposed solutions, including design guidelines. Griffiths (2012) also highlighted ethical issues related to learning analytics, providing valuable insights for researchers. As evident, all user data, including digital footprints, are confidential and must be handled in accordance with ethical guidelines.

Use of learning analytics in formative assessment and evaluation processes

According to the results of t-SNE analysis (Figure 5: university, assessment, evaluation, academic, performance), text mining (Figure 6: university, student, online, teaching, learning, assessment, evaluation, e-learning) and social network analysis (Figure 7: student success, formative assessment, e-learning, online education, MOOCs, higher education), learning analytics emerges as an effective solution to measure and evaluate student success and performance in higher education.

Formative assessment and evaluation are essential for tracking and improving student achievement and performance in higher education. Learning analytics facilitates these processes by leveraging big data in online environments (Lang et al., 2017). Formative assessment specifically evaluates a student's learning process, allowing educators to draw meaningful conclusions by tracking student progress.

Learning analytics and formative assessment share a strong relationship as they both utilize big data to inform instructional decisions and enhance student learning. Together, they provide a comprehensive perspective on student learning processes (Zhang et al., 2023). Learning analytics offers valuable support to formative assessment by supplying data that enables teachers to better understand how students learn, which helps them make more informed instructional decisions. It also promotes educational progress by offering guidance to both students and teachers during formative assessment processes (Gašević et al., 2022).

When integrated, formative assessment and learning analytics allow educators to maintain continuous communication with student data, adapt teaching strategies to meet individual student needs, and implement a more data-driven and personalized teaching approach (Merikko et al., 2022). These models become particularly effective when supported by detailed data that illuminates students' learning activities. This highlights the potential of learning analytics to serve as a powerful tool for assessing and improving learning processes in higher education.

Learning analytics in the future of online learning processes in higher education

Learning analytics is inherently suited to utilizing data collected from online environments. This potential is highlighted through t-SNE analysis (Figure 5: online, higher, education), text mining (Figure 6: higher, education, institutions, online, e-learning), and social network analysis (Figure 7: distance education, distance learning, online education, online learning, e-learning, blended learning, flipped classroom, MOOCs, educational technology). Accordingly, learning analytics plays a pivotal role in enhancing the effectiveness of online learning processes in higher education.

With the widespread integration of digital technology into higher education, learning analytics significantly influences teaching and learning practices. The data collected through online environments provide actionable insights to improve students' learning experiences (Viberg et al., 2018). For higher education institutions, key benefits of learning analytics include improving students' learning outcomes and motivation while simultaneously reducing dropout rates (Glick et al., 2019). Looking ahead, learning analytics is anticipated to become a central component of educational practices in environments such as blended learning, flipped classrooms, and MOOCs.

Conclusion and Suggestions

This study conducted a systematic literature review of articles on learning analytics, using the Scopus database to analyze 1,064 articles published between 2004 and January 2024. The keyword "learning analytic*" was used to identify relevant studies. The findings indicate that research on learning analytics has significantly increased, particularly in recent years. The field gained initial momentum in 2011 following the formal definition of learning analytics. A notable surge in publications occurred in 2012, reflecting the growing interest in this emerging area. The peak in publications in 2019 and 2020 can be attributed to the widespread adoption of online learning during the COVID-19 pandemic. More recently, advancements in artificial intelligence in 2023 may have further stimulated interest and activity in learning analytics research.

The USA emerged as the leading contributor to learning analytics research, followed by Spain, Australia, the United Kingdom, and China. This geographic trend highlights the prominence of developed countries in advancing learning analytics, likely supported by substantial investments in technology and research infrastructure. Certain institutions and researchers have also played pivotal roles in shaping the field, with Monash University (Australia), the University of South Australia, and The Open University (United Kingdom) leading in contributions. Prominent researchers include Dragan Gašević, Bart Rienties, Hendrik Drachsler, Hiroaki Ogata, and Mohammed Saqr. These findings align with Bozkurt and Sharma (2022), who highlighted the influence of key researchers and institutions in driving collaborations and shaping the field of learning analytics. Research findings shows that some leading researchers specialize in learning analytics research, and the institutions where they work have evolved into learning analytics research centers. This trend highlights the influence of these researchers in shaping the field, particularly in defining research topics and driving the direction of learning analytics as a discipline.

The results also suggest that meaningful advancements in the field can be achieved by addressing specific sub-topics. These include: (1) the use of learning analytics in personalized learning processes, (2) data-driven decision-making processes in learning analytics, (3) ethical considerations and the use of personal data in learning analytics, (4) the application of learning analytics in formative assessment and evaluation processes, and (5) the role of learning analytics in the future of online learning in higher education. These thematic areas represent critical avenues for future research and practical applications.

This study has certain limitations. It focused solely on articles indexed in the Scopus database, and future research could expand the scope by incorporating articles from other databases. This would provide more comprehensive and complementary findings. The dominance of the USA in learning analytics research may reflect its significant investments in educational technologies (Guzman-Valenzuela et al., 2021). Other countries could enhance their presence in the field by increasing funding for research and collaboration initiatives. International cooperation in learning analytics research would also facilitate the exchange of knowledge and foster advancements in the field.

Finally, establishing learning analytics laboratories or units within universities, particularly those emphasizing online and distance education, could significantly advance both theoretical and practical research. These labs could support the development of dashboards and other tools to help online learners monitor their progress and assessment results, thereby enhancing the overall learning experience.

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Anıl Harun Kılıç: Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing; Serkan İzmirli: Supervision, Conceptualization, Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

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