

From Predictive Analytics to Explainable AI in Higher Education: A Bibliometric Mapping

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ABSTRACT: As higher education increasingly relies on data-driven decision-making, the use of artificial intelligence (AI) to predict student success and dropout rates is gaining further importance. The primary aim of this study is to understand the evolutionary research trends of data-driven student success management. A PRISMA-based bibliometric analysis of 457 articles is implemented using the R software version 4.5.3 and the bibliometrix package (Version 5.0). Published articles are retrieved from Web of Science Core Collection indexes (SSCI, AHCI, ESCI), covering a three-decade period (1996-2025). The rigorous inclusion/exclusion criteria restricted the dataset to English-language, and peer-reviewed journal articles. Furthermore, co-word analysis and conceptual structure mapping, utilizing the Louvain clustering algorithm, were applied to extract the thematic architecture of the domain. Performance analysis reveals China and U.S. universities as the most influential affiliations shaping the structural volume of this research field, with Applied Sciences emerging as the dominant journal. Additionally, the network analysis indicates an international collaboration rate of 25%. The thematic map reveals that while predictive modeling-based Early Warning Systems (EWS) have matured into Basic Themes, driving Motor Themes included generative artificial intelligence and psychological constructs. Furthermore, Emerging Themes show that explainable artificial intelligence (XAI) is drawing a transformative pathway to the field. Higher education managers should integrate XAI while addressing ethical AI governance. Future higher education data-driven management should focus on building transparent systems leading to the empowerment of human decision-makers.

Keywords: Explainable Artificial intelligence, Predictive learning analytics, Student success management, Algorithmic transparency, Bibliometric mapping.

I. INTRODUCTION

Higher education is undergoing significant structural changes. It is shifting from spontaneous and submissive to more sophisticated and data-driven management [1, 2]. In an era of demographic shift concerning students' enrollments and characterized by increased regulatory controls, academic success has transcended traditional education systems and become a key strategic challenge for university leadership [3-5]. Previously, university leaders relied on demographic data and mid-term assessments to implement comprehensive support systems [6]. However, the widespread integration of learning management systems (LMS) and virtual learning environments (VLE) has transformed online learning platforms into complex, data-rich systems. Hence, university administrators are provided with valuable information about learning performance and academic achievement pathways. Consequently, modern university management must consider that student academic performance should be governed as a data-informed process with predicted outputs having straightforward consequences on institutional resource allocation.

Based on the databases of the most important online learning platforms (LMS/VLEs), educational data mining has achieved significant technical milestones in predicting student dropout. However, these systems largely operate as 'black boxes', highly complex artificial intelligence models that output decisions without providing any understandable reasoning or explanation for how they reached those conclusions. However, as algorithms become more complex, a significant gap becomes apparent: from a theoretical management perspective, the pursuit of absolute predictive accuracy reduces the managerial value of these models. This study utilizes bibliometric mapping to empirically verify whether the literature structurally reflects this conceptual gap. Predicting student dropout rates is operationally constrained if the key factors for academic success remain hidden from the lecturers who are supposed to support students. Furthermore, student dropout represents a social and financial burden for universities, directly increasing education costs, negatively affecting merit-based public funding, and reducing funding opportunities for graduates [7]. Therefore, the use of advanced analytical methods is evaluated based on criteria such as high return on investment (ROI) and cost-effectiveness. Consequently, dynamic decision support systems should lead to targeted financial or academic support before a student withdraws officially [8-10].

Taken together, these economic factors suggest that the academic community has overestimated the need for reform of predictive algorithms while simultaneously underestimating the investments required for their implementation. In higher education, AI serves as a tool for financial risk management and resource allocation, necessitating cost modeling to justify planned actions. Despite clear strategic and financial incentives, significant mistrust of algorithms is likely to hinder the implementation of predictive analytics. There is a clear discrepancy between highly accurate opaque algorithmic outputs and management interventions required by classroom educators. In general, higher education managers and educational consultants are hesitant to use algorithms to highly implement student-impacting interventions based on specific neural networks without any knowledge-based reasoning [11-13].

To resolve this shortcoming, leaders need Explainable Artificial Intelligence (XAI). They need transparent algorithms that recognize behaviors that trigger high-risk alerts, such as rare access to learning forums or low engagement in forums [14-16]. The findings clearly show that the transition from pure predictive analytics to AI is not just a software improvement, but an urgent organizational need. However, this study reveals that this area is an under-researched frontier. Without explainability, strategic predictive models are frequently limited in operational integration due to a lack of actionable insights for decision-makers. Trust issues are exacerbated by the growing focus on ethical standards and the complexity of decision-making processes. With the implementation of predictive models at universities that can identify at-risk students, concerns about algorithmic complexity, data corruption, and systemic bias are growing [17, 18]. Signs of poor academic performance can emerge and wrongly affect disadvantaged or marginalized groups, or even exclude them from institutional support [19, 20]. From a management perspective, the introduction of uninterpretable models without a robust XAI governance framework leads to poor institutional outcomes [21]. Therefore, while ethical AI is omitted in educational data mining research, it remains of major importance in data-driven management of student success.

Although the literature on the interaction between machine learning and higher education has increased annually by a remarkable 18.05% over the past three decades (1996–2025), the knowledge remains highly fragmented and divided between computer science, pedagogical theory, and operational research. The prior bibliometric studies are limited to documenting the collection of algorithmic research and do not address the foundational predictive analytics, nor the indispensable transition to (XAI) and ethical leadership to effectively address management challenges concerning student retention. Specifically, existing bibliometric reviews fail to examine the misalignment between the technical metrics provided by predictive models and the actionable interventions required by higher education institutions. Indeed, existing reviews fail to explain how raw student data can be transformed into a strategic organizational capability. Moreover, they overlook the behavioral trust bottleneck surrounding opaque algorithms and entirely omit the necessary pedagogical interventions and ethical governance to close the analytics loop. Furthermore, there is a lack of coherent and comprehensive synthesis written for institutional decision-makers that could uncover this myopia. To address this gap, this study aims to map the exact evolutionary transition from accuracy-driven models to

explanation-driven frameworks, providing an integrated socio-technical roadmap for institutional decision-makers. By examining the path of change, intellectual, and conceptual structures, this study goes beyond simple algorithmic predictions and considers clear strategic interventions. To improve university leadership's ability to implement digital transformation, this study addresses the following research questions:

- RQ1: What trends, impacts, and networks can be identified in AI-driven student success research from 1996 to 2025?
- RQ2: Which countries, institutional affiliations, and academic journals are the most influential actors driving the research on data-driven student success management?
- RQ3: How is the fragmented literature structured, and to what extent do predictive models dominate the literature?
- RQ4: Which future research directions should be privileged to overcome the algorithms trust bottleneck, and to effectively integrate (XAI) into student retention management?

II. A SOCIO-TECHNICAL ARCHITECTURE FOR EDUCATIONAL DATA MINING

Instead of providing a comprehensive raw bibliometric analysis, this work focuses on the field of Socio-Technical Systems (STS). The managerial problems described above, caused by algorithm mistrust and the disconnection of black box models from workable interventions, cannot be solved solely through IT optimization. Rather, a combination of organizational resource theory, behavioral psychology, and pedagogical ethics is required. To address theoretical fragmentation and avoid conceptual overload, these disciplines are synthesized into a unified conceptual model showing clear directional relationships: predictive analytics (data resources) require XAI (transparency bridge) to cultivate institutional trust, which in turn enables actionable pedagogical interventions under the guardrails of ethical governance. Therefore, the research direction underlying the current study aims to map three interconnected concepts: technical interfaces such as, learning management systems, human-algorithm interfaces for instance, explainable artificial intelligence, and the final managerial output such as, student success. It is expected that the aligned literature with the search string tenet fosters what is prescribed by management theory: predicting student dropout is a matter of information systems. However, it should be under the control of the previously mentioned theoretical pillars, and this is exactly what the current literature failed to balance. Crucially, this conceptual model is explicitly operationalized to guide the bibliometric methodology: the theories directly inform the keyword thesaurus construction, dictate the interpretation of the Louvain clustering algorithm, and contextualize the density and centrality of the resulting thematic map.

1. DECISION SUPPORT AND THE RESOURCE-BASED VIEW OF STUDENT DATA

The explanations of the high annual growth rate of 18.05% in educational data mining research literature can be detected in the Resource-Based View (RBV) of the firm and the Organizational Behavior Theory, precisely, the Dynamic Capabilities Theory. According to the traditional (RBV), a true competitive advantage is achieved when scarce and unique resources are available to the firm, and they are used effectively [22-24]. In the context of today's higher education, such sustained advantage for the institutions is provided within (VLEs) or (LMS) frameworks [2, 25, 26]. Furthermore, structural financial distress and learner demographics shift are creating an urgent need for the universities to transform LMS navigation pathways into economic indicators to be able to mitigate attrition [5, 27, 28]. Institutions are not only focusing on student attendance, they are also tracking microdata such as learning volume, collaborative learning, and digital activities, which are important leading indicators of long-term academic endurance [29-31]. Therefore, data-driven student success is becoming a critical organizational capability, allowing higher education institutions to protect academic revenues, enhance funding, institutional image, and legitimacy.

However, having data does not automatically equate to having actionable data. Unstructured digital data is well-suited for planning until it is transformed into predictive analytics, enabling managers to make precise decisions based on human expertise. Rather than merely summarizing IT theories, this study considers the RBV as an overarching framework to demonstrate that algorithms must transition from passive

data exploitation into dynamic capabilities. Operationalizing this within our bibliometric framework, these resource-centric concepts guide the thematic mapping to visualize how the literature reflects the consensus that in determining how algorithmic accuracy fails to guarantee institutional success without actionable utility. Viewed through this theoretical lens, we postulate that academic attention was turned toward building dropout prediction models and omitting managerial utility, a structural imbalance that our empirical bibliometric analysis aims to formally measure. Consequently, integrating these models into a comprehensive Decision Support System is an imperative for the universities to accumulate usable information for decision-making rather than amassing technological debt.

2. ALGORITHMIC TRUST, AVERSION, AND THE NECESSITY OF XAI

A literature review shows that technological advances in deep learning and graph neural networks have enabled highly accurate predictions of learning performance over the years. In the last decade, research in organizational development has focused on the use of machine learning, deep learning, and predictive analytics to forecast early academic failure [32-34]. The field has evolved from simple statistical models to more complex methods, including graphical neural networks (GNNs) for modeling complex social interactions and ensemble techniques, which are known to predict multi-year dropout [35-37]. Currently, there is still growing interest in the use of Generative artificial intelligence (GenAI) in the context of higher education as it is redefining personalized student support and constituent relationship management throughout the academic lifecycle [38, 39].

Nevertheless, these sophisticated models are not widely adopted by institutions. Indeed, algorithms developed to model complex social relationships, predict first-year engineering dropout rates, or detect cyberbullying using complex network analysis (CBNet) create opaque black boxes and fail in providing explainability [40-42]. By explaining the limitations of algorithmic biases and the sociological role of trust in automation, this institutional adoption failure explanation is rooted in algorithmic aversion Theory and the underlying socio-technical dynamics of trust in automation [43-45]. The Behavioral management literature demonstrates that decision-makers, especially educators, will reject the algorithm's predictions if they cannot understand the basic reasoning on which the model is built [46-48].

Therefore, the presence of the term explainable artificial intelligence (XAI) in this study's search string suggests a solution for the algorithmic aversion. (XAI) forms an important socio-technical bridge and offers a unique perspective on the democratization of data [49-51]. By translating confusing matrices into localized educational risk factors, such as unexpected drops or poor performance in a formative quiz, XAI provides educators with required justifications for effective interventions [14, 52, 53]. However, adopting a critical perspective reveals that XAI is not a flawless panacea. The literature often overlooks the inherent limitations of explainability, particularly the mathematical trade-offs between a model's interpretability and its raw predictive performance. Furthermore, providing simplified explanations for complex deep learning models introduces the severe risk of 'pseudo-explanations,' which can induce false institutional trust without resolving underlying systemic biases. Operationalizing algorithmic aversion in the current bibliometric study allows us to precisely map how the literature attempts to transition towards XAI (emerging clusters) while maintaining a critical awareness of these socio-technical risks. Viewed using the behavioral lens, we theoretically hypothesize the actual bibliometric landscape shows an unbalanced focus between predictive model inputs for accurate prediction on one hand and models' interpretability required by human managers on the other. The extent to which the academic literature aligns with this theoretical framing is explored in our subsequent structural mapping. This academic rush toward algorithmic perfection harmed student retention efforts. Indeed, a model that fails to explain its basis to skeptical teachers is structurally weak and administratively ineffective.

3. THE LEARNING ANALYTICS INTERVENTION LIFECYCLE AND ETHICAL GOVERNANCE

The evolving scientific framework guiding student success strategic management emphasizes the crucial importance of predictive analytics for achieving high performance. However, these predictive analytics remain useless if they do not trigger effective pedagogical actions. The Learning Analytics (LA) Intervention Lifecycle illustrates that a flawed implementation of computational analytics fails to achieve the four

developmental phases: data collection, predictive modeling, human intelligence, or automation, and finally, the pedagogical intervention [54-56]. Hence, predicting dropout is useless unless it triggers the fourth phase, which is pedagogical intervention [57, 58]. The use of historical data to identify vulnerable students leads to supplementary issues concerning algorithmic output reliability, risk of discrimination, and data privacy [59-61]. Furthermore, a fair individualized learning assistance provision dictates that researchers must urgently address ethical AI governance issues and consider them as an active component of the intervention lifecycle. The forthcoming bibliometric analysis highlights a gap concerning these issues. This integrated operationalization directly guides our thematic map interpretation, allowing us to evaluate whether the structural evolution of the literature successfully closes the loop of the Learning Analytics lifecycle, transforming predictive metrics into governed, ethical student support.

III. METHODOLOGY

To systematically map the intellectual structure of AI-driven student success management and ensure the reproducibility of our findings, this study employs a rigorous bibliometric and science mapping approach. Bibliometrics is highly suited for this management-focused analysis, as it transcends subjective narrative reviews by quantitatively decoding the evolutionary trajectories, collaboration networks, and thematic shifts of a fragmented research domain. The data collection and filtering processes were strictly governed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The current bibliometric analysis is implemented using the bibliometrix package (Version 5.0) within the R software (Version 4.5.3).

1. DATABASE SELECTION AND SEARCH STRATEGY

The data was retrieved from the Web of Science Core Collection as it is highly recognized for providing high-impact and peer-reviewed literature in various disciplines, especially in Information Systems, educational technology, and strategic management. Data extraction was conducted on March 17, 2026, utilizing the Web of Science (WoS) Core Collection, recognized as the premier database for high-impact, peer-reviewed academic literature. To mitigate selection bias while maintaining the strict metadata standardization required for exact replicability, alternative databases such as Scopus, Dimensions, Lens, and Google Scholar were excluded. The search was limited to the following indexes: Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), and the Emerging Sources Citation Index (ESCI).

To capture the socio-technical aspects previously mentioned in the theoretical framework, a Boolean search string was designed considering the algorithmic technology, the managerial objective, and the institutional context. The exact Topic Search (TS) was as follows: TS=("machine learning" OR "deep learning" OR (predict* NEAR/2 analytic*) OR "explainable artificial intelligence" OR "graph neural networks" OR "generative artificial intelligence") AND TS=("higher education" OR "universit*" OR "college*" OR "e-learning" OR "learning management system*" OR "virtual learning environment*") AND TS=("student success*" OR (academic NEAR/2 achieve*) OR "learning performance" OR (dropout NEAR/2 predict*) OR "student retention*")

2. PRISMA-GUIDED DATA COLLECTION AND FILTERING

The application of the previously mentioned search string yielded 727 published academic documents for the period 1996 to 2026, as there are no records on the Web of Science Core Collection before 1996. Raw data must rigorously go through the PRISMA protocol to ensure that collected data meet expected quality standards. A PRISMA flow diagram is included in Figure 1 to clarify the filtering logic and document counts:

- Initial Screening (Date and Source Integrity): As 2026 is not yet complete and to allow reliable interpretation of annual production evolution, the 45 indexed published documents from 2026 were excluded from the analysis, along with 3 open publisher invited reviews to prevent editorial bias. At the end of this stage, the count of published documents was reduced to 679.
- Eligibility by Document Type: At this stage, to ensure expected quality standards, we removed 182 conference proceeding papers, 7 early access articles, 3 data papers, 3 editorial materials, 2 retracted papers,

and 1 publication with an expression of concern. Proceeding papers were excluded because bibliometric analysis, especially science mapping techniques, requires highly standardized metadata, and it is well documented that proceeding papers suffer incomplete citations records and unstandardized affiliations. Hence, the final count of academic documents was 481, comprising 455 research articles and 25 review articles.

- Secondary Software Filtering: The document export format was full record and cited references for the 481 collected academic documents. There was no need to merge files as the final count is less than 500. Raw files were then processed using the Bibliometrix R package [62]. Using the biblioshiny interface, additional early-indexed 2026 papers were excluded, leading to a final count of 475 papers at the end of this stage.
- Language Standardization: Only documents written in English were targeted at this stage, resulting in the exclusion of 18 documents in Afrikaans, French, Korean, German, Russian, Spanish, and Turkish. The final count of considered academic papers in the current bibliometric analysis is 457 documents.

3. DATA NORMALIZATION, EXTRACTION, AND ANALYSIS TOOLS

To transition from data collection to strategic analysis, the 457 documents were imported into the R-package Bibliometrix (via the Biblioshiny web interface). This powerful analytical tool was selected for its ability to conduct both descriptive performance analysis and sophisticated science mapping.

3.1 Reference Normalization

A common methodological flaw in bibliometric analyses is the fragmentation of citation networks due to varying reference formats. To construct an accurate Thematic Map, resolving these discrepancies was paramount. Using Biblioshiny's reference-matching and disambiguation algorithms, we conducted a rigorous normalization of the cited references. The original export contained 19,304 original citations. Through the automated matching process using the Jaro-Winkler method, 275 variant citations (representing 1.4% of the total network) were successfully merged and standardized into 19,029 unique citations. This highly normalized matrix served as the definitive empirical foundation for the study, ensuring that the subsequent thematic mapping perfectly reflects the evolutionary shift from foundational predictive analytics to the strategic imperatives of Explainable AI (XAI) and generative interventions.

3.2 Thesaurus and Synonym Cleaning

To prevent semantic fragmentation and cluster dilution during the subsequent co-word analysis, a rigorous keyword normalization process was executed utilizing a custom thesaurus. Because bibliometric algorithms cannot inherently distinguish between functionally synonymous terms, chronological buzzwords, or singular/plural variants, failing to normalize author keywords artificially weakens the mathematical weight of core research themes. Utilizing Biblioshiny's synonym parameters, a comprehensive harmonization of the dataset was conducted to ensure the resulting thematic map accurately reflects macro-level strategic shifts rather than superficial lexical variations. The custom thesaurus reduced the count of keywords from 1322 to 1226 and structurally consolidated the literature across four primary theoretical dimensions:

Target Variables and Predictive Outcomes: Positive institutional objectives were heavily consolidated to form a unified, mathematically robust anchor. Academic performance absorbed 17 functional synonyms, including student success, academic achievement, and isolated terms like performance. Conversely, negative risk indicators were standardized into precise operational nodes, unifying variations into dropout prediction, student dropout, student attrition, and student retention. Furthermore, early warning systems successfully absorbed operational shorthand such as students at risk and early prediction. It should be noticed that while academic performance and student success are completely different in traditional educational research, they are used interchangeably by authors in the context of educational datamining and machine learning to represent the quantifiable target variable of the predictive algorithm.

The Contextual and Environmental Framework: To stabilize the demographic and infrastructural context of the thematic map, broad institutional terms including university, college, school, and undergraduate education were universally elevated to the definitive node higher education. Similarly, the digital learning

environments were strictly standardized: learning management system absorbed proprietary brand names like Moodle and platform-specific outputs like LMS data, while e-learning and virtual learning environment unified dozens of chronological and conceptual synonyms (for example, distance education, electronic learning).

Algorithms and Methodological Shorthand's: To eliminate lexical noise caused by generic methodological terms, the thesaurus elevated isolated words to their formal domain-specific equivalents. Most notably, the broad structural node predictive modeling was formed by absorbing generic terms such as prediction, model, and models. Additionally, core computational methodologies including machine learning, deep learning, ensemble learning, and artificial neural networks were established as definitive, consolidated nodes by absorbing their respective abbreviations for example, ML and specific sub-techniques. The Strategic Frontier: Finally, to accurately map the theoretical paradigm shift from black-box analytics to transparent, automated interventions, emerging technical concepts were unified. Explainable artificial intelligence absorbed variations such as XAI, and generative AI absorbed commercial brand shorthand's such as ChatGPT.

This deliberate, manual semantic refinement ensures that the empirical foundation of the thematic network is flawlessly optimized, allowing the true structural evolution of AI-driven student success to emerge without the interference of algorithmic fragmentation.

3.3 Science Mapping and Thematic Analysis

Parameters to resolve methodological depth weaknesses and ensure exact replicability, precise parameters were established. A co-word analysis was conducted to generate the theme map, utilizing all keywords. The data was normalized using the association strength method, with a minimum keyword frequency equal to 5, and the total number of words mapped was 250. To partition the network into coherent thematic bubbles, the Louvain clustering algorithm was utilized, while the map's structural axes were plotted utilizing Callon centrality and Callon density computations. Furthermore, to map historical paradigm shifts, the thematic evolution methodology was executed utilizing the stability index. The parameters for this evolutionary mapping were strictly set with a min weight index of 0.1 and a balancing centrality vs. occurrence parameter equal to 0.5.

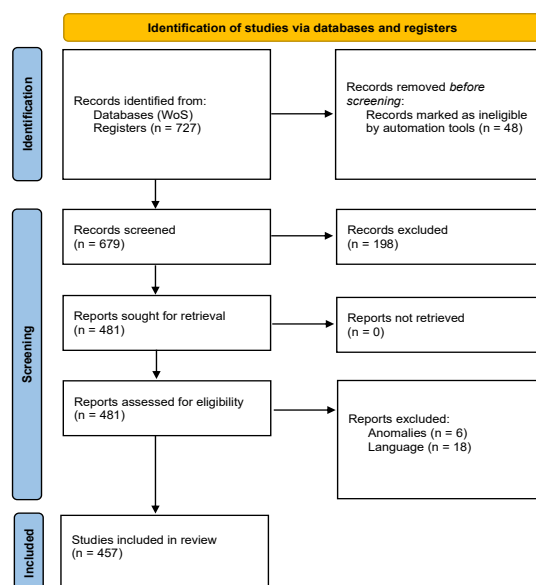


FIGURE 1. PRISMA 2020 protocol.

IV. DESCRIPTIVE BIBLIOMETRICS

1. ANNUAL SCIENTIFIC PRODUCTION

The analysis of 457 high-impact articles from 1996 to 2025 uncovered a fast evolution of the literature about data-driven student success management. The average annual growth for the three decades covered by the current study is 18.05%. This growth rate is a Compound Annual Growth Rate (CAGR) computed using the bibliometrix package. While during the years (1996-2019) the discipline experienced a steady accumulation of literature, the growth became notably higher for the last six years. Indeed, as enhanced by Figure 2, the year 2020 is identified as an inflection point with a total number of publications of 25, then the number of published articles increased from 75 articles in the year 2024 to an unprecedented peak of 123 publications during the year 2025. This growing trajectory, especially during the recent years, proves an increased academic interest in the discipline, which is identified as an essential strategic imperative for university leaders around the world. This accelerated growth rate could not be interpreted by database indexing anomalies as data were retrieved in March 2026 when the 2025 indexing process was supposed to be structurally mature and in a stabilization window. Hence, data-driven student success management is becoming a pillar for navigating digital transformation successfully.

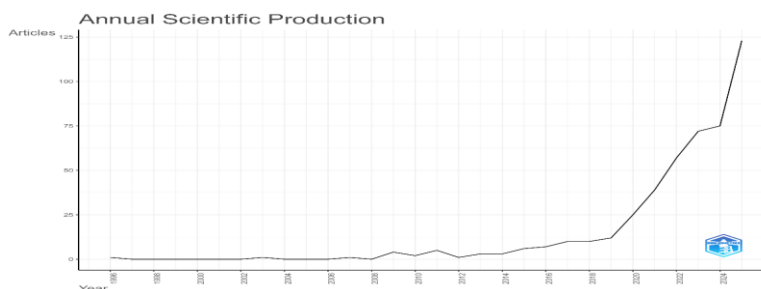


FIGURE 2. Annual scientific production (1996–2025) (raw annual publication counts).

2. BIBLIOMETRICS INDICATORS

The descriptive overview of the finalized dataset provides foundational insights into the growth trajectory, contributor profiles, and publication channels of the research domain. The analysis reveals a steady structural growth in annual scientific production, reflecting expanding academic interest in computational educational research. A total of 457 high-impact documents were analyzed, written by 1,527 unique authors. To move beyond descriptive counts, the Collaboration Index was computed, yielding a value of 3.58. This mathematical indicator confirms that the domain exhibits a highly collaborative and interconnected multi-authored ecosystem. To evaluate author productivity dynamics with greater statistical depth and technically interpret publication distributions, Lotka's Law was applied, and Figure 3 provides Lotka's Law plot. As visualized in the introduced Lotka's Law plot, the empirical distribution indicates that 93.91% of authors (1,434 individuals) contributed a single document to the corpus, while 5.17% (79 authors) published two papers, and less than 1% authored three or more documents (12 authors with 3 papers and 2 authors with 4 papers). The graphical distribution perfectly aligns with Lotka's mathematical model, reflecting a rapidly expanding socio-technical field where foundational concepts attract a large cohort of transient researchers, while the core conceptual architecture remains anchored by a specialized, highly productive nucleus of scholars.

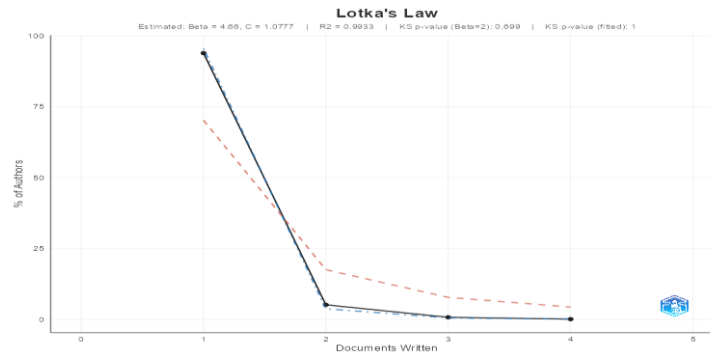


FIGURE 3. Lotka's law.

To evaluate scientific impact with higher precision, mitigate the biases of raw publication counts, and avoid inferring unverified causal motivations, the h-index was utilized as an advanced localized metric. Figure 4 illustrating both Authors' Local Impact and Journals' Local Impact has been introduced to visually benchmark this performance. The technical interpretation of the Author Local Impact figure reveals that Gasevic Dragan leads the domain with a local h-index of 4 and a substantial citation footprint of 352 total citations across 4 publications. This is closely followed by Delen Dursun, who exhibits an h-index of 3 and a high citation footprint of 299 citations. Other prominent scholars mapped in the figure, such as Fan Juanjuan (h-index = 3, TC = 56), Hassan Saeed-Ul (h-index = 3, TC = 97), and Hwang Gwo-Jen (h-index = 3, TC = 52), demonstrate strong localized influence. The concentration of citations among these core authors indicates their pivotal role in establishing the theoretical and algorithmic benchmarks of the domain. Concurrently, the Source Local Impact analysis provides a technical evaluation of journal performance and field-specific diffusion. Applied Sciences emerges as the most impactful publication venue with a local h-index of 14, and a g-index of 23. IEEE Access also exhibits substantial structural influence with a local h-index of 11. Educational technology-focused platforms such as Education and Information Technologies (h-index = 7, g-index = 11) and Computers and Education (h-index = 5, g-index = 5) serve as vital thematic bridges, channeling computational engineering models into the broader educational research community.

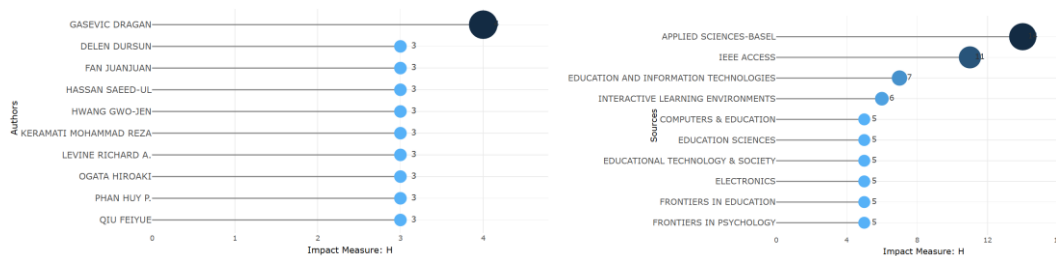


FIGURE 4. Authors' and sources' local impact.

To capture the exact temporal entry and structural breakthrough of transparent paradigms within the literature, a diachronic network was added to this bibliometric indicators' subsection. The visual diagram technically maps the chronological introduction of contemporary terminologies. Notably, the diagram shows that the keyword explainable artificial intelligence (XAI) is completely missing in 2023, a period where the network remained focused on optimizing black-box predictive accuracy metrics. However, a major structural pivot is visualized in the subsequent year: the diachronic network explicitly shows XAI is present in 2024, formally introduced as a distinct, independent node. This sudden appearance empirically signals a domain-

Table 1. Core sources based on Bradford’s law and local citation scores.

Bradford’s Law Zone 1 Journals	Number of Local Citations	Number of Published Articles
Applied Sciences	245	23
IEEE ACCESS	364	21
Education and Information Technologies	329	11
Education Sciences	113	8
Educational Technology & Society	117	8
Frontiers in Education	57	8
Interactive Learning Environments	129	8
International Journal of Advanced Computer Science and Applications	50	8
Scientific Reports	54	8
Frontiers in Psychology	135	7
Journal of College Student Retention-Research Theory and Practice	101	7
Sustainability	159	7
Cogent Education	9	6
Electronics	2	6
BMC Medical Education	1	5
Computers & Education	558	5
IEEE Transactions on Learning Technologies	142	5
Information	38	5

While the primary purpose of this analysis is to identify the core journals of the field, it is important to notice that Bradford’s Law Zone 1 is composed of 18 journals publishing 156 articles, Zone 2 consists of 72 journals publishing 149 articles, and Zone 3 consists of 156 journals publishing 152 articles. Therefore, the Bradfordian scattering effect is confirmed.

4. GEOGRAPHICAL AND INSTITUTIONAL CONTRIBUTIONS

The target of the geographical analysis of scientific publications is the identification of top affiliations in the discipline. The applicable criteria are the number of published articles and the number of citations. At the country level, China has the greatest influence on publications and citations, followed by the USA, Saudi Arabia, and Australia. This is supposed to highlight the country’s efforts in modernizing higher education and the support for factual decision-making in higher education institutions, specifically in student success management. Saudi Arabia’s prominent global position in this socio-technical domain is directly underpinned by macro-level national funding mechanisms and explicit institutional strategic initiatives. Under the overarching framework of Saudi Vision 2030, the Kingdom has prioritized digital transformation and artificial intelligence through the establishment of the Saudi Data and Artificial Intelligence Authority (SDAIA) and the launch of the National Strategy for Data and AI. This national mandate is operationally fueled by the Ministry of Education’s Institutional Funding Program, which directly injects competitive research grants into universities to optimize public infrastructure and higher education efficiency.

At the institutional level, the California State University System, San Diego State University, and King Abdulaziz University are leading the scientific production in the field. Consequently, it is revealed that predicting and reducing student dropout rates on a large scale is costly and provides these institutions with high benefits, which drive them to improve research on predictive analytics.

Table 2. Top 10 affiliations.

Affiliations	Number of Published Articles	Country
California State University System	17	United States of America
San Diego State University	13	United States of America
King Abdulaziz University	10	Kingdom of Saudi Arabia
King Khalid University	9	Kingdom of Saudi Arabia
Universiti Tenaga Nasional	9	Malaysia
University of Jordan	9	Jordan
Asia University Taiwan	7	Taiwan
Ibn Zohr University of Agadir	7	Morocco
Mindanao State University System	7	Philippines
Beijing Normal University	6	China

V. NETWORK AND THEMATIC ANALYSIS

1. COLLABORATION NETWORKS AND CO-CITATION ARCHITECTURE

Institutional and international co-authorship networks have a high importance in the field of educational data mining as they are the knowledge transfer catalysts. It is noticed that approximately 25% of the published articles are the result of international collaborations. The co-citation network (representing the broader circle of experts) in Figure 6 reveals an interesting dichotomy. Foundational theories of student retention (for example, Tinto's integration models) are excessively cited alongside foundational machine learning architectures (for example, Breiman's Random Forest, Chawla's SMOTE for imbalanced data). The co-citation structure suggests that the field was built on a mix of classification mathematics and structural pedagogical theory. Moreover, the third cluster is the cluster of algorithmic trust and XAI frontier which anchored in machine learning transparency framework. This network confirms that the field has matured from abstract sociological attrition models, through opaque black-box optimization, and finally to the era of explainable student success management.

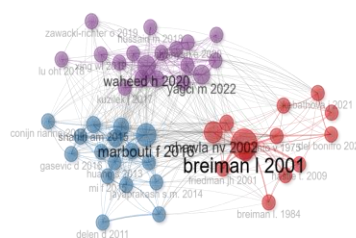


FIGURE 6. Co-citation network.

2. THEMATIC MAP: THE STRUCTURAL PARADIGM SHIFT

The Thematic map was developed using adapted and standardized vocabularies for representing the conceptual architecture of the field. Each element of the thematic map represents a cluster, and it is plotted along two dimensions. The first dimension considers the relevance of the discipline and is called centrality,

the second considers the internal development of the cluster and is called density. The thematic map was generated using the bibliometrix package (version 5.0) within the R statistical computing environment (version 4.5.3). To ensure the thematic analysis is mathematically grounded rather than interpretive, precise network parameters were established. Keyword co-occurrence weighting was normalized utilizing the Association Strength metric to eliminate scale bias from highly frequent generic terms. Cluster formation was executed utilizing the Louvain clustering algorithm, which heuristically maximizes network modularity by grouping the top $n = 250$ merged keywords into dense sub-communities based on internal edge density. Furthermore, to address potential methodological vulnerabilities regarding cluster stability, a dual-validation framework was implemented prior to interpretation. First, parameter sensitivity testing was conducted by varying the keyword node inclusion depth (testing $n = 200$ and $n = 300$) and altering the normalization metric (Jaccard Index).

The core topological structure, specifically the distinct separation between foundational predictive modeling blocks and emerging socio-technical clusters, remained structurally invariant, confirming the robustness of the partitions. Second, the subsequent thematic evolution mapping serves as a longitudinal stability verification, demonstrating that these clusters persist as deeply embedded research fronts over a three-decade period rather than acting as transient statistical artifacts. It should be noticed that thematic mapping without thesaurus cleaning led to highly decentralized and unreliable map. The use of consolidation rules (Appendix) allowed to resolve lexical issues without forcing the relationships. Evolutionary shift toward algorithm transparency framework emerged smoothly. The thematic map is divided into four strategic quadrants:

- **Basic/Transversal Themes (High Centrality, Low Density):** This quadrant encompasses all teaching and learning infrastructure of the field. It is composed of highly relevant nodes such as academic performance, higher education, learning analytics, e-learning, AI, system, LMS, early warning systems, impact, and engagement. This underpins the theoretical framework: Digital infrastructure is required to provide predictive models with reliable data for early warning signals detection.
- **Motor Themes (High Centrality, High Density):** This area is based on current literature and includes students, deep learning, motivation, strategies, generative AI, self-efficacy, science, learning performance, perceptions, and knowledge. The discipline recognizes the importance of both advanced algorithms and student psychology for effective student success management. Indeed, the literature is focusing on algorithms that address psychological constructs such as self-efficacy, motivation, and student perceptions. Furthermore, the literature increasingly explores how advanced algorithms can be conceptually aligned with the student psychological tenacity and the pedagogical experience.
- **Niche Themes (Low Centrality, High Density):** This highly specialized area encompasses specific validation procedures, including support, selection, regression, meta-analysis, statistics, rates, efficacy, validation, predictive learning analytics, and imputation. Focus is on the statistical validation of methodology accuracy (including meta-analysis, imputation, and validation). Although the cluster is somewhat broader in academic discourse, the Niche theme is highly concentrated on valid and reliable methodologies that ensure the mathematical integrity and efficiency of predictive learning analytics, regression statistics, and the data collection process.

Emerging Themes (Low Centrality, Low Density): This area is important for the exploration of the future of the discipline. It encompasses machine learning, predictive modeling, educational data mining, student dropout, student retention, dropout prediction, classification, XAI, random forest, and student attrition. It was expected that student dropout, student retention, and student attrition are the foundational themes of the discipline. However, from a conceptual synthesis standpoint, their appearance alongside XAI and random forest reveals a paradigm shift, indicating that research focus is interpretively moving away from absolute accuracy of black box predictions toward explainable dropout predictions. Furthermore, the bottom left quadrant is for emerging or declining themes, while speculative, an interpretive reading of this positioning suggests that the foundational motivation for the entire field as student dropout and student retention are acting as declining traditional vocabulary of the field as also supported by the thematic

evolution in Figure 8. Student dropout and student retention are shadowed by XAI, GenAI, and psychological constructs. Finally, the low density reveals that the uncovered theme is at a formative stage.

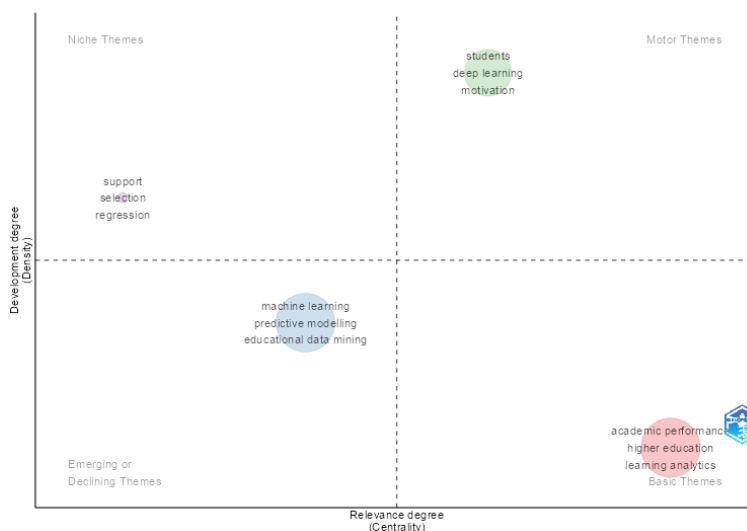


FIGURE 7. Thematic map.

To map the chronological trajectory of these clusters and empirically evaluate paradigm shifts, a thematic evolution analysis was conducted. The evolutionary pathways across four milestone periods (1996–2015, 2016–2019, 2020–2023, and 2024–2025) were computed utilizing an Inclusion Index threshold to ensure thematic bridges are only drawn between significant conceptual nodes. Three events were considered while determining these periods: first publications about XAI started at 2016, the Covid 19 pandemic and the confirmed attention to XAI into the literature in 2024 as demonstrated by the diachronic network in Figure 5.

- The Foundations and Incubation Era (1996–2015)

During the initial 20-year span, the conceptual structure was highly fragmented and fundamentally descriptive. This period reflects an early exploratory phase where the literature focused on establishing baseline digital learning environments rather than deploying advanced predictive mathematics.

- The Algorithmic Rush (2016–2019)

The network topology undergoes a profound consolidation during this pre-pandemic window. Disparate tracking metrics merge into a dense, central node anchored by academic performance and predictive analytics. The structural inclusion of specific methodologies like support vector machines and neural networks indicates a concentrated shift toward optimizing predictive accuracy metrics. The literature during this phase structurally prioritizes mathematical performance, establishing the black-box models that would later require regulatory intervention.

- Digital Transformation and Systemic Shock (2020–2023)

Coinciding with the mass data-generation shock of the COVID-19 pandemic, the network exhibits rapid conceptual expansion [63]. The thematic pathways demonstrate that the monolithic academic performance cluster splits into highly specialized sub-themes, most notably intersecting with learning management systems and student engagement. This period marks the systematic integration of advanced algorithms such as deep learning and ensemble learning into daily educational infrastructure, creating a dense, highly interconnected socio-technical web.

- The Ethical Governance and XAI Era (2024–2025)

The final structural shift in the network topology from 2023 onward indicates that recent academic literature has increasingly prioritized algorithmic interpretability over standalone predictive performance. The evolutionary map reveals that machine learning branch is becoming the most important branch and it

evolves the XAI node. Explainable Artificial Intelligence is appearing at this era induced by selection and predictive modeling branches.

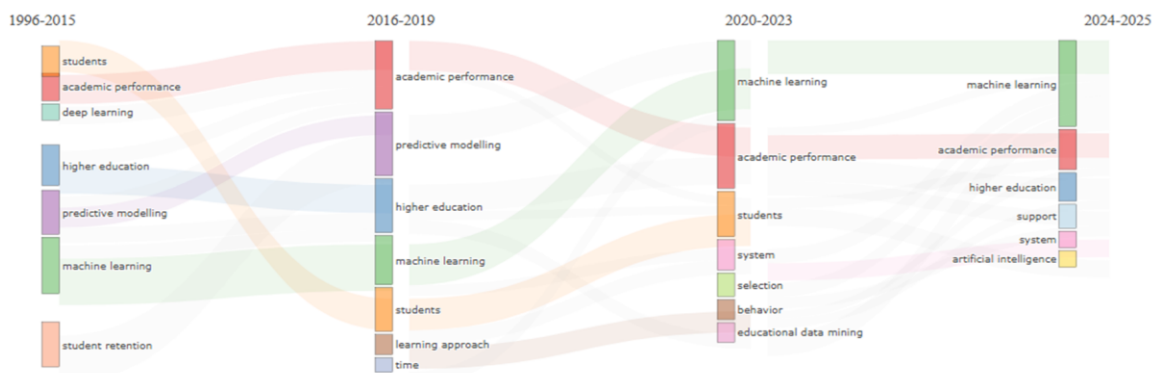


FIGURE 8. Thematic evolution.

3. THEMATIC INTERPRETATION AND ALIGNMENT WITH THEORETICAL FRAMEWORK

While Algorithmic Aversion provides the theoretical framing for the 'black box' problem, our thematic evolution map provides the empirical bibliometric evidence that the academic field is actively restructuring to solve it. Techniques such as machine learning and predictive modeling have been among the most widely studied. For decades, these techniques were undisputable. However, as a speculative look into the field's future trajectory, they are now closely intertwined with XAI in the new technology field as a signal of a paradigm shift [64, 65].

In high-stakes, human-centric domains such as education and healthcare, empirical evidence suggests that decision-makers are increasingly hesitant to rely solely on black-box predictions [66]. Hence, there will be no effective actionable interventions without considering black box predictions through the lens of XAI. Transparent algorithms and interpretable models are building the new frontier of the discipline, which must deal with economic early warning systems, empower student psychological tenacity, and improve pedagogical reality.

3.1 The Resource-Based View (RBV) and Strategic Analytics

Through the lens of the Resource-Based View (RBV), raw educational data and traditional Early Warning Systems (EWS), which our mapping identified as foundational Basic Themes, can no longer provide a sustained competitive advantage. Because standard predictive models are easily replicable across institutions, they are not rare or inimitable. Instead, our findings show that the field is shifting toward complex, human-centric interventions (identified as Motor Themes). Within the RBV framework, it is the integration of Generative AI and student psychological constructs (like self-efficacy) that now constitutes a firm's true strategic resource. The ability to not just predict, but dynamically manage student success, is the modern competitive advantage for university leadership.

3.2 Algorithmic Aversion and the Rise of XAI

The concept of Algorithmic Aversion provides the exact theoretical mechanism explaining the field's structural pivot away from black-box analytics. Algorithmic aversion dictates that human decision-makers (such as academic advisors and institutional managers) will fundamentally reject highly accurate predictive models if they cannot understand the underlying rationale. This theory provides a robust conceptual lens to interpret the structural alignment of our findings in the Emerging Themes quadrant. The sudden, high-growth trajectory of Explainable AI (XAI) in the recent literature is the academic community's direct response to algorithmic aversion. By prioritizing algorithmic transparency, researchers are attempting to break the trust bottleneck and foster technological acceptance among non-technical end-users.

3.3 *The Learning Analytics (LA) Lifecycle and Actionable Interventions*

Finally, the Learning Analytics (LA) Lifecycle dictates that data collection and predictive modeling are only the preliminary stages of a continuous loop, the lifecycle is only completed when data triggers a pedagogical intervention that alters student outcomes. As a broader conceptual synthesis of these macro-level metrics, our thematic map illustrates keyword structures that mirror the conceptual maturation of this lifecycle within the published literature base. While early literature stalled at the prediction phase (the mathematical accuracy found in the Basic Themes), the current strategic frontier has shifted to the intervention phase. The prominent emergence of Generative AI and XAI demonstrates that researchers are now focused on closing the LA Lifecycle loop, ensuring that predictive insights successfully translate into actionable, ethical, and personalized management interventions.

VI. DISCUSSION: MANAGERIAL IMPLICATIONS FOR HIGHER EDUCATION

The results of this bibliometric analysis clearly demonstrate that the success of artificial intelligence in education extends far beyond computer science and now represents a key management challenge for professionals. For university leadership, the transition from an impenetrable black box to realistic and actionable insights is structurally reflected in the recent literature across three distinct dimensions.

1. *RESOURCE OPTIMIZATION AND THE ECONOMICS OF EARLY WARNING SYSTEMS*

Dropout rates represent a significant financial burden for universities. Early Warning Systems in education are increasingly enhanced by economic actions. Given declining student numbers, advanced analytics implementation is frequently assessed through financial indicators, such as Return on Investment (ROI) [67]. The literature indicates that leveraging EWS efficiently requires financial resources to support at-risk students, through psychological counseling, or academic advising, and deploy them proactively before the dropout process starts [68, 69]. Therefore, these predictive algorithms are considered essential for the optimization of resource allocation.

2. *TRUST, ALGORITHMIC AVERSION, AND THE XAI MANDATE*

The contradiction between considering XAI as an emerging theme and the contemporary discussion about the urgent need for explainable student success management is resolved by the thematic evolution and the diachronic network. Indeed, XAI is an emerging theme when considering the three-decade baseline period, however, for the period 2024-2025, the thematic evolution shows XAI as foundational and highly active Basic theme which justifies the urgent call for algorithmic transparency in the literature.

The most critical managerial bottleneck identified in this study is the psychological friction between black-box deep learning models and frontline academic advisors. Human educators inherently exhibit algorithmic aversion when asked to base life-altering student interventions on opaque mathematical outputs [70, 71]. Therefore, viewed as a conceptual synthesis of recent co-citation networks, the recent emergence of XAI nodes in the bibliometric network suggests a growing consensus that transparent frameworks serve as a prerequisite for technological adoption. As indicated by the thematic map's emerging quadrant, the academic discourse increasingly positions Explainable AI acts as the vital socio-technical bridge [72]. By translating complex network analyses into localized, pedagogical risk factors for example, isolating a specific drop in LMS forum engagement, XAI democratizes data, empowering educators with the transparent justifications required to execute their interventions with confidence [66].

3. *POLICY AND ETHICAL GOVERNANCE IN ALGORITHMIC PROFILING*

Using black box predictions to identify at-risk students without any explainability can lead to false early warning signals. Clearly, actionable actions triggered by false signals and allocated resources to achieve them are a waste. Furthermore, unsupervised dropout predictions for early identification of vulnerable students without clear ethical guidelines increase the risk of algorithmic and systemic biases, and they may lead to discrimination issues [17]. Furthermore, serious privacy concerns exist regarding the continuous collection of behavioral data in virtual learning environments [21, 73].

As demonstrated by the thematic evolution, the research field has rapidly entered the Ethical Governance and XAI Era (2024-2025), hence future research must engage with the emerging international regulatory frameworks. Specifically, the European Union AI Act, which classifies the artificial intelligence systems in education as High-Risk AI Systems. To comply with this, higher education institutions are required to implement data governance and algorithm transparency. Moreover, future educational analytics architectures must comply with the UNESCO's 2021 Recommendation on the Ethics of Artificial Intelligence, which mandates the protection of student data privacy and mitigates algorithm bias against marginalized students. These imperatives validate the urgent implementation of XAI frameworks.

This bibliometric trajectory highlights the growing academic call for a comprehensive and clear ethical policy concerning artificial intelligence governance. Scholars emphasize that this includes auditing the algorithm to avoid unfairly disadvantaging minority groups, ensuring clear consent procedures for data use by learning platforms, and guaranteeing that predictive models serve a specific supportive purpose and are not used for punitive measures [74]. To be more specific, the literature frequently highlights specific technical approaches, such as SHAP (SHapley Additive exPlanations) and Counterfactual Explanations [75-77]. However, the choice for XAI implementation should also balance transparency, efficiency, and cost [78]. Synthesizing the thematic evolution mapped in our bibliometric analysis, a comprehensive conceptual framework (Figure 9) that illustrates the paradigm shift from traditional predictive analytics to actionable management is proposed. As illustrated in the figure, the current reliance on black-box algorithms creates an algorithmic trust bottleneck. To overcome this, our framework highlights the necessary methodological pivot toward Explainable AI (XAI), which ultimately empower human decision-makers to implement effective interventions.

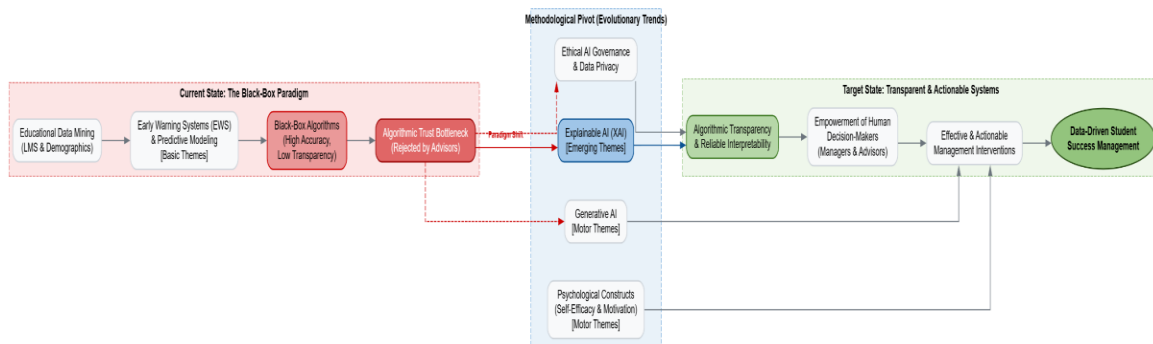


FIGURE 9: Conceptual model diagram.

Despite the structural prominence of XAI and ethical governance within the recent literature, these bibliometric trends must be contextualized against practical implementation barriers. The current mapping reveals an optimistic academic focus, but often lacks acknowledgment of the inherent limitations of XAI in applied settings. Firstly, providing explainability does not automatically guarantee interpretability or fairness, complex XAI outputs can still overwhelm non-technical educational stakeholders. Secondly, institutional resistance to AI adoption extends far beyond explainability. Faculty reluctance is frequently driven by concerns over workflow disruption, threats to pedagogical autonomy, and the ethical implications of continuous student surveillance. Furthermore, the literature's rapid conceptual shift toward advanced XAI frameworks risks masking severe infrastructural inequalities. The financial and computational AI implementation costs required to maintain real-time, transparent predictive infrastructure remain prohibitively high for under-resourced institutions, potentially widening the digital divide in data-driven student success management.

4. FUTURE RESEARCH AGENDA AND LIMITATIONS

This thematic map provides a comprehensive overview of the discipline as represented in the dataset and highlights key gaps that will likely continue to burden higher education institutions in the coming years.

- **The Integration of Multimodal Data:** Future research directions must consider and expand the integration of big data into the learning management system (LMS). Programs designed to promote student engagement require big data analytics, including biometrics, eye-tracking, and natural language processing from forum posts and social media, to gather comprehensive data on student engagement. Future research needs to answer the following question: How can multimodal data streams be synchronized within an LMS to predict real-time student dropout?
- **Generative AI and Automated Interventions:** Future research should explore how Generative AI can evolve from a predictive tool to a practical intervention tool, enabling self-directed learning activities and personalized learning environments to address the challenges students face during their studies [38, 79]. Specifically, future research needs to answer the following question: How can GenAI trigger automated mechanisms that generate personalized learning for at-risk students?
- **Multi-Institutional and Cross-Cultural Datasets:** The main shortcoming of the existing literature is its reliance on datasets from individual universities. However, to be able to prove the robustness of XAI frameworks, they should be applied to massive, cross-cultural datasets. Hence, future research needs to answer the following question: To what extent XAI frameworks maintain their fairness in the case of cross-cultural datasets?

Additionally, to advance the methodological scope of this field, future studies should include extended longitudinal thematic evolution tracking, employ comparative databases for example, cross-referencing Web of Science with Scopus or Dimensions, and utilize scientometric triangulation to validate bibliometric findings across multiple algorithms and analytical tools. Furthermore, while a custom thesaurus was rigorously constructed to standardize synonymous author keywords prior to the co-word analysis, the merging process did not undergo formal independent validation by external domain experts. Consequently, this represents a methodological limitation. Additional limitations are noticed because of non-English documents, proceeding papers, and WoS database restrictions.

Additionally, while the Boolean search string was systematically constructed based on core socio-technical and educational management frameworks, it did not undergo a formal audit or validation by a professional librarian or external information specialist. Although rigorous precautions were taken, such as iteratively testing keywords and applying a custom thesaurus to clean keyword variations, the lack of external query validation represents a methodological limitation that could potentially result in the inadvertent omission of some peripheral publications or niche terminology.

VII. CONCLUSION

A detailed bibliographic and thematic analysis of 457 articles demonstrates the relevance of each individual study to the development of an integrated approach. For over three decades, the academic literature on student success management has predominantly relied on an opaque, black box mathematical approach based on predictive models. However, as demonstrated by the current bibliometric analysis, the precision of predictions alone is increasingly viewed as insufficient from a managerial perspective. The thematic trajectory suggests that the future of higher education management research is pivoting away from a sole reliance on black box prediction accuracy, moving toward the transparency of deep learning algorithms. By building explainable artificial intelligence (XAI), integrating meaningful performance indicators, and deploying generative AI for personal interaction, universities can bridge the gap between digital capabilities and human interaction. Ultimately, successful digital campuses are responsible for creating appropriate, transparent, and ethical systems that do not replace advisors but directly support them.

To summarize, this study provides three explicit contributions. First, the theoretical contribution lies in systematically mapping the conceptual paradigm shift from standalone predictive analytics to ethically governed, Explainable AI frameworks within educational research. Second, the methodological contribution

is demonstrated through the application of advanced, dual-validated bibliometric clustering and diachronic network analysis to extract robust structural trajectories from the literature. Finally, the practical contribution equips university administrators with a data-driven framework to mitigate algorithmic aversion and prioritize transparent, actionable AI interventions in higher education governance.

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Author Contributions

All authors made an equal contribution to the development and planning of the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available from the authors upon request.

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Not applicable.

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Appendix: Reproducibility Protocol

This protocol is provided to ensure full compliance with open science guidelines and to enable complete replication of the science mapping and performance analysis presented in this study.

1. DATABASE SEARCH ARCHITECTURE (WEB OF SCIENCE)

- Database Source: Web of Science Core Collection (Clarivate)
- Citation Indexes: Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), Emerging Sources Citation Index (ESCI).
- Exact Search String: TS=("machine learning" OR "deep learning" OR (predict* NEAR/2 analytic*) OR "explainable artificial intelligence" OR "graph neural networks" OR "generative artificial intelligence") AND TS=("higher education" OR "universit*" OR "college*" OR "e-learning" OR "learning management system*" OR "virtual learning environment*") AND TS=("student success*" OR (academic NEAR/2 achieve*) OR "learning performance" OR (dropout NEAR/2 predict*) OR "student retention*")
- Temporal Parameters: 1996 to 2025 (Inclusive)
- Refinement Refilters: Document Types: Articles | Languages: English
- Data Export Format: Full Record and Cited References, Format: Plain Text / Tab-delimited.
- Total Corpus Extracted: N = 457 records.

2. CUSTOM CLEANING THESAURUS RULES (DE-DUPLICATION TOKENS)

To prevent network fragmentation caused by lexical variations, the following custom thesaurus rules were systematically applied prior to executing the co-word clustering analysis:

Standardized Target Keyword (Parent Node)	Synonymous Raw Extracted Terms Merged (Child Nodes)	Methodological Rationale
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Academic Performance	Student Academic Performance, Academic-Performance, Academic Achievement, Achievement, Student Performance, Students' Performance, Performance, Academic Performances, Academic-Achievement, Failure, Student Success, Academic Success, Academic-Success, Success, Student-Success, Academic Student Success, Students Performance	Consolidates highly correlated outcome indicators and semantic variations into a singular baseline node to accurately measure the network weight of student progression metrics.
Dropout Prediction	Student Dropout Prediction	Isolates predictive modeling attempts targeted specifically at student attrition from general student lifecycle events to ensure structural specificity.
Student Dropout	Dropout, Dropouts	Eliminates basic pluralization discrepancies and syntactic fragmentation to prevent artificial inflation of distinct nodes representing student withdrawal.
Student Attrition	Attrition	Standardizes specialized institutional research vocabulary to maintain alignment with broad educational retention and drop-out studies.
Student Retention	Retention	Resolves lexical isolation by grouping standard baseline operational goals regarding institutional commitment to persistence.
E-Learning	Online Learning, Online, E-learning, E -Learning, Electronic Learning, Distance Education, Distance Learning, Online Education	Harmonizes non-contiguous instructional modalities and minor punctuation/spacing anomalies
Virtual Learning Environment	Virtual Learning Environment (VLE), Virtual Learning System, Virtual Learning	Synchronizes platform architecture definitions and acronym tags to provide a uniform conceptual node for digital space variables.
Higher Education	Higher-Education, Education, Higher Education Institutions, Higher Education Institutions (HEIS), Postsecondary Education, University, Universities, College, Undergraduate Education, School	Clusters broad institutional contexts and demographic levels to isolate structural trends occurring at the university level while removing minor hyphenation artifacts.
Educational Data Mining	Educational Data Mining (EDM), Data Mining	Collapses methodologically redundant parent-child concepts and acronym variants to stabilize the centrality measures of technical data extraction methods.

Learning Analytics	Analytics, Data Analytics, Predictive Analytics, Learning Analytics (LA), Academic Analytics	Synthesizes broad analytical frameworks parsing student data footprints, correcting for localized naming choices and sub-specialty overlap.
Machine Learning	Machine Learning (ML), Machine Learning Algorithms, Machine Learning Models, Interpretable Machine Learning	Unifies theoretical, structural, and descriptive machine learning terminology into a single functional methodology token to avoid fragmentation in basic themes.
Artificial Neural Networks	Neural Networks, Neural-Network, Neural-Networks	Counteracts punctuation variations (hyphenated vs. unhyphenated strings) to ensure correct network co-occurrence mapping for deep modeling frameworks.
Generative Ai	Generative Artificial Intelligence, ChatGpt	Merges specific commercial and technical instances into their overarching paradigm class, allowing for an accurate macro-assessment of advanced AI trends.
Students	Student, University Students, College-Students, University-Students, Undergraduate	Grouping basic demographic subjects under a uniform node to strip out descriptive noise and stabilize network focus on operational methodologies.
System	Systems	Neutralizes standard grammatical inflections (singular vs. plural forms) to maintain proper co-word cluster boundaries.
Deep Learning	Deep Learning Techniques, Deep Learning Approach	Groups procedural and algorithmic phrasing variants into a single conceptual asset, adjusting for stylistic differences across papers.
Ensemble Learning	Ensemble, Stacked Ensemble, Boosting Ensemble Technique, Ensemble Selection	Groups distinct sub-algorithms and architectural strategies into a cohesive high-level node representing unified model combination methods.
Explainable Artificial Intelligence	Explainable Ai, Explainable Ai (XAI), Explainable Artificial Intelligence (XAI)	Resolves structural acronym fragmentation across emerging transparent modeling vocabularies to accurately assess the rise of ethical AI.
Learning Management System	Learning Management Systems, Learning Management System (LMS), Learning Management Systems (LMS), LMS, Moodle, LMS Data, Moodle Logs, LMS Log	Concentrates trace-log indicators, digital footprints, and specific software engines into an infrastructure node, resolving severe multi-acronym fragmentation.
Artificial Intelligence,	Artificial-Intelligence, Ai, Artificial Intelligence (AI), AI in Education	Consolidates general domain tags, sub-context application boundaries, and common abbreviations to

Predictive Modelling	Predictive Modeling, Predictive Models, Predictive Model, Prediction, Models, Model	accurately capture macro-level technological themes. Eliminates multi-word spellings variations (British vs. American English syntax like <i>modelling</i> vs <i>modeling</i>) and collapses pluralized nouns to prevent structural inflation and ensure the core statistical prediction node reflects accurate domain density.
MOOC	MOOCS, Massive Open Online Course, Massive Open Online Courses	Standardizes acronym variants and full-text expressions across both singular and plural forms to centralize the technological theme of large-scale open digital instructional delivery.
Early Warning Systems	Early Prediction, At-Risk, Students at Risk	Harmonizes broad descriptive student vulnerability states (<i>at-risk</i>) and technical forecasting milestones (<i>early prediction</i>) into a unified structural node reflecting proactive pedagogical mitigation frameworks.

3. COMPUTATIONAL EXECUTION ENVIRONMENT & CODE SYNTAX (R PACKAGE)

The computational workflow was processed using R (Version 4.5.3) and the bibliometrix package (Version 5.0).