Research Trends in Learning Analytics for Decision Sciences: A Bibliometric Exploration

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Abstract

This study investigates the landscape of scientific publications in learning analytics from 2013 to the present using bibliometric indicators. A comprehensive search strategy identified 648 relevant publications from the Scopus database. Descriptive and bibliometric analyses were conducted to gain insights. Findings reveal the Journal of Learning Analytics as a prominent contributor, indicating its significance in the field. "Computers in Human Behavior" exhibited substantial impact with high h-index (23) and g-index (32), reflecting the dissemination of highly cited articles. An upward trend in publication numbers over time signifies growing interest in learning analytics research. Australia emerged as the most influential country, suggesting significant contributions to the field. Authorship patterns predominantly featured single-authored documents, with two or three-author collaborations being common. Larger multi-author collaborations were less frequent.

Key-words: Learning Analytics, Bibliometric Analysis, Scientific Publications, Scopus Database, , h-index. g-index. Research Trends. Author Collaboration, Bradfords law analysis.

1. Introduction

The most frequent definition of learning analytics is the measurement, collection, analysis, and reporting of data on learners and their surroundings for the purposes of understanding and optimising learning and the environments in which it occurs [1]. Learning Analytics (LA) refers to the collection, analysis, and reporting of data about students and their learning environment to improve education [2]. It helps track student learning behaviours, supports timely interventions, and provides useful feedback to teachers, students, and administrators [3]. LA enables educators to understand their students better and use resources more efficiently[4]. The main objective of learning analytics is to reveal and contextualise information from learning data that has previously been hidden, then prepare it for various stake holders [5]. Learning analytics takes the advantages of availability of learning data sets from different Learning Management Systems(LMS) and other systems [6]. Technology-Enhanced Learning (TEL) research in learning analytics is expanding quickly. The domains of business intelligence, online analytics, educational data mining, and recommender systems are particularly solid foundations for it [6]. The main objective of learning analytics is to reveal and contextualise information from learning data that has previously been hidden, then prepare it for various stake holders [5].

From its inception, Learning Analytics has been focused with addressing problems connected with the increased availability, quantity, speed, and kind of data in learning configurations. The first International Learning and Knowledge Conference, held in Banff in 2011, framed Learning Analytics as a problem in need of a solution: the increase of data outpaces organisations' ability to make sense of it. This is particularly valid when it comes to knowledge, teaching, and learning [7]. The concept of learning analytics may be traced back to the 1920s and the work of Pressey (1927), who created the first automated teaching machine. Pressey's (1927) work might be argued to represent the beginning of intelligent tutoring systems (ITS), one of the primary areas from which learning analytics draws [8]. Numerous industries, including health, finance, insurance, aviation, entertainment, and telecommunications, have long recognised the benefits of exploiting the insights generated by large-scale data analysis [8]–[10]. There is increasing evidence that the exploratory methods of data mining can be useful even in a carefully designed assessment context [11]. Learning analytics will not be defined by the source of data but by its size. The size of the data is characterised by two distinct points : The first is the overall quantity of data involved and the second element of the size is the granularity of the individual data points [12]. Learning analytics can be used to evaluate programmes and play a key role in programme redesign. The integration of learning analytics in this context enables access to previously unavailable data and insights [8]. Within Learning analytics, there is a large range of common methods for solving learning challenges or applications. Most of these approaches, such as visualisation, prediction, clustering, outlier identification, connection mining, causal mining, social network analysis, process mining, and text mining, are commonly regarded to be universal across data mining kinds.

Others, such as data distillation for human judgement, model discovery, knowledge tracing, and non-negative matrix factorization, have gained popularity in education [13].

1.1 **Evolution of Learning analytics**

According to Peña-Ayala, (2018) , the LA chronology may be divided into three eras, each of which is strongly tied to the establishment and growth of the Society for Learning Analytics Research (SoLAR).

i. First Era : The first era corresponds to the earliest works published before 2011 that examines how to use the faculty time is rewarded and what academic duties are most highly prized in order to bring legitimacy for the full scope of academic work [15]. In 1996, another publication delved into the scholarship of engagement report introduced by Boyer. In his analysis of the American Higher Education System, Boyer emphasized the importance of academia actively participating as a strong collaborator in addressing our society's crucial challenges in social, civic, economic, and moral realms [16]. In 2006, a study employed the four-function paradigm, which includes goal-attainment, latent pattern maintenance, integration, and adaptation, to provide an analytical framework for examining important aspects in the emerging literature on the scholarship of teaching and learning. The research aimed to analyse the construct and its implications [17].

ii. Second Era: The second era commenced with the inaugural International LAK Conference in 2011, aiming to foster and facilitate global research, collaboration, and dissemination within the field of Learning Analytics (LA). From that point until 2013, a variety of papers were presented and compiled in the respective LAK proceedings, along with various conference tracks, workshops, and journals [18]–[20].

iii. Third Era: The third and ongoing era of Learning Analytics (LA) began in 2014 with the establishment of SoLAR (Society for Learning Analytics Research) and the launch of its Journal of Learning Analytics (JLA). Since then, the field of LA has experienced significant growth, gaining prominence in conferences and earning inclusion in journals indexed by TR-JCR (Thomson Reuters' Journal Citation Reports). This development has further solidified the presence and importance of LA within the academic and research community [21].

Table 1: Key Research Areas in Learning Analytics and Educational Data Mining

Research Topic	***Description***	***Reference***
Analysisng the Educational Theories	To explore the integration of learning theories and learning analytics in	[22]
Analysing pedagogical strategies	The objective is to employ Educational Data Mining (EDM) and Learning Analytics (LA) techniques with a specific focus on analysing code from programming courses, programming assignments, and submissions.	[23]
Analysing programming code	The aim is to utilize Learning Analytics (LA) techniques with a specific emphasis on analysing code from programming courses, programming assignments, and submissions.	[24]
Collaborative learning and teamwork group	The objective is to analyse collaborative learning dynamics and predict the team grade within team work groups. This analysis aims to gain insights into the factors that contribute to successful collaboration and predict the overall performance of teams.	[25]
Curriculum mining/analytics	The objective is to analyse the program structure, course grading, and administrative curricular data with the aim of enhancing curriculum development and improving program quality, among other goals. By examining these aspects, valuable insights can be derived to inform decision-making processes and drive improvements in curriculum design, implementation, and assessment.	[26]
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Dash Boards and visual learning analytics	The objective is to utilize a visualization technique to explore and gain insights from relevant user traces collected in online environments, with the ultimate goal of enhancing human learning.	[27]
Deep Learning	The objective is to utilize neural network architectures that incorporate multiple layers of processing units within the domain	[25]

Research Topic	***Description***	***Reference***
	of Educational Data Mining (EDM) and Learning Analytics (LA) research.	
Discovery causal relationships	The objective is to identify causal relationships among attributes within an educational dataset. By conducting a thorough analysis, researchers aim to uncover meaningful connections and determine the cause-and-effect relationships between different variables or attributes.	[28]
Early warning systems	The goal is to uncover causal relationships among attributes within an educational dataset. The objective is to investigate and identify the cause-and-effect connections between various variables or attributes.	[29]
Emotional learning analytics	The objective is to conduct a comprehensive study on the role of affect during learning and emphasize the significance of emotions in the learning process. This research aims to examine and understand how emotions influence and shape learning experiences.	[30]
Game learning analytics	The objective is to utilize data-mining and visualization techniques to analyse player interactions within serious games. By applying these techniques, researchers aim to extract valuable insights from the data generated by player interactions.	[31]
Interpretable and explanatory learner models	The goal is to create "white box" machine learning models that are interpretable, explanatory, usable, and highly comprehensible. The objective is to develop models that provide clear insights into their decision-making processes and are easily understandable by humans.	[32]
Measuring Self-regulated Learning	The objective is to employ Learning Analytics techniques to assess the self-regulated learning features and behaviours of students. By utilizing these techniques, researchers aim to measure and analyse various aspects of self-regulated learning, such as goal setting, self-monitoring, strategy use, and reflection.	[33]
Multimodal learning analytics	The objective is to leverage machine learning and increasingly affordable sensor technologies to uncover new types of learning insights that occur across multiple contexts. By utilizing these technologies, researchers aim to capture and analyse data from various sources and contexts to gain a deeper understanding of the learning process.	[34]

Research Topic	***Description***	***Reference***
Orchestrating learning analytics	The aim is to conduct a comprehensive study on the adoption of Learning Analytics (LA) at the classroom level, examining its implications for practice and other influential factors.	[35]
Sentiment discovery	The objective is to develop an automated system that can identify the underlying attitudes, sentiments, and subjectivity within learners and learning resources.	[36]
Understanding navigation paths	The objective is to uncover process-related knowledge and explore navigational learning patterns by analysing event logs recorded by e-learning systems.	[37]
Writing analytics	The objective is to utilize text mining and analytics tools to extract insights from text data derived from various sources such as forums, chats, social networks, assessments, essays, and other relevant textual content. By applying these tools, researchers aim to uncover valuable information, patterns, and trends within the text data.	[38]

The table1 provides a comprehensive overview of various research domains within Learning Analytics (LA) and Educational Data Mining (EDM). It highlights key areas such as student behaviour analysis, curriculum mining, collaborative learning, emotional learning analytics, and self-regulated learning. These domains leverage advanced techniques, including machine learning, deep learning, sentiment analysis, and visualization methods, to extract meaningful insights and enhance educational practices. Despite the vast amount of research available, the field of Learning Analytics lacks a structured overview of its intellectual progress, key contributors, and emerging trends. This is where a bibliometric analysis becomes essential. A bibliometric study systematically examines publication trends, citation networks, author collaborations, and keyword co-occurrences to provide a clearer picture of how the field has evolved over time. By identifying the most influential research themes, a bibliometric analysis helps scholars understand the developmental trajectory of Learning Analytics and recognize the most impactful contributions.

One of the key reasons for conducting a bibliometric analysis is to identify knowledge gaps. While several studies explore individual topics, there may be areas that are underrepresented or require further investigation. A bibliometric approach helps uncover these gaps by analyzing the frequency and distribution of research topics. Additionally, it enables the assessment of research impact, allowing scholars to evaluate which papers, authors, and institutions have significantly contributed to advancing Learning Analytics. Another important factor is the evolution of methodologies in Learning Analytics. Over the years, the field has transitioned from traditional statistical techniques to more sophisticated machine learning and deep learning approaches. A bibliometric analysis helps track these methodological shifts and highlights the adoption of new frameworks, algorithms, and analytical tools in education research. This insight is valuable for researchers who want to stay updated with the latest advancements and align their studies with cutting-edge methodologies.

2. Review of Literature

2.1. Learning analytics for Decision Sciences

Learning Analytics (LA) is considered a bricolage field, meaning it is an interdisciplinary area of research that integrates multiple well-established disciplines [39]. It combines theories and methodologies from fields such as machine learning, data science, education, cognitive psychology, statistics, computer science, neuroscience, and the social and learning sciences [4], [40]. Although LA is often described as an emerging research field, it is built upon a strong foundation of these related disciplines, which provide the theoretical and methodological basis for its development [41], [42].

Learning analytics is a fast-growing field in educational technology that combines data science with educational research to improve learning methods and environments [43]. This interdisciplinary approach uses big data and analytics to gain insights into student learning that were not possible before [44]. Several machine learning models, including Decision Trees, Random Forest, Support Vector Machines, and Neural Networks, have been extensively used in LA research to improve learning outcomes and personalize education [45].

These studies highlight the application of various supervised learning techniques in learning analytics to enhance student performance prediction and educational decision-making. Decision Trees have been widely used to predict student performance and identify at-risk students [46]–[49], offering interpretable models that help educators intervene early. Random Forest models further improve prediction accuracy by analysing multiple educational features to assess student success [45], [50]. Support Vector Machines (SVMs) are effective in classifying students based on learning behaviours and academic achievements, though earlier work such as Burges (1998) laid the foundation for their application in this domain. Additionally, Artificial Neural Networks (ANNs) have been leveraged for personalized learning and early warning systems, enabling adaptive interventions [51], [52].

Unsupervised learning techniques, such as K-Means clustering, hierarchical clustering, and Principal Component Analysis (PCA), play a significant role in learning analytics by uncovering hidden patterns in educational data. K-Means clustering is widely used to group students based on similar learning behaviours, enabling personalized recommendations. [53], [54] emphasized its effectiveness in identifying learning styles and engagement patterns, which can enhance adaptive learning systems. Similarly, [9] highlighted its application in intelligent tutoring systems to optimize student interventions.

Recurrent Neural Networks (RNNs) have been widely utilized in adaptive learning environments to predict student learning paths based on sequential data. [55] demonstrated the application of RNNs in modeling student performance over time, particularly in intelligent tutoring systems. The study emphasized how RNNs capture dependencies in student responses and learning behaviors, thereby improving personalized learning recommendations.

Convolutional Neural Networks (CNNs) have been applied in education to analyze visual learning materials and assess student engagement in video-based learning environments. [23] explored how CNNs can automatically extract meaningful features from video lectures and educational images, enhancing multimedia learning analytics. Their findings suggest that CNN-based models can improve the effectiveness of online learning by personalizing content delivery based on student interactions.

Reinforcement learning (RL) techniques have gained traction in learning analytics for dynamically adapting educational content and improving student engagement. Q-Learning, a model-free RL algorithm, has been employed in intelligent tutoring systems to recommend learning resources based on students' evolving needs. [56] demonstrated how Q-Learning personalizes learning pathways by optimizing resource allocation, ensuring that students receive the most relevant content at each stage of their learning journey. Their findings highlight the effectiveness of reinforcement-based strategies in adaptive learning environments.

Natural Language Processing (NLP) has been extensively used in learning analytics to extract insights from student-generated textual data, enabling personalized learning experiences and improved educational outcomes. Sentiment Analysis plays a crucial role in understanding students' emotions and attitudes toward learning. [57] explored how sentiment analysis techniques can assess students' engagement levels by analyzing textual data from online discussions and feedback. Their findings suggest that emotional cues in text can serve as early indicators of student motivation and academic success.

Text Mining has been widely applied to extract key insights from student feedback, enabling educators to identify common themes, concerns, and areas for improvement. [36] demonstrated how text mining techniques facilitate automatic classification of student reviews and responses, aiding in data-driven decision-making for curriculum enhancement. Their study underscores the importance of automated feedback analysis in modern education. Furthermore, Latent Dirichlet Allocation (LDA), a topic modeling technique, has been utilized to analyze course discussions and online interactions. Lan et al. (2019) applied LDA to cluster discussion threads, revealing patterns in students' learning behaviors and engagement levels. Their research highlights the effectiveness of LDA in uncovering hidden topics in educational discourse, allowing instructors to tailor course materials and interventions accordingly.

2.2. Bibliometric Analysis in Learning Analytics

The concept of Bibliometric analysis refers to analysing how disciplines have changed intellectually over time [58]. Analysing the bibliometric data quantitatively is the cornerstone of the bibliometric analysis [59]. Furthermore, longitudinal studies of bibliometric trends, such as citations and impact factors, have helped us understand scienctometrics in other dimensions. [60].

In the area of Learning analytics, the Bibliometric studies are very few. Some of the authors have done bibliometric analysis on educational data mining, those studies also considered in the present paper. The following are the suitable samples. [2] identified in their systematic review, there are a considerable number of learning analytic approaches that use effective techniques to support students at risk of dropping out and achieving study success. [61] synthesised the trends and critical issues of Learning Analytics with reference to practises in massive open online courses (MOOCs) and used the eight-step process proposed by [62] to guide the systematic literature Review in analysing publication outlets, research purposes and methods, stake holders, and researchers' geographical locations and subjects. According to [63] Learning analytics, has acquired a higher degree of maturity, particularly in its applications for higher education. However, little learning analytics research focuses on other educational levels. As per his review the preference for traditional algorithms in comparison to deep neural networks. [64] analysed the articles which are published in the area of Learning analytics and provided an overview of Learning analytics research by exploring the trends in Learning Analytics Practices and examined the advances in Learning Analytics using the structural Topic Modelling based on bibliometric methodology. [65] analysed the Scopus Indexed articles in the educational data mining and identified the patterns, citation and co-citation analysis and bibliometric coupling was used for the creation of knowledge and the development of new ideas.

3. Methodology

Bibliometric analysis techniques can be categorized into two main categories as shown in Fig.1.- (1) performance analysis and (2) science mapping. Performance analysis primarily focuses on evaluating the contributions of research constituents, while science mapping aims to explore the relationships and connections between these constituents within the research domain [59] . Performance analysis delves into assessing the impact, productivity, and citation metrics of individual researchers, institutions, or publications. On the other hand, science mapping techniques utilize visualizations and network analysis to uncover patterns, collaborations, and knowledge flows among researchers, disciplines, or research topics. This study included science mapping and performance analysis. Performance analysis is descriptive technique that is commonly used in reviews to describe the different attributes of study [59], [66]. Descriptive analysis includes citation analysis, publication by year, author, country, and affiliation. The Keyword analysis under science mapping is the part of the bibliometric research [59] .

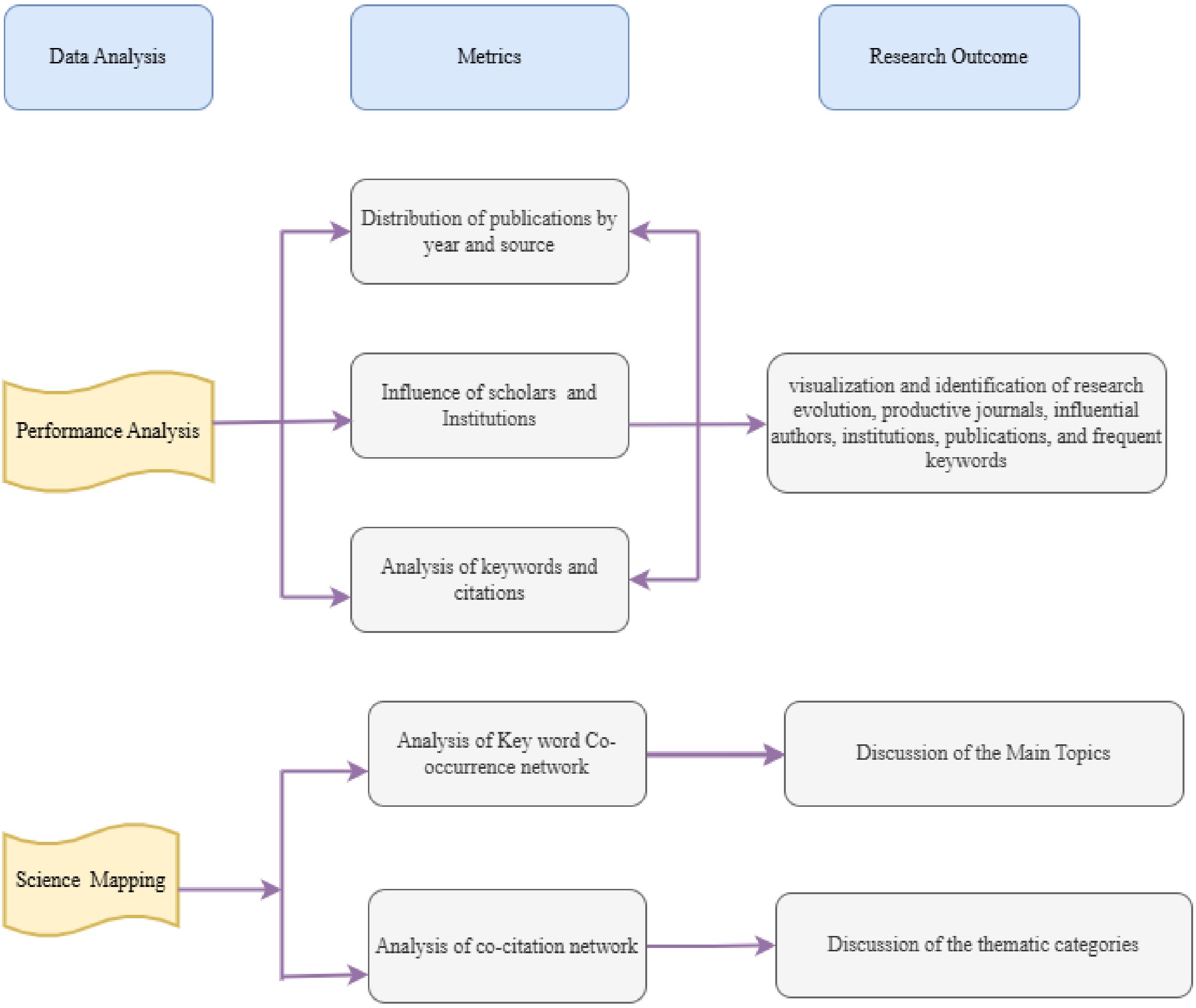

Fig.1. Analysis Approach

3.1. Performance Analysis

Performance analysis in bibliometric analysis refers to the evaluation and assessment of the research contributions and impact of various research constituents, such as individual researchers, institutions, or publications [58], [66], [67] . It involves analysing quantitative indicators and metrics derived from bibliographic data to assess the performance and productivity of research entities. Performance analysis often involves the use of various bibliometric indicators, such as citation counts, h-index, journal impact factor, and publication counts, among others. These indicators help gauge the influence and visibility of research outputs and provide insights into the scholarly impact of researchers, institutions, or publications within a particular field or discipline.

3.2 Science Mapping:

Science mapping is a methodological approach that examines the relationships and connections between research constituents within a given field or domain [59]. It utilizes various techniques, such as bibliometric analysis, network analysis, and visualization tools, to uncover patterns, trends, and interactions among researchers, institutions, disciplines, or research topics [58], [59], [66], [67]. By analysing the bibliographic data, citation networks, co-authorship networks, and co-citation patterns, science mapping provides a visual representation of the intellectual structure and knowledge dissemination within a specific research area. It helps researchers identify key influential works, leading researchers or institutions, and emerging research trends. Science mapping facilitates the exploration of interdisciplinary collaborations, identification of research clusters, and recognition of research frontiers. It assists in understanding the diffusion of knowledge, mapping research trajectories, and identifying areas for potential collaborations or research investments.

3.3 Citation analysis

Links are made between co-authors of an article using this method. The authors are the unit of analysis. This analysis highlights the writers' networks and collaborations with their respective nations and institutions. The down side is that co-authoring does not always indicate collaboration [58]. The analysis of citation patterns in scholarly communication has been widely utilised to discover scientific collaboration, map the landscapes of scholarly disciplines, evaluate the influence of research outputs, and observe knowledge transfer between domains (Liu, 2013). Citation analysis is typically understood as referring to the examination of bibliographic references, which are part of the scholarly communication apparatus [68]. Citation analysis examines the success of writers, papers, or journals based on their citation rates. Documents, authors, and journals are the units of analysis. Its advantages include the ability to locate important studies in the sector. The disadvantage is that the cumulative citation rate of new articles will be low, with older papers receiving the majority of citations [58].

3.4 Bibliometric Tools:

We have utilized VOS Viewer for graphical analysis of citations, co-citations, and co-occurrences [69], [70] . Additionally, we employed R-programming for citation analysis to identify the most significant documents and authors in our research [71].

3.5 **Identification of Documents**

The identification of the keywords used for the research paper selection is the firsts step in the Bibliometric analysis.   The following Boolean string was used in the initial search to find articles that included Learning Analytics

"TITLE-ABS-KEY ("Learning analytics") AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD , "Learning Analytics") OR LIMIT-TO (EXACTKEYWORD , "E-learning") OR LIMIT-TO (EXACTKEYWORD , "Learning Systems")) "

3.5.1 Initial Search:

Only publications published between 2014 and March 6th,2025 were taken into consideration when we searched the Scopus database for bibliographic data on Learning analytics on May 24th, 2023 at 5.27 PM. During the first search 12274 articles were retrieved, which were subsequently narrowed using the criteria specified in the Fig.2. as per the PRISMA frame work. The Scopus searches as per the mentioned substring of the limitations, found 660 English documents. This bibliometric data was analysed using analytical tools in two approaches, as illustrated in Fig. 2. The study design includes performance analysis using the Biblioshiny package in R and science mapping through the VOS viewer software.

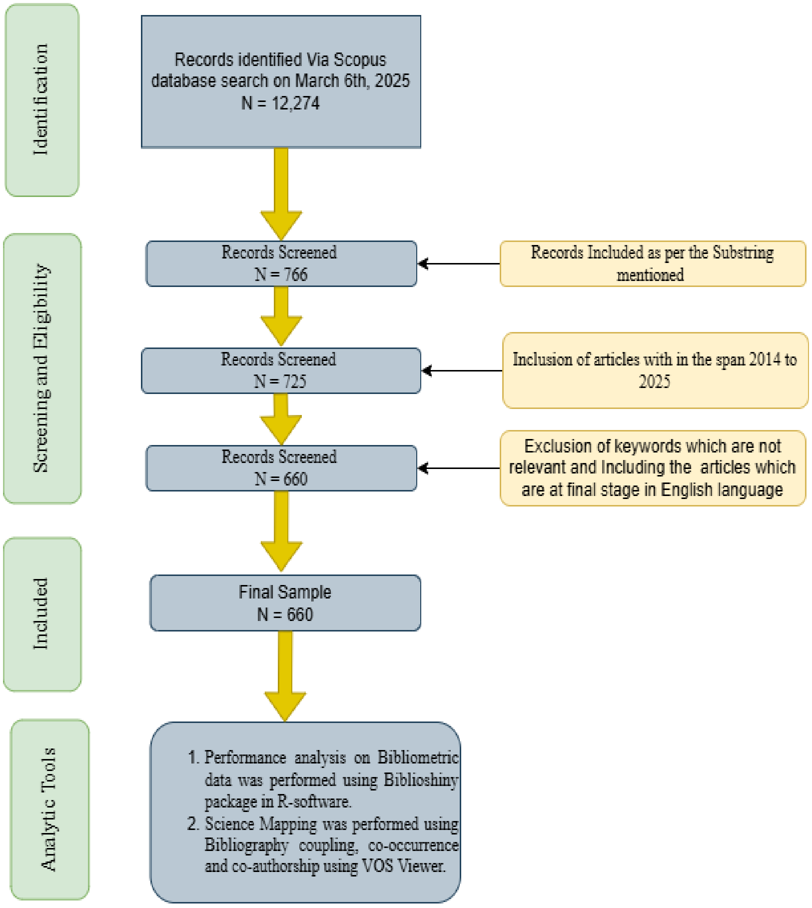

Fig.2. Design of the study

4. Results of Bibliometric analysis

As indicated in fig.2, we divided the data analysis for this study into two stages: permonace analysis and science mapping.

4.1. Summary of Bibliometric Data

A bibliometric examination of the state of Learning Analytics in Decision Sciences from 2014 to 2024 is shown in Table 2. It offers important information about the influence of citations, author contributions, collaboration patterns, and publishing trends.

Table 2. Description of Bibliometric Data

Type of Meta data	***Description***	***Results***	
		2014:2025	2014- 2024
MAIN INFORMATION ABOUT DATA	Sources (Journals, Books, etc)	371	366
	Documents	660	653
	Annual Growth Rate % (After Excluding the documents from Jan-2025 to 6th March, 2025)		21.68
	Document Average Age	4.71	4.76
	Average citations per doc	14.22	14.37
	References	22860	22490
	DOCUMENT CONTENTS		

Type of Meta data	***Description***	***Results***	
		2014:2025	2014- 2024
	Keywords Plus (ID)	2507	2482
	Author's Keywords (DE)	1597	1569
AUTHORS	Authors	1904	1878
	Authors of single-authored docs	62	62
AUTHORS COLLABORATION	Single-authored docs	64	64
	Co-Authors per Doc	3.34	3.34
	International co-authorships %	21.82	21.44
DOCUMENT TYPES	Article	269	266
	Book	5	5
	book chapter	50	50
	conference paper	282	281
	conference review	17	17
	data paper	1	1
	editorial	7	7
	Erratum	1	1
	Note	4	4
	retracted	1	1
	review	23	20

The bibliometric dataset gives a comprehensive picture of academic publications from 2014 to 2025, across 660 documents across 371 sources. The year-on-year growth rate of 21.68% clearly indicates a growing field and the results from the research. Analysis of keywords reveals 2507 Keywords Plus and 1597 Author's Keywords, attesting to the thematic diversity of the research. A total of 21.82% of shared document is shared by people from different countries, and average co-authors per document equal 3.34. Most of the documents are articles, and 64 of them have a single author, showing that there is a mixture of individual and group research.

4.2 Year wise citation analysis

Citation analysis is the study of the frequency, patterns, and graphs of citations in research articles to evaluate the impact and influence of publications, authors, or journals [72]. Between 2014 and March 6th, 2025, 12,274 documents have been identified for the review on Learning analytics from the Scopus database. After having a series of screening steps, the final data set was refined to 660 publications. To perform the year wise analysis, have been excluded the documents for the year2025, after that 653 documents confined for the year wise citation analysis. Table.3 presents a citation analysis of research publications from 2014 to 2024, highlighting citation impact trends, average citations per article, and yearly citation velocity.

Table 3. Year-wise Citation Metrics and Publication Trends

Year	*MeanTCperArt*	*N*	*MeanTCperYear*	*CitableYears*	*Total Citations* [a]	*Yearly Citation Velacity* [b]
2014	12.71	17	1.06	12	216.07	1.059
2015	25.03	32	2.28	11	800.96	2.275
2016	33.12	43	3.31	10	1424.16	3.312
2017	17.31	48	1.92	9	830.88	1.923
2018	13.57	49	1.70	8	664.93	1.696
2019	19.82	74	2.83	7	1466.68	2.831
2020	31.26	69	5.21	6	2156.94	5.210
2021	11.43	56	2.29	5	640.08	2.286
2022	10.13	67	2.53	4	678.71	2.533
2023	4.75	77	1.58	3	365.75	1.583
2024	1.12	121	0.56	2	135.52	0.560

[a]Total Citations = MeanTCperArt * N, [b]Yearly Citation Velocity = MearnTCperArt/CitableYears

The bibliometric data highlights the growth of research output and its impact over time. The number of publications (N) has steadily increased, reaching its highest in 2024 (121 articles). However, the Mean Total Citations per Article (MeanTCperArt) and Yearly Citation Velocity have declined in recent years, indicating that newer publications have not yet accumulated significant citations. The years 2016 and 2020 stand out as the most impactful, with high citation counts and strong citation velocity, suggesting significant academic contributions during those periods. In contrast, recent publications (2023 and 2024) have lower citation metrics due to their recent entry into scholarly discourse.

4.3 Journal Impact and Citation Analysis

The fig.3. presents a country-wise distribution of research publications, distinguishing between Single Country Publications (SCP) and Multiple Country Publications (MCP) (i.e., collaborations with researchers from other countries).

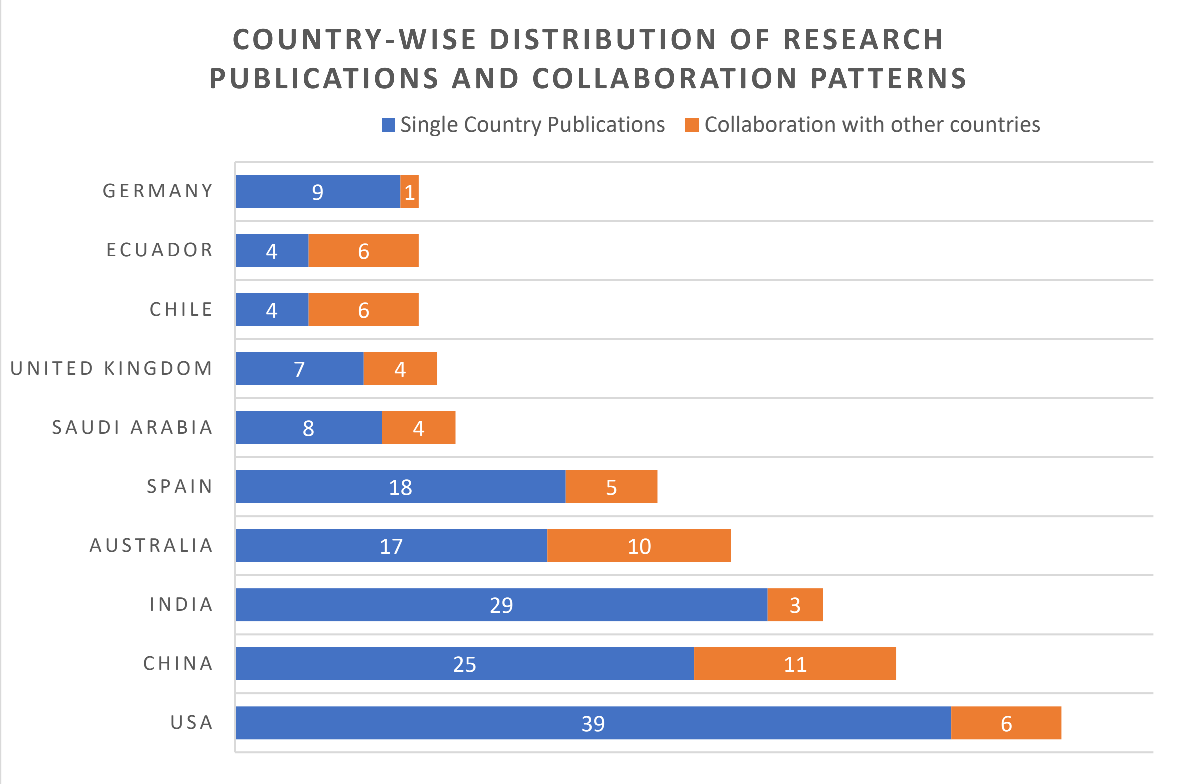

Fig.3. Country-wise Distribution of Research Publications and Collaboration Patterns

This Fig.3. illustrates the country-wise distribution of research publications and collaboration patterns, highlighting both Single Country Publications (SCP) and Multi-Country Publications (MCP). The USA leads with 45 publications, of which 39 are SCP and 6 are MCP, indicating a low international collaboration rate of 13.3%. China follows with 36 publications, but a higher MCP percentage of 30.6%, showing stronger international ties compared to the USA. India (32 publications) exhibits the lowest MCP percentage (9.4%), reflecting a predominant domestic research focus. Australia (27 publications) and the UK (11 publications) have a balanced research approach, with MCP rates of 37.0% and 36.4%, respectively, indicating substantial global collaboration. Spain (23 publications) and Saudi Arabia (12 publications) also maintain moderate collaboration levels at 21.7% and 33.3% MCP, respectively. Interestingly, Chile and Ecuador (both with 10 publications) show the highest MCP rates at 60%, suggesting a strong reliance on international research partnerships. Germany, with 10 publications but only 1 MCP (10.0%), shows minimal global engagement. These patterns indicate that while some nations prioritize self-sufficiency in research, others leverage international networks for broader impact.

4.4: **Bradfords law analysis:**

This analysis helps identify the most influential journals in the field, aiding researchers and librarians in optimizing literature searches and journal selection.

Bradford's law, a fundamental principle in bibliometrics, describes the distribution of articles across journals in a given field. [73] explored the law theoretically, proposing a mixed Poisson model to elucidate its uncertainties and applications. Bradford's Law of Scattering states that if journals in a specific research domain are arranged in descending order of productivity (i.e., number of articles published), they can be divided into three zones with a nearly geometric progression in the number of journals. The law helps to identify core journals in a field. The journals have divided into three zones as mentioned in Table.4.

Table.4. Bradford's Law Distribution of Journals in Learning Analytics Research

Zone	***Range of Ranks***	***Number of Journals***	***Number of Articles***
Zone1 (core Journals)	1-18	18	221
Zone2 (Moderate Journals)	19-154	136	222
Zone 3 (Pheripheral Journals)	155-371	217	217
	Total	371	660

The core journals in Zone 1 contribute 33.48% of the total research articles, indicating their significant impact on the field. Researchers should prioritize these journals for literature reviews and citations, as they contain the most influential studies. Additionally, publishing in these high-impact journals can enhance the visibility and credibility of their research in Learning Analytics. Journals in Zone 2 contribute 33.63% of the articles, indicating that expanding research scope beyond core journals is beneficial. These journals may offer emerging trends and interdisciplinary insights. While Zone 3 has the highest number of journals (58.48%), it contributes the lowest number of articles per journal. This zone can be explored for niche research areas, regional studies, or alternative perspectives in learning analytics.

The Fig.4. represents the core sources of Learning Analytics research using Bradford's Law, which helps in identifying the most influential journals in a particular field. The y-axis represents the number of articles, while the x-axis (log rank) represents the sources (journals, conference proceedings, etc.) ranked in descending order of their article contributions.

The shaded region represents the core journals that publish the majority of articles in Learning Analytics research. These sources contribute significantly to the dissemination of knowledge in this field. The curve shows a steep decline at the beginning, indicating that a few journals publish a large number of articles (Zone 1). The middle section (Zone 2) consists of journals publishing a moderate number of articles. The tail end (Zone 3) includes numerous journals with only a few articles each, contributing to scattered knowledge distribution. The most influential sources include Lecture Notes in Computer Science, ACM International Conference, CEUR Workshop Proceedings, British Journal of Education, Communications in Computer Science, and Journal of Learning Analytics. These journals and conference proceedings serve as primary reference points for Learning Analytics research.

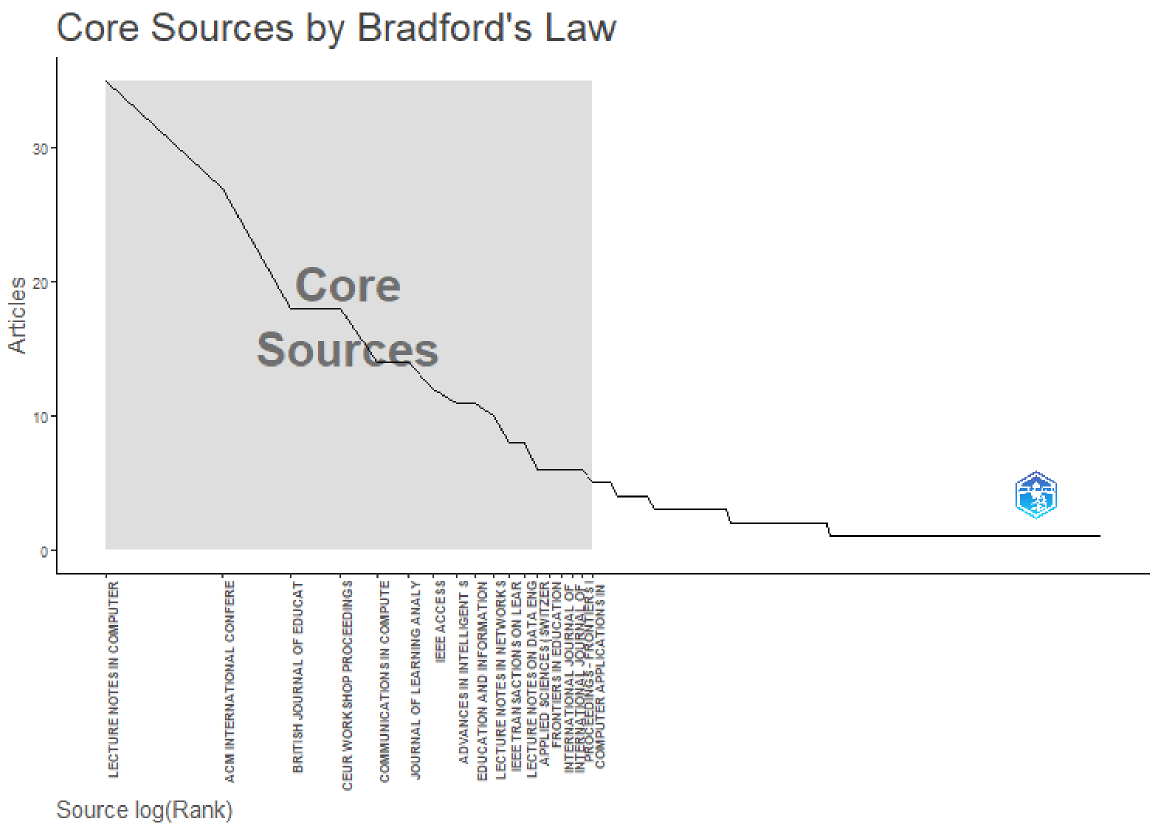

Fig.4. Core Sources as per Bradford's Law

4.5 Author Impact and Citation Analysis

The H-Index graph as shown in the fig.5. illustrates the research impact of various authors, with GARCÍA-PEÑALVO FJ leading at H-Index 6, followed by RANGWALA H (H-Index 5), indicating their strong scholarly influence. The majority of authors, including MARTINEZ-MALDONADO R, LUJÁN-MORA S, HILLIGER I, HERNÁNDEZ-LEO D, GASEVIC D, DE LAET T, CONDE MÁ, and OCHOA X, have an H-Index of 4, suggesting a relatively uniform level of research productivity and citation impact. The distribution highlights a small gap between the top contributors and the rest, showing that while most authors maintain steady contributions, GARCÍA-PEÑALVO FJ and RANGWALA H exhibit relatively greater research influence.

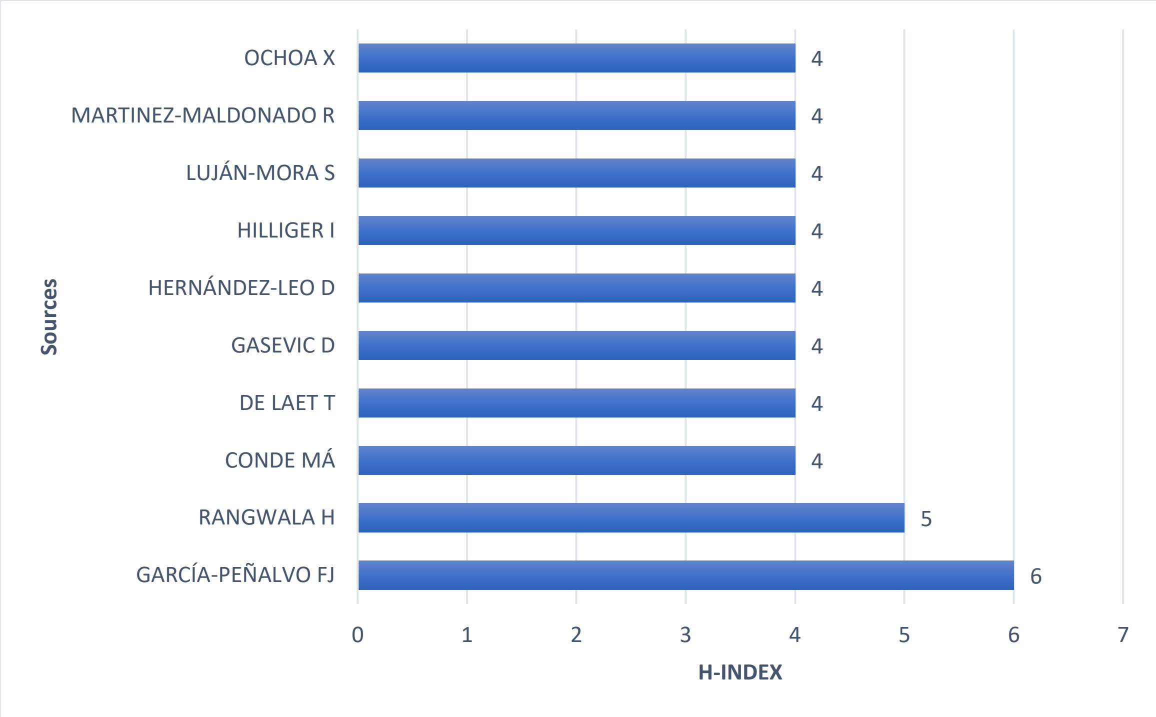

Fig.5. Sources Local Impact by H-index

The bibliometric analysis highlights GARCÍA-PEÑALVO FJ as the most influential researcher with the highest h-index (6) and g-index (8), indicating sustained research impact since 2014. RANGWALA H (h-index: 5, TC: 141, m-index: 0.71) demonstrates rapid career growth with significant citations despite a more recent start in 2019. GASEVIC D (CPP: 43.00) and DE LAET T (CPP: 33.00) have the highest citations per paper, suggesting high research influence per publication. HILLIGER I (m-index: 0.67) and PÉREZ-SANAGUSTÍN M (m-index: 0.67) are emerging scholars showing rapid research growth. The data also reveals that recent contributors (2019-2020) are making a strong impact, while established researchers from 2014-2015 maintain steady academic productivity. Overall, the analysis identifies key contributors, emerging researchers, and variations in research influence across the field.

4.6 Author Productivity Analysis Based on Lotka's Law

Lotka's Law of Author Productivity, also known as Lotka's Law or the Inverse Square Law of Scientific Productivity, is an empirical law that describes the relationship between the productivity of authors and the number of authors at different productivity levels in scientific or scholarly fields. The law was formulated by Alfred J. Lotka, an American mathematician and statistician, in the 1920s [74]–[76].

Research on author productivity using Lotka's Law shows different levels of adherence across various academic fields. [77] examined the "Visi Pustaka" Journal from 2016 to 2021 and found that 75% of authors contributed only one article, with significant differences from Lotka's expected distribution. [78] using R software, studied author impact and found that the data did not follow Lotka's Law, recommending that future research should use broader datasets for a more comprehensive analysis Table.5 presents the analysis of author productivity based on Lotka's Law, which predicts an inverse square relationship between the number of articles and the number of authors. According to the data, 1,702 authors have published only one article, which matches the expected number exactly, showing no deviation. However, as the number of articles increases, the actual number of authors deviates significantly from the expected values. For example, only 145 authors have published two articles, compared to an expected 426, and the number of authors continues to decline for higher productivity categories, with only 1 author each having seven and eight publications. The frequency of authors contributing multiple articles is much lower than predicted by Lotka's Law, suggesting that while the overall distribution aligns with the principle of diminishing frequency as the number of publications increases, the data shows large deviations. This indicates that fewer authors contribute multiple publications, a pattern consistent with the general trend in academic publishing, but the actual distribution does not perfectly align with the theoretical inverse square law. This discrepancy could be attributed to variations within the dataset, academic discipline-specific factors, or other external influences on research output.

Table.5. Author Productivity analysis as per Lotka's Law

N.Articles	***N.Authors***	***Freq***	***Expected Number of authors ($(N\_exp = 1702/n^2)$)***	***Deviation***
1	1702	0.893908	1702	No Deviation
2	145	0.076155	426	Large Deviation
3	29	0.015231	189	Large Deviation
4	19	0.009979	106	Large Deviation
5	7	0.003676	68	Large Deviation
7	1	0.000525	35	Large Deviation
8	1	0.000525	27	Large Deviation

4.7 **Word Cloud**

The word cloud as in Fig.6. visualizes the key terms and concepts related to decision-making in the context of educational data mining and learning analytics. The most prominent terms, "decision making" and "students," are highlighted in large fonts, indicating that they are central to the research focus.

Fig.6. Word Cloud

These terms suggest that the study revolves around using data mining techniques and learning analytics to make informed decisions about student performance, academic success, and educational practices. Other notable terms such as "data mining," "learning systems," "educational data mining," and "learning analytics" emphasize the role of advanced data analysis methods in improving educational outcomes. Concepts like "artificial intelligence," "academic performance," and "machine learning" show the integration of technology and advanced computational techniques in decision-making processes.

4.9 Interpretation of Bibliographic data through Science Mapping:

Through the analysis of bibliographic data, citation networks, co-authorship networks, and co-citation patterns, science mapping offers a visual depiction of the intellectual landscape and knowledge dissemination within a particular field of research. This powerful tool enables researchers to uncover influential works, prominent researchers and institutions, and emerging trends in their respective fields. Science mapping is instrumental in facilitating interdisciplinary collaborations, identifying research clusters, and recognizing cutting-edge research areas. It aids in comprehending knowledge diffusion, mapping research trajectories, and pinpointing opportunities for fruitful collaborations and research investments.

4.9.1 Bibliographic Coupling with Sources

The Normalized Local Citation Score is a metric that quantifies the citation impact of a journal. It is normalized to a common scale, allowing for comparisons between different journals. The scores in the table range from 0.24 to 3.02. Journals with higher scores are generally considered to have a greater citation impact and are often seen as more influential within their respective fields. The journals in the **Fig.7.** appear to be ranked based on their Normalized Local Citation Scores. Journals with higher scores are likely to have a more significant impact in terms of citations and influence within their respective fields. Based on this understanding, the journals with relatively higher Normalized Local Citation Scores in the table (closer to 3.0) is Internet and Higher Education (3.02).

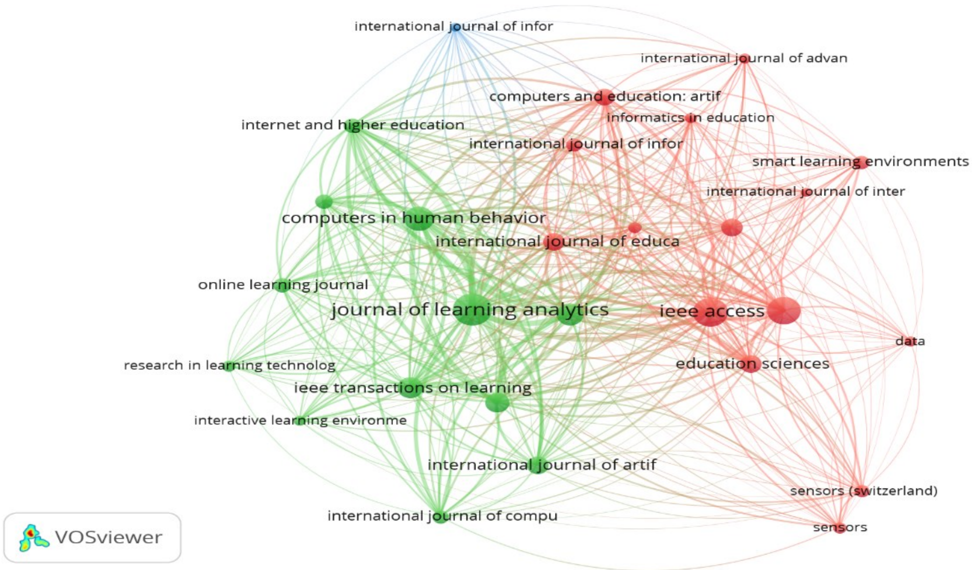

Fig.7. Bibliographic Coupling with Sources

4.9.2 Bibliographic Coupling with countries:

The Fig.8. summarizes the frequency of interactions between various countries. Here are some key observations: Australia has the highest number of interactions with the United Kingdom, with a frequency of 21.Australia has frequent interactions with countries like Germany (7), Netherlands (9), Norway (6), Saudi Arabia (6), and Serbia (6).Some countries have relatively lower interaction frequencies with other countries. For example, Belgium has a low frequency of interactions with Austria (1), South Africa (1), and Switzerland (1).Chile has multiple interactions with Brazil (8) and China (3), indicating stronger ties with these countries compared to others. China has moderate interactions with Canada (2), India (2), and Malaysia (3), reflecting its engagement with diverse countries. The United States has several interactions with Australia (11), China (11), and the United Kingdom (5), suggesting its involvement in multiple international relationships. Spain has significant interactions with Finland (8), Germany (6), the Netherlands (4), and the United Kingdom (8), indicating broad engagement across different regions

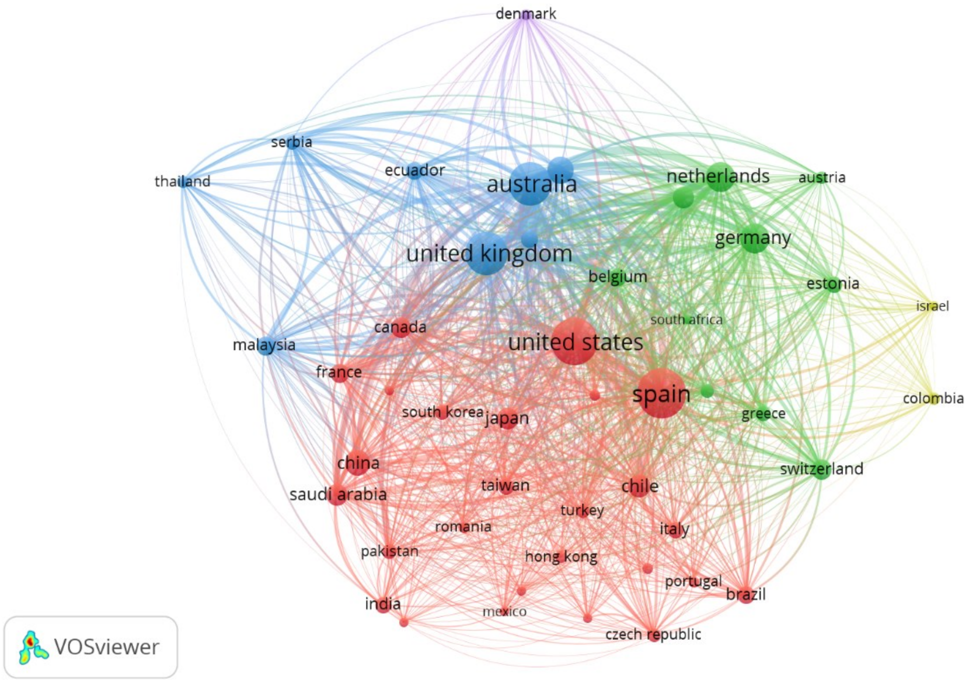

Fig.8. Bibliographic Coupling with Countries

4.9.3 Co-occurrence network with Keywords

In a co-occurrence network, each keyword is represented as a node, and the links between nodes indicate the frequency or strength of co-occurrence between keywords. By visualizing this network, we can identify clusters or groups of keywords that tend to appear together, revealing underlying themes or research areas. Co-occurrence network analysis enables us to identify the most frequently co-occurring keywords, which can provide insights into the dominant themes or topics within a particular field of study. It helps us understand the relationships between different concepts and how they relate to each other in the literature[79]. **Fig.9.** illustrates the co-occurrence network based on the keywords. The analysis reveals that among the keywords, "learning analytics" holds the highest level of influence. It is followed by "computer-aided instruction," which holds the next level of priority in terms of its presence and association within the network. The figure visually represents the interconnectedness and relative significance of these keywords within the research domain.

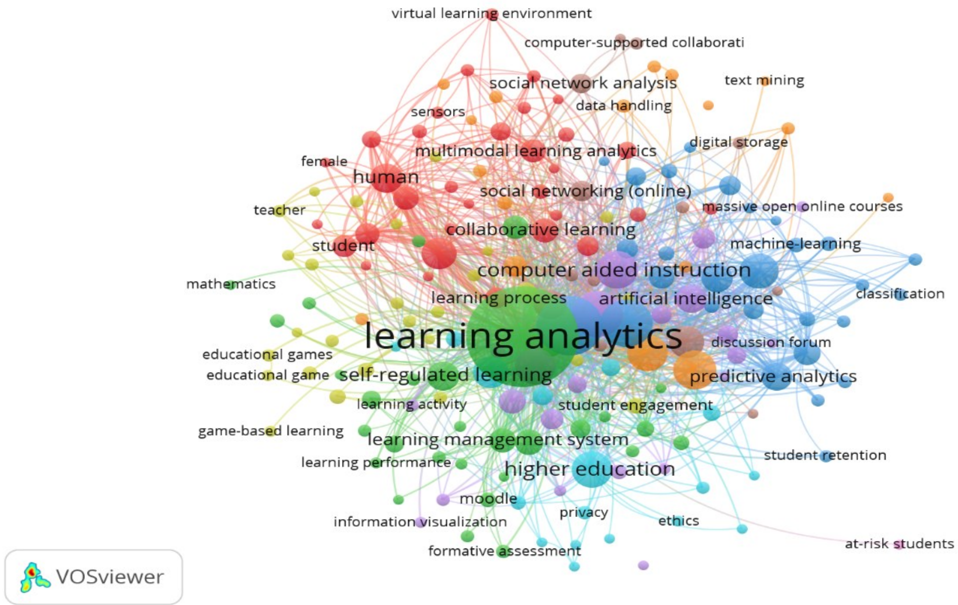

Fig.9. Co-occurrence network with Key words

4.9.4 co-occurrence network with author keywords

A co-word analysis is performed by looking at the abstract's keywords, titles, and common words. Words are the unit of analysis. Most crucially, it analyses the actual content of the documents, whereas other approaches just analyse bibliographic metadata. Furthermore, this strategy ignores the disadvantage of words being handled differently and having distinct meanings [58].

Co-occurrence network analysis with author keywords is a valuable method in research analysis that provides insights into the relationships and patterns among keywords used by authors in their publications. By examining the co-occurrence of keywords within a set of articles or papers, this approach uncovers underlying thematic connections and identifies important concepts and research trends. In a co-occurrence network, each keyword is represented as a node, and the connections between nodes indicate the frequency or strength of co-occurrence between keywords. The size or thickness of the connections often represents the strength of the relationship. By visualizing this network, researchers can gain a holistic view of the research landscape and identify key themes or clusters of related concepts. Moreover, this approach enables the identification of emerging trends by highlighting keywords that are appearing more frequently over time or in specific clusters. It can help researchers identify gaps in the existing literature or areas where further research is needed. Fig.10 indicates the co-occurrence analysis as per the author's key word, as per that most influential key word is learning analytics and after that educational data mining has greater importance.

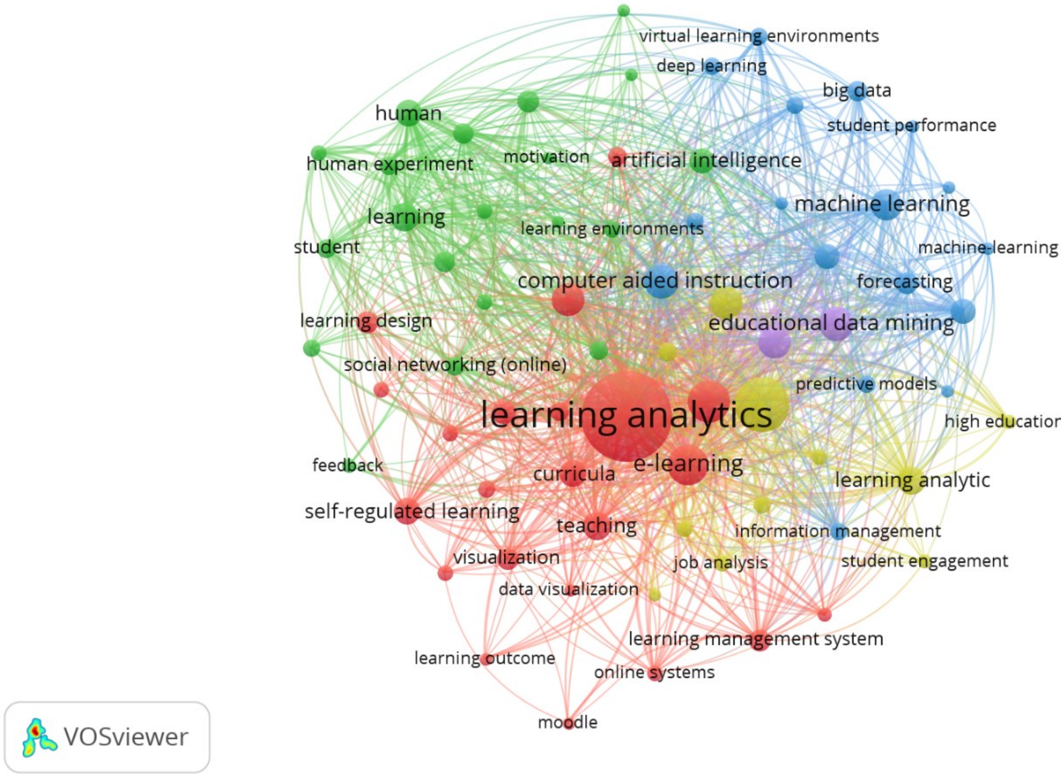

Fig.10. Co-occurrence network with author key words

5. Discussion

The screening process began with 12,274 records identified from the Scopus database. The first filter reduced the dataset to 766 articles based on a specific substring. Subsequent steps included selecting articles from 2014 to 2025, narrowing the sample to 725 records. After excluding irrelevant keywords and ensuring articles were in their final stages of publication and in English, the final sample comprised 660 articles, ensuring high relevance and quality for analysis. A total of 660 documents were identified from 371 sources, reflecting an annual growth rate of 21.68%. The average age of documents in this period was 4.71 years, with an average of 14.22 citations per document. The total number of references reached 22,860. In terms of content, there were 2,507 instances of Keywords Plus and 1,597 Author's Keywords.

The total number of authors was 1,904, with 62 single-authored documents and 64 single-authored papers. Each document had an average of 3.34 co-authors, and international co-authorship accounted for 21.82% of the total.

From a thematic perspective, the presence of 2507 Keywords Plus and 1,597 Author's Keywords reflects the broad interdisciplinary applications of co-creation. The concept extends beyond traditional business environments and finds relevance in analytics**,** Educational data mining**,** Machine Learning**,** Learning Management Systems and Social networkings**.**This diversity suggests that Learning analytics is not confined to a single discipline but serves as a strategic framework for fostering collaboration between organizations, customers, and society**.**

5.1 Theoretical Implications

The Mean Total Citations per Article (MeanTCperArt) peaked in 2016 (33.12) and 2020 (31.26) before declining, indicating the lasting impact of mid-2010s research. The recent drop (2023: 4.75, 2024: 1.12) suggests newer studies are still gaining traction. The highest citation velocity (2020: 5.21) aligns with the rise of AI-driven learning and online education during COVID-19. Despite a record 121 publications in 2024, the low citation rate (1.12) indicates that recent works lack established theoretical influence. Future research should synthesize emerging studies to strengthen theoretical models. As per Bradford's Law, a steep decline in article concentration after the core sources, confirming that a few high-impact journals dominate theoretical discourse in Learning Analytics. Recognizing these sources—such as *Lecture Notes in Computer Science, ACM International Conference*, and *Journal of Learning Analytics*—can aid in refining theoretical frameworks and identifying key knowledge gaps in the field.

5.2 Practice Implications

Institutions can integrate high-impact research into curriculum development and policy-making, ensuring alignment with the latest advancements. Additionally, identifying influential research sources supports collaborative opportunities and funding strategies, fostering impactful contributions to Learning Analytics.

The deviation from Lotka's Law suggests that research output in Learning Analytics is influenced by discipline-specific factors. Most authors contribute only one article, highlighting the need for strategic collaborations and institutional support to sustain research productivity. Encouraging high-impact authors, fostering interdisciplinary collaboration, and recognizing prolific contributors can enhance scholarly engagement and knowledge dissemination.

The Normalized Local Citation Score helps researchers and institutions prioritize high-impact journals for literature reviews and publication strategies. Journals like *Internet and Higher Education* (3.02) hold significant influence, making them key sources for advancing research. The co-occurrence network analysis highlights dominant research themes, with *learning analytics* and *computer-aided instruction* emerging as central topics. International collaboration trends indicate strong ties between Australia, the UK, the US, and other nations, emphasizing the need for global research partnerships. Understanding keyword relationships helps identify emerging trends and gaps in literature, guiding future research directions.

5.3 Future Directions of the Research in Learning Analytics

Future research should focus on AI-driven personalized learning, integrating multi-modal data sources like eye-tracking and sentiment analysis to enhance student engagement insights. Addressing ethical and privacy concerns through transparent AI models is crucial, along with optimizing cross-institutional data sharing for curriculum development. Bibliometric analyses should track emerging trends like educational data mining and blockchain for credentialing.

Exploring learning analytics' impact on pedagogy, gamification, and VR/AR-based education can improve student motivation. Advanced AI techniques such as LLMs, explainable AI, and reinforcement learning can enhance analytics effectiveness. Research should also focus on scalable models for diverse educational settings and bias mitigation to promote equitable learning opportunities. These advancements will drive personalized, ethical, and data-driven education for improved student and institutional outcomes.

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