SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 1.1, (2026), pp. 961-987
Open Access. Online & Print

DOI: 10.5281/zenodo.11425175

INTEGRATING AI AND LEARNING ANALYTICS IN TEACHER DECISION-MAKING: A BIBLIOMETRIC STUDY (2015–2025)

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Received: 11/11/2025
Accepted: 18/12/2025

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ABSTRACT

Teacher decision-making, recognized as "the basic teaching skill" since Shavelson's foundational work, has evolved dramatically with artificial intelligence (AI) and learning analytics (LA) integration. This bibliometric study examines the research landscape through comprehensive analysis of 318 publications from Scopus spanning 2015-2025, using VOSviewer and R Studio biblioshiny to analyze publication trends, geographic distribution, thematic structures, and citation networks. The analysis reveals a four-phase development pattern culminating in exponential growth in 2024 (163% increase), indicating critical achievement. Geographic analysis shows concentrated research activity in the USA (49.4%), China (39.9%), and India (37.1%), raising concerns about cultural biases and global applicability. Thematic mapping identifies five interconnected research clusters demonstrating successful integration of technological capabilities with educational theory: pedagogical implementation, computational analysis, systematic integration, learner-centered perspectives, and advanced analytics. Co-citation analysis reveals four collaborative research communities bridging technical and educational domains, with motor themes (machine learning, data mining) driving field advancement while basic themes (students, decision making) require deeper development. Citation patterns indicate that research quality and international collaboration significantly enhance impact, with collaborative publications receiving 35% more citations. The findings demonstrate successful evolution toward human-AI collaboration models that augment rather than replace teacher expertise, though challenges persist in geographic equity and practical implementation across diverse educational contexts.

KEYWORDS: Artificial Intelligence, Learning Analytics, Teacher Decision-Making, Bibliometric Analysis, Educational Technology, Human-AI Collaboration.

1. INTRODUCTION

Teaching, fundamentally characterized as a complex activity that requires a combination of different knowledges, attitudes, skills and values (Unciti, 2023), demands continuous decision-making that occurs within contexts of increasing complexity, where educators must navigate high student ratios and diversity, new socializing functions that are now required of teachers, and major changes in education. The foundational recognition by Shavelson (1973) that decision-making constitutes "the basic teaching skill" and Hunter's (1979) assertion that "teaching is decision making" has evolved into sophisticated frameworks acknowledging the multidimensional nature of educational choices.

Teacher decision-making stands at the heart of educational effectiveness, encompassing critical choices about when to intervene with struggling students, how to adapt instruction to meet diverse learning needs, and how to personalize feedback to maximize individual growth. It is influenced by multiple interconnected factors including professional experience (McCarty et al., 2021), psychological elements (McMillian, 2003), instructional environments (Marschall et al., 2024; Xu & Stefaniak, 2024), and collaborative opportunities (Pashiardis, 1994). While experienced teachers demonstrate greater flexibility and learner-centered approaches, novice teachers depend more heavily on predetermined instructional frameworks (Westerman, 1991). Their daily pedagogical choices are significantly affected by emotional well-being and mental capacity (McCarty et al., 2021), with practitioners frequently relying on instinctive judgment rather than systematic data analysis to guide their instructional decisions (Vanlommel & Schildkamp, 2019). This reliance on intuition, while valuable, becomes increasingly insufficient in complex educational environments where data-driven insights could significantly enhance decision accuracy and student outcomes, underscoring the urgent need for technological solutions that can augment human judgment with systematic analytics. These data-driven approaches enable teachers to move beyond what Sugar et al. (2004) identified as primarily "personal decisions" based on individual attitudes, toward more systematic and objective evaluation of educational situations.

While Shulman (1987) conceptualized the Model of Pedagogical Reasoning and Action which describing teaching as a systematic six-step operational process encompassing comprehension, transformation, instruction, evaluation, reflection, and new comprehension that requires educators to navigate intricate cognitive demands in real-time educational contexts. Skeel (1989) further emphasized that technology should serve as a tool to develop and enhance teachers' decision-making, enabling them to practice and refine complex pedagogical choices in their teaching process. Building upon this foundational understanding, contemporary Artificial Intelligence (AI) and Learning Analytics (LA) have evolved beyond simulation-based training to provide real-time, data-driven support for active pedagogical decisions. AI and LA integration in educational decision-making offers substantial benefits including enhanced personalization of learning experiences (Nazaretsky, Bar, et al., 2022; Ouyang et al., 2023; Selwyn, 2022), improved operational efficiency through task automation (Alotaibi, 2024; Alwaqdani, 2024), and data-driven insights that support informed pedagogical decisions about planning and interventions (Alotaibi, 2024; Maqoqa, 2025; Sajja et al., 2023).

AI and LA tools enhance teacher pedagogical decisions through three critical functions. First, student clustering and analytics that identify learning needs for targeted instruction (Alotaibi, 2024; Nazaretsky, Bar, et al., 2022; Sajja et al., 2023; Vorobyeva et al., 2025). Second, engagement and feedback analysis that provides real-time insights about student motivation and preferred activities (Dann et al., 2024; Wiedbusch et al., 2022). Third, adaptive content delivery that automatically adjusts materials to individual progress and preferences (Dann et al., 2024; Voicu, 2025; Vorobyeva et al., 2025). Additionally, AI and LA enhance teacher operational efficiency by automating time-consuming administrative tasks including grading and assessment, attendance tracking, scheduling and resource allocation, and admissions reporting (Ahmad et al., 2022; Ajuwon et al., 2024; Mukkala et al., 2025; Arya & Verma, 2024).

However, these advantages are accompanied by significant challenges, particularly the need for extensive professional development to help teachers effectively interpret and integrate analytics into their practice (Celik, 2023; Tammets & Ley, 2023), alongside persistent concerns about data privacy, security, and algorithmic bias that may undermine trust in AI-generated insights (Karakuş et al., 2025; Wang, 2021). As Floridi et al. (2018) also observe, there remains ongoing debate about when and where AI technologies are appropriate for use, or indeed, whether they are appropriate at all in educational contexts (Cukurova et al., 2019), highlighting the need for careful consideration of how these technologies can best serve educational goals. This complex landscape of opportunities and obstacles highlights the critical importance of thoughtful implementation strategies that maximize technological benefits while addressing legitimate concerns about educational equity, professional autonomy, and data protection. This leads us to argue that AI and LA should serve as an augmentative tool that enhances rather than replaces human expertise in educational settings. Therefore, the complexity of this intersection necessitates systematic investigation to understand the current research landscape, identify key trends and influential contributions, and map the evolution of this critical field.

Through comprehensive bibliometric analysis, this study aims to illuminate who is conducting research at this intersection, where these investigations are taking place, what methodological approaches are being employed, and how this field is evolving in a decade to now (2015-2025) to better support evidence-based educational practice in an increasingly data-rich and AI-enhanced learning environment, specifically in teacher decision making. The specific established research questions are presented.

RQ1. Research Landscape and Growth Dynamics

What are the bibliometric characteristics of research production in AI and learning analytics for teacher decision-making, including temporal growth patterns, geographic distribution, and source venues?

RQ2. Intellectual Structure and Thematic Organization

What is the conceptual structure of this research field as revealed through co-citation analysis, keyword co-occurrence networks, and thematic mapping?

RQ3. Research Impact and Knowledge Networks

How do citation patterns, author collaborations, and institutional networks shape the intellectual influence and knowledge diffusion in this domain?

The significance of this investigation extends beyond academic documentation to address critical gaps in understanding how AI and LA can effectively support teacher decision-making within contemporary pedagogical frameworks. Furthermore, this systematic mapping becomes essential for informing evidence-based implementation strategies that maximize LA and AI's augmentative potential while preserving essential human elements of teaching practice. This study will provide crucial guidance for navigating the tension between data-driven decision-making and intuitive pedagogical judgment identified by scholars like Sugar et al. (2004), while addressing Cukurova et al. (2019) call for transparent, human-centered AI approaches that enhance rather than replace teacher expertise, ultimately contributing to more effective and equitable integration strategies in educational settings.

2. LITERATURE REVIEW

This section provides a comprehensive overview of the theoretical foundations underlying AI and learning analytics in teacher decision-making. We examine the historical evolution of teacher decision-making research, explore the theoretical frameworks guiding AI and learning analytics implementation in educational contexts, and investigate how these technologies specifically enhance teacher decision-making processes. The review establishes the conceptual groundwork for understanding the intersection of artificial intelligence, learning analytics, and pedagogical decision-making.

2.1. Teacher Decision-Making Evolution

In the 1970s, scholars first began studying how teachers make decisions. Shavelson (1973) and Bishop (1976) catalyzed that decision-making has been at the heart of teaching. Moreover, scholars such as Clark and Peterson (1986) organized this early research into four main areas: how teachers plan lessons, how they think during teaching, how they explain student success or failure, and what beliefs guide their choices. However, Calderhead (1981) pointed out a problem with this early research. He argued that researchers were only looking at thinking processes but ignoring teachers' personal beliefs and the situations they worked in. This criticism led to a broader understanding that teachers do not just follow logical rules - they make decisions based on their values, experiences, and the communities they work with (Datnow & Hubbard, 2016; Lloyd, 2019).

Further to around the 1990s and 2000s, researchers became excited about using data to help teachers make better decisions. They believed that if teachers could systematically collect and analyze student information, they would make better choices about how to teach (Cooke et al., 1991; Evered, 1994). This approach, called data-driven decision making, seemed promising (Datnow & Hubbard, 2016; Villeneuve & Bouchamma, 2023). However, implementation challenges emerged as teachers experienced difficulty to use data in their daily work. The information was often difficult to understand, and it did not always help them decide what to do next. Even when schools provided computer systems to help with data analysis, many teachers still relied on their experience and intuition rather than formal data analysis (Kopcha et al., 2020). For instance, teachers commonly used student performance data to guide instructional changes, though most relied on ungraphed rather than visual data (Cooke et al., 1991; Kishor, 1994). However, while data format did not significantly affect judgments, trends and collection frequency strongly influenced decisions (Shavelson, 1973). Data-based activities promoted reflective practice (Rigopoulos, 2024), but simply providing more data did not automatically improve outcomes, emphasizing that context and quality of use are crucial (Brew & Saunders, 2020; Clough et al., 2009; Datnow & Hubbard, 2016; Rigopoulos, 2024).

As computers became more common in schools between 2000s to 2010s, researchers developed new tools to help teachers make decisions. These decision support systems could analyze large amounts of student data and provide recommendations (Bresfelean & Ghisoiu, 2010). Teacher dashboards emerged that showed student progress, attendance, and test scores in easy-to-read formats. However, studies found that most of these systems were quite basic. They could show what happened in the past, but could not predict what might happen next or suggest specific actions for teachers to take (Klein, 2007; Klein & Ronen, 2003). Many teachers still found these tools less helpful than their professional judgment and experience with students.

Recent research has taken a more balanced approach. Instead of trying to replace teacher judgment with data, researchers now focus on supporting teachers' natural decision-making abilities. They recognize that good teaching decisions come from combining multiple sources of information: student data, classroom observations, professional knowledge, and personal relationships with students (Ho, 2022; Smith et al., 2024). New technologies use such as Artificial Intelligence (AI) and Learning Analytics (LA), exist to provide better insights while respecting teachers' expertise (Kashif et al., 2024). In this scenario, research recognizes that teacher decision-making is complex and cannot be reduced to simple formulas. The field has moved from trying to make teaching more scientific to recognizing that teaching is both an art and a science. The best teachers integrate data, experience, professional knowledge, and understanding of their students' needs. Henceforth, the goal is to help teachers become more thoughtful and effective decision-makers who can adapt to their students' changing needs.

2.2. AI And Learning Analytics in Education

The integration of artificial intelligence (AI) and learning analytics (LA) in educational environments is grounded in several foundational learning frameworks that guide technological implementation. For instance, Self-regulated learning by Pintrich and De Groot (1990), dominates learning analytics research, though this dependency highlights gaps in innovative theoretical constructs that capture dynamic interactions between AI technologies and self-regulation (Chang & Sun, 2024; Prasad & Sane, 2024). Constructivist theories by Wilson (1996) further support AI integration through intelligent tutoring systems and collaborative platforms that facilitate active learning, with AI-powered chatbots engaging learners in critical thinking dialogues (Burton, 2024). Moreover, connectivism framework of Siemens (2005) provides a particularly relevant framework by emphasizing distributed knowledge across networks, with core principles including that learning occurs through connecting specialized nodes and may reside in non-human appliances (Corbett & Spinello, 2020; Herlo, 2017). This framework aligns with AI systems' capacity to connect learners to relevant resources and communities through distributed networks of people and technology.

Machine learning applications demonstrate practical theoretical implementation with 88% of studies utilizing supervised approaches for predicting student performance through decision trees, support vector machines, and random forests (Ersozlu et al., 2024). However, theoretical considerations reveal important challenges regarding learner agency. Current research indicates generic AI tools may reduce cognitive engagement and self-regulated learning, emphasizing the need for pedagogically optimized systems that prioritize learning processes over efficiency (Downes, 2022). In this scenario, Cognitive Load Theory informs AI applications through learning analytics using clustering algorithms to analyze student performance patterns for personalized interventions (Lan & Zhou, 2025). In conclusion, Computer-aided instruction systems application ideally through automated grading, interactive content, and intelligent tutoring features (Kaousar et al., 2008; Srivani & Manhar, 2020).

Educational data mining leverages sophisticated techniques for institutional decision-making, with artificial neural networks providing unbiased information extraction from student data through robust pattern recognition in complex educational domains (Okewu et al., 2021). The distinction between human-centered and AI-centered self-regulation remains critical, ensuring technological advantages enhance rather than undermine learner self-capacity (Chang & Sun, 2024). These theoretical foundations collectively demonstrate that effective AI integration requires careful balance between technological capabilities and fundamental learning processes to maximize educational outcomes while preserving learner autonomy and critical thinking development.

2.3. Enhancing Teacher Decision-Making Through Ai/La

The integration of artificial intelligence (AI) and learning analytics (LA) in educational settings draws from several theoretical frameworks that help educators navigate this complex technological landscape. The well-established Technological Pedagogical and Content Knowledge (TPACK) framework has evolved to include ethical considerations, creating what researchers call the Intelligent-TPACK model. This expanded framework recognizes that teachers must skillfully blend their understanding of technology, pedagogy, and subject matter while maintaining ethical standards in AI-enhanced instruction (Celik, 2023; Rasdiana et al., 2024). Educational frameworks like DigCompEdu and P21 have similarly been reimagined to address the unique digital competencies teachers need when working with AI tools (Ng et al., 2023). Professional vision models further emphasize how crucial it is for educators to integrate AI meaningfully into their ongoing professional development, enabling them to teach more adaptively and make better-informed decisions about their students' learning (Tammets & Ley, 2023). These frameworks collectively acknowledge that successful AI integration in education requires more than just technical know-how—it demands a thoughtful synthesis of pedagogical wisdom and technological capability.

In practice, AI and learning analytics are transforming how teachers understand and respond to their students' learning needs through sophisticated data analysis and personalized approaches. Teachers can now harness AI to examine detailed student performance data, creating opportunities for truly personalized instruction and more responsive curriculum development (Ahmad et al., 2022; Salas-Pilco et al., 2022; Wiedbusch et al., 2022). Meanwhile, machine learning algorithms work behind the scenes to process complex behavioral and statistical information, helping educators spot learning gaps that might otherwise go unnoticed and design targeted interventions (Salas-Pilco et al., 2022). The immediacy of real-time feedback systems, including innovative wearable awareness tools, gives teachers instant insights into student engagement levels, allowing them to adjust their instruction on the fly (Holstein et al., 2019). What makes these tools particularly valuable is when they are co-designed with teachers' input, ensuring they actually work in real classroom environments rather than just in theory (Holstein et al., 2019; Lawrence et al., 2024). AI-powered clustering algorithms can group students based on their specific learning needs, facilitating more targeted instruction and smooth transitions between individual and collaborative work (Ifenthaler & Schumacher, 2023; Lawrence et al., 2024), while predictive analytics help teachers anticipate exactly when students might need additional support (Ifenthaler & Schumacher, 2023; Salas-Pilco et al., 2022). The effectiveness of these technological advances ultimately depends on teachers' readiness to embrace AI—a readiness that encompasses their cognitive understanding, practical abilities, vision for integration, and ethical awareness—all of which predict how well they will innovate and make data-driven instructional decisions (Wang et al., 2023). Building trust in these AI systems through comprehensive professional development and transparent decision-making processes remains essential for widespread adoption (Alwaqdani, 2024; Nazaretsky et al., 2022).

3. METHOD

This section outlines the systematic bibliometric methodology employed to analyze the research landscape of AI and learning analytics for teacher decision-making. We detail the research design incorporating established bibliometric techniques, describe the comprehensive literature search and identification process, specify the inclusion and exclusion criteria applied during study selection, and explain the data screening procedures and analytical approaches used to examine 318 publications spanning 2015-2025

3.1. Research Design with Bibliometric Techniques

The design systematically applies document **co-citation** analysis as conceptualized by Small (1973) to identify core knowledge clusters by examining how frequently pairs of documents appear together in reference lists, revealing conceptual relationships and intellectual connections within the research domain. This approach builds upon and complements Kessler's (1963) earlier foundational work on bibliographic coupling, where two documents are considered coupled if they both cite one or more documents in common, with coupling strength increasing with the number of shared citations. While Kessler's bibliographic coupling provides a retrospective view of document similarity, Small's co-citation analysis offers a forward-looking assessment that can change over time as documents receive future citations, making it a dynamic classification system. Extending this foundation, the framework simultaneously employs author co-citation analysis developed by White and Griffith (1981) to map the field's intellectual structure by analyzing citation patterns among influential scholars, uncovering research traditions and knowledge networks that shape the discipline. This author-level analysis was later enhanced by Zhao and Strotmann (2008) who combined White and Griffith's work with Kessler's concepts to develop author bibliographic coupling analysis, creating a comprehensive approach to understanding both document and author relationships. The framework is further completed through keyword **co-occurrence** analysis following Zupic and Cater's (2015), which establishes thematic relationships by examining frequently co-occurring terms in titles, abstracts, and keywords, providing insights into the field's conceptual structure and emerging research trends that complement the citation-based approaches developed by the earlier scholars.

3.2. Literature Search and Identification

We selected Scopus as our primary databases because they contain high-quality academic sources and work well with bibliometric analysis tools like VOSviewer and the R Studio biblioshiny. Our search covered publications from 2015 to 2025 to capture recent developments in how AI and learning analytics support teacher decision-making in educational settings.

To develop our search strategy, we first analyzed frequently used keywords in existing research and identified nine key terms: "artificial intelligence," "machine learning," "learning analytics," "educational data mining," "teacher," "decision-making," "personalization," "adaptive learning," and "predictive analytics." We combined these terms into a comprehensive search query for Scopus.

TITLE-ABS-KEY((("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network" OR "intelligent system*" OR "automated" OR "algorithm*") AND ("learning analytics" OR "educational data mining" OR "academic analytics" OR "data-driven" OR "predictive analytics" OR "educational analytics" OR "learning data" OR "student data")) AND ("teacher*" OR "educator*" OR "instructor*" OR "faculty" OR "teaching staff" OR "academic staff") AND ("decision making" OR "decision-making" OR "pedagogical decision*" OR "instructional decision*" OR "educational decision*" OR "teaching decision*" OR "classroom decision*" OR "assessment decision*" OR "intervention*" OR "personali*ation" OR "adaptive learning" OR "individuali*ed instruction"))*

This approach helped us systematically identify studies that specifically examine how AI and learning analytics technologies assist teachers in making better educational decisions.

3.3. Inclusion and Exclusion Criteria

Six inclusion criteria were applied: first, studies must focus on AI or learning analytics applications that support teacher decision-making in educational settings. Second, participants should be teachers, educators, or instructors in formal educational environments (schools, universities, or training centers). Third, only peer-reviewed journal articles, conference papers, and book chapters were included. Fourth, all publications must be peer-reviewed to ensure quality. Fifth, studies published between 2015 and 2025 were selected to capture recent developments. Sixth, documents must be written in English for consistent analysis.

Five exclusion criteria were used: first, studies where AI or learning analytics were only briefly mentioned or discussed theoretically without practical application were excluded. Second, research focusing on non-educational contexts or non-teaching professionals (such as corporate trainers or technology vendors) was excluded. Third, papers that mentioned AI or learning analytics in abstracts but did not study related to teacher decision making were excluded. Fourth, conference abstracts, editorials, and non-peer-reviewed publications were excluded. Fifth, non-English publications were excluded to maintain consistency in analysis.

3.4. Data Screen

Figure 1 presents the PRISMA flow diagram detailing our systematic literature selection process. The initial database search yielded 740 potentially relevant records, from which we removed 3 duplicates, resulting in 737 unique studies.

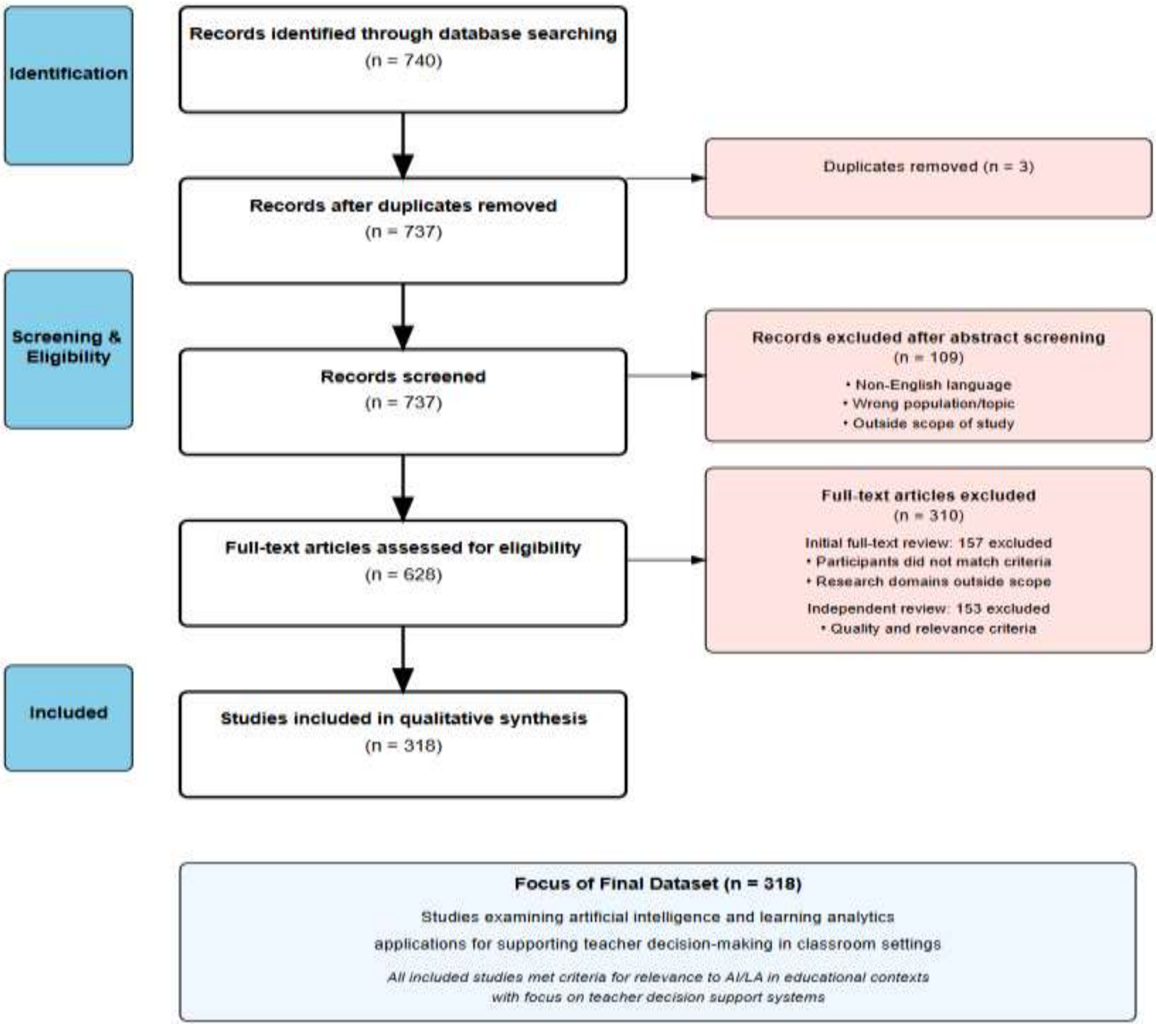

Figure 1: PRISMA Flow Diagram of Study Selection Process From 2015-2025.
(This Systematic Flowchart Displays the Screening Methodology from Initial Database Search to Final Dataset Selection, Ensuring Transparency and Methodological Rigor in Study Identification and Inclusion)

Abstract screening using predetermined inclusion criteria led to the exclusion of 109 studies due to language restrictions (non-English), population misalignment, or topical irrelevance to our research focus. The remaining 628 articles underwent rigorous full-text assessment by two independent reviewers who evaluated participant demographics, methodological quality, and research domain alignment, resulting in the exclusion of 157 studies that failed to meet inclusion criteria or lacked sufficient methodological rigor.

A final independent verification round was conducted to ensure inter-rater reliability and minimize selection bias, leading to the exclusion of an additional 153 articles based on refined criteria application and quality thresholds. Our systematic three-stage screening process yielded a final dataset of 318 high-quality studies that specifically examine artificial intelligence and learning analytics implementations designed to enhance teacher decision-making capabilities in classroom environments. This rigorous selection methodology ensures that our final corpus represents the most relevant and methodologically sound research available, forming the empirical foundation for our comprehensive review and analysis of AI and learning analytics applications in educational contexts.

3.4. Data Extraction and Analysis

We extracted key bibliographic information from Scopus including document titles, author details, abstracts, keywords, citation counts, and institutional affiliations. Our analysis followed a two-phase approach to examine the research landscape comprehensively. In the first phase, we performed descriptive analysis to understand basic publication patterns. We used R Studio with the biblioshiny package to analyze publication trends over time and across different countries. Then, geographic visualizations and interactive maps were created using Tableau to show where research activity is most concentrated globally.

The second phase involved deeper network analysis to uncover relationships within the literature. We employed R Studio's biblioshiny and VOSviewer for bibliometric tools to examine how studies cite each other and identify clusters of related research topics through keyword co-occurrence analysis. This combined approach allowed us to both quantify publication patterns and visualize the intellectual structure of research on AI and learning analytics in teacher decision-making (Aria & Cuccurullo, 2017).

4. RESULTS

This section presents the comprehensive findings from our bibliometric analysis of 318 publications examining AI and learning analytics for teacher decision-making. We analyze the volume growth and temporal trajectory of research output, examine geographic and institutional distribution patterns, investigate citation analysis and research impact, and explore the conceptual and intellectual structure of the field through various network analyses and thematic mapping techniques.

4.1. Volume Growth and Trajectory Over Time

This subsection examines the temporal evolution of research output in AI and learning analytics for teacher decision-making, analyzing annual publication trends and geographic distribution patterns to identify growth phases and regional research contributions over the 2015-2025 period.

4.1.1. Year-Wise Growth of Articles

The annual production data (Figure 2) reveals a distinct four-phase evolution pattern in the field. The foundational phase (2015-2017) demonstrates minimal research activity with publications remaining consistently low (n=6-7) documents annually. The emergence phase (2018-2019) shows initial growth with publications (n=11) in 2018 before slightly declining (n=10) in 2019. The acceleration phase (2020-2023) begins with a notable spike to (n=20) in 2020, followed by a temporary dip to (n=18) in 2021, then steady growth through (n=26) documents in 2022 and (n=35) in 2023.

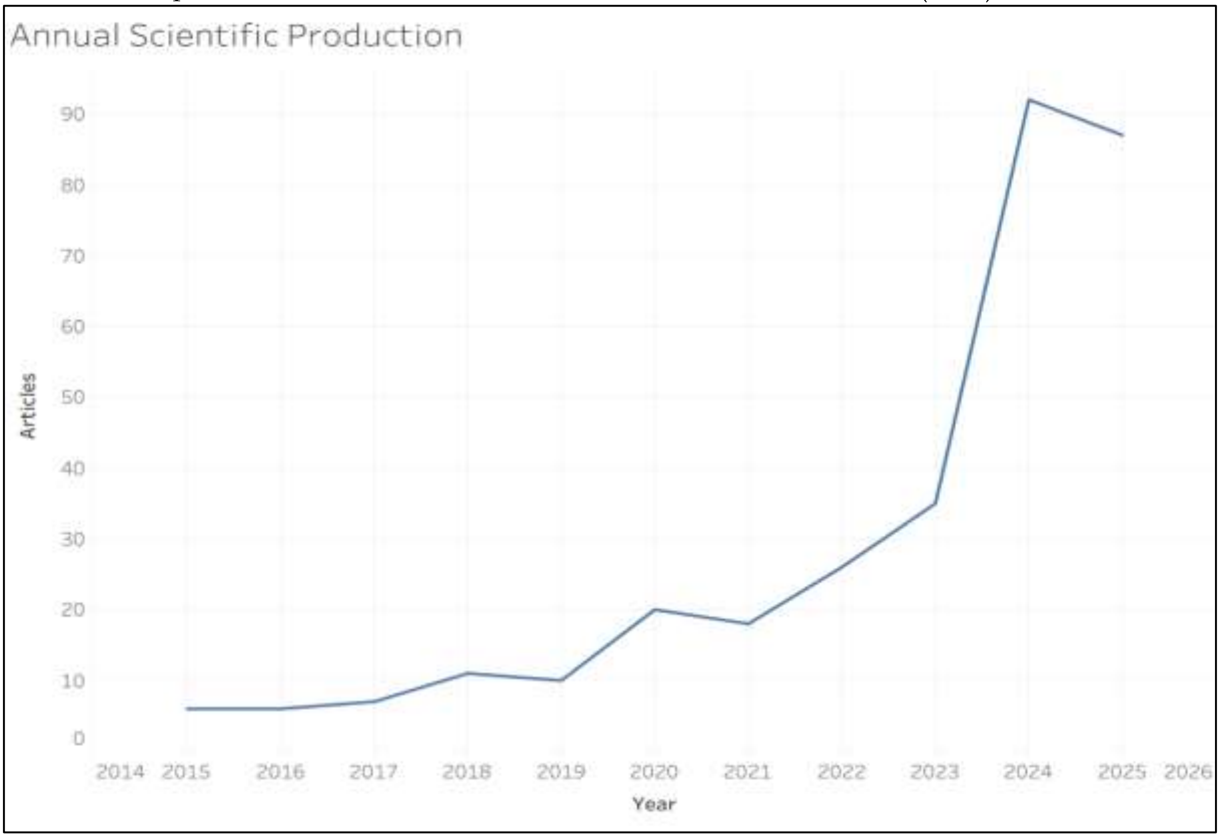

Figure 2: Annual Scientific Production in AI And LA For Teacher Decision-Making From 2015-2025.
(This temporal chart tracks yearly publication volume to reveal growth patterns and field development phases over the decade-long study period)

The 2024 data demonstrate a notable increase in research output with publications rising to (n=92) documents—a 163% increase from the previous year, representing the largest annual growth observed in our dataset. This publication pattern may indicate growing academic interest in AI and learning analytics for teacher decision-making, though the factors driving this increase warrant further investigation beyond our bibliometric scope. The reduction to (n=87) documents in 2025 appears to reflect incomplete data collection for the current year, as our analysis was conducted during 2025, and therefore should not be interpreted as indicative of field trends without additional temporal data.

4.1.2. Country's Production Over Time

The geographical distribution of research production (Figure 3) reveals significant variations in both research volume and temporal patterns across countries over the examined period. The United States demonstrates the highest cumulative production, with publications growing steadily from 5 in 2015 to 157 in 2025, showing particularly notable increases from 2020 onwards. China exhibits a distinctive growth pattern, beginning with zero publications from 2015-2017, followed by gradual emergence with 7 publications in 2018, and substantial acceleration from 2021 onwards, reaching 127 publications in 2025 to become the second-highest producer. India shows minimal early activity with only 1 publication in 2015, followed by marked acceleration from 2022 onwards, reaching 118 publications in 2024, representing the most rapid recent growth trajectory among all countries examined.

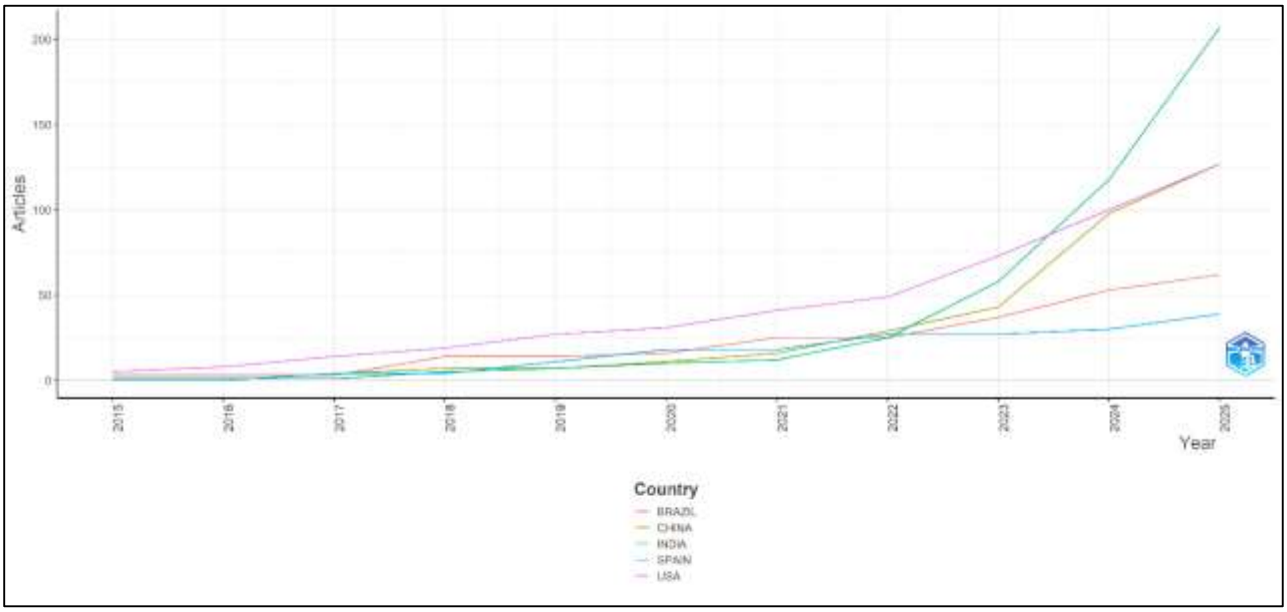

Figure 3: Top Five Countries Production Over Time in AI And Learning Analytics for Teacher Decision-Making From 2015-2025.
(This Longitudinal Analysis Shows Research Output Patterns Across Leading Nations to Identify Geographic Distribution and Temporal Engagement Variations)

Brazil and Spain demonstrate more moderate but consistent research activity throughout the period, with Brazil progressing from 3 publications in 2015 to 53 in 2025, and Spain growing from 1 publication in 2015 to 39 in 2025. The temporal patterns reveal a clear distinction between countries that maintained steady research activity from the beginning of the period (USA) versus those that show concentrated growth in recent years (China, India), resulting in a more distributed global research landscape by 2025 compared to the earlier period when research production was more concentrated among fewer countries.

4.2. Source Context Analysis

Our source distribution analysis illustrates the temporal evolution and publication venue dynamics in AI and learning analytics for teacher decision-making research from 2015 to 2025 (Figure 4). This period can be categorized into three distinct phases. The Early Stage (2015-2018) had minimal publication activity across all venues, with fewer than 5 publications annually in any single source.

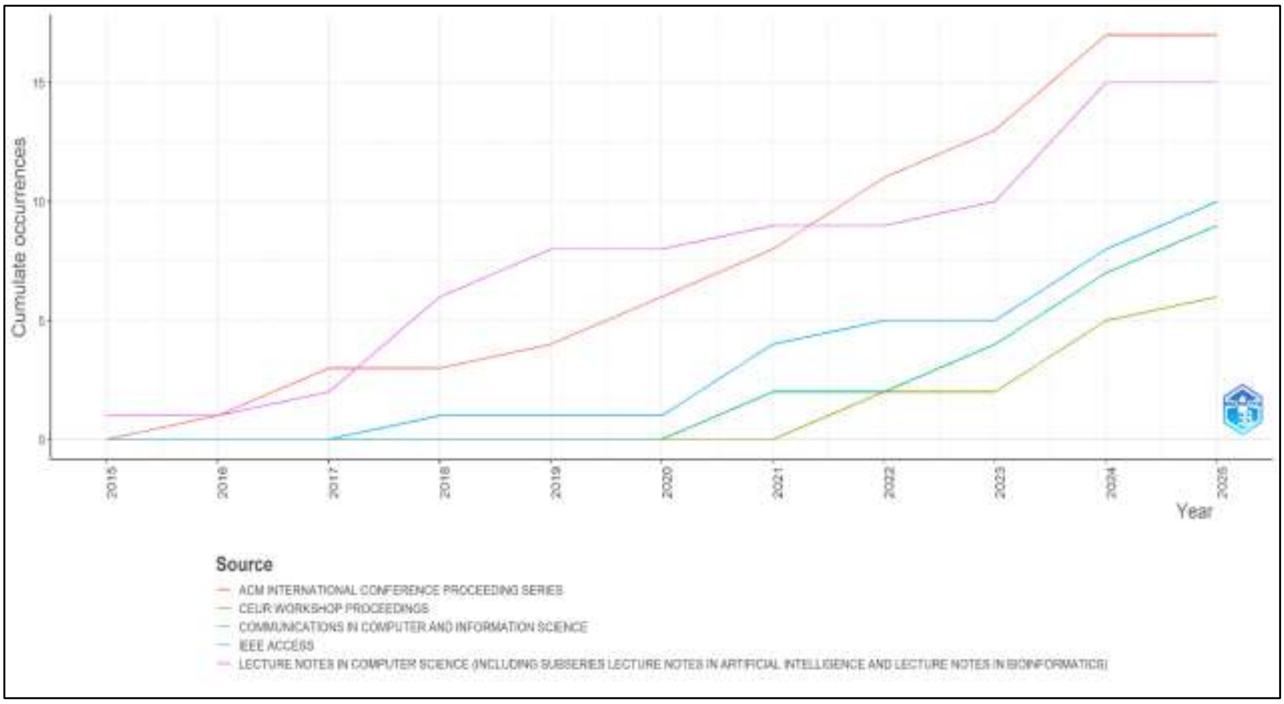

Figure 4: Source Distribution Analysis From 2015-2025.
(This Venue Analysis Displays Publication Patterns Across Academic Outlets to Understand Dissemination Channels and Knowledge Sharing Preferences in The Field)

The Growth Stage (2019-2022) marked gradual increases across multiple venues, with ACM International Conference Proceeding Series and IEEE Workshop Proceedings beginning to show consistent upward trends, reflecting increased academic interest and technological advancement in the field. The Acceleration Period (2023-2025) saw the most substantial growth, with ACM conferences reaching approximately 17 publications and IEEE workshops climbing to 15 publications, indicating growing research maturity and broader academic adoption. Throughout these periods, conference proceedings demonstrated consistent dominance over traditional journal publications in our dataset. ACM International Conference Proceeding Series showed steady growth from 2019 onwards, peaking in 2024-2025 with sustained high output. IEEE Workshop Proceedings followed a similar trajectory with notable acceleration from 2020.

Communications in Computer and Information Science remained relatively stable until 2022, then experienced marked growth. IEEE Access maintained modest but steady increases throughout the period, while Lecture Notes in Computer Science showed minimal activity until recent years.

The predominance of conference and workshop venues over journal publications in our analysis suggests this field prioritizes rapid knowledge dissemination and collaborative exchange typical of emerging technological domains.

4.3. Geographic And Institutional Distribution

This subsection analyzes the global landscape of research activity, examining both country-level production patterns and institutional contributions to understand the geographic concentration of research efforts and identify leading organizations in the field.

4.3.1. Country's Scientific Production

Our global distribution analysis (Figure 5) shows the geographic spread of AI and learning analytics for teacher decision-making research across the 318 documents analyzed. The United States leads with 157 publications (49.4% of total output), followed by China with 127 publications (39.9%) and India with 118 publications (37.1%). These three nations collectively account for the majority of research production in this field. Brazil contributes 53 publications (16.7%), representing significant activity in Latin America, while Australia provides 37 publications (11.6%) from the Oceania region.

The map demonstrates uneven distribution of research activity across continents relative to the total dataset. European countries display moderate participation, with the United Kingdom, Germany, Spain, and other EU nations contributing varying numbers of publications, typically representing 1-10% of the total 318 documents each. Most African countries show minimal representation, contributing less than 1% of total publications or no research output in this domain.

Figure 5: Leading Countries by Scientific Production From 2015-2025.
(This Global Map Visualizes Research Concentration Across Countries to Illustrate Geographic Distribution and Identify Regional Research Activity Patterns)

Asian countries present a mixed pattern, with high productivity concentrated in China and India while many other Asian nations contribute less than 5% of total research output. The visualization indicates that the top five countries (USA, China, India, Brazil, Australia) account for approximately 65% of all 318 documents, while the remaining 35% is distributed among numerous other countries with smaller individual contributions.

4.3.2. Leading Institution Over Time

The leading institutions in our analysis (Figure 6) reveal the temporal emergence and productivity patterns of leading research institutions in AI and learning analytics for teacher decision-making. The data shows that institutional engagement in this field has been concentrated primarily in the period from 2020 onwards, with minimal activity before this timeframe. Kohat University of Science and Technology demonstrates the earliest institutional entry, beginning research activity around 2020 and showing steady growth to reach approximately 9 documents by 2025. Central China Normal University exhibits the most dramatic institutional growth pattern, maintaining no research output until 2023, then experiencing rapid acceleration to reach approximately 13 articles by 2024, representing the highest institutional productivity in the dataset.

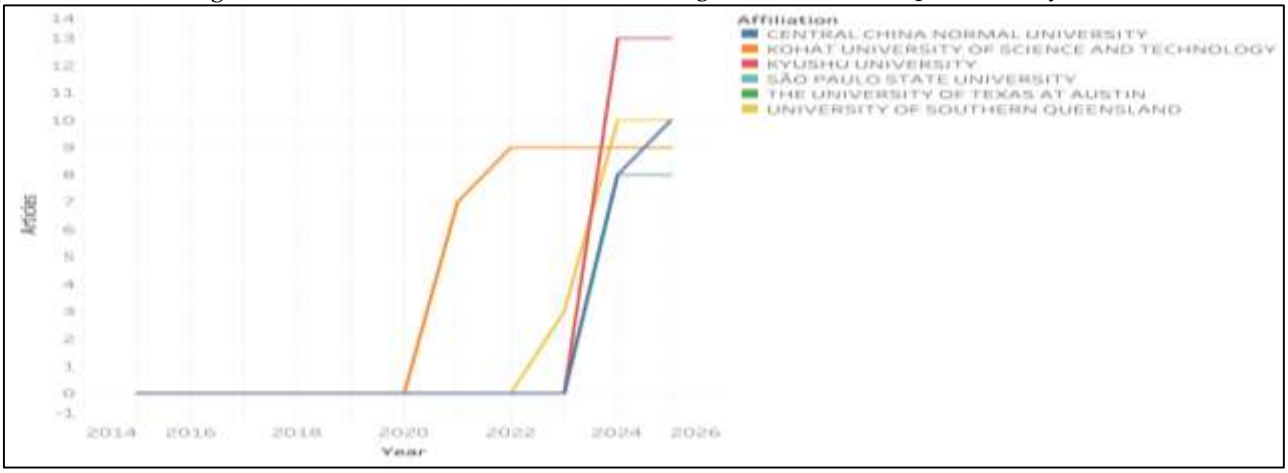

Figure 6: Leading Institutions Over Time From 2015-2025.
(This Timeline Tracks Institutional Research Productivity to Show the Emergence and Development of Leading Research Organizations in The Field)

Several institutions show concentrated research activity within specific timeframes. Kyushu University demonstrates sustained productivity from 2023 onwards, reaching approximately 10 articles by 2025. The University of Texas at Austin and University of Southern Queensland both exhibit similar patterns, beginning research contributions around 2023 and maintaining steady output through 2025, reaching approximately 8 documents each. São Paulo State University shows a distinctive pattern with research activity concentrated in 2024, reaching approximately 9 articles. The temporal distribution indicates that institutional engagement in this research domain has been largely concentrated in recent years, with most leading institutions beginning substantial research contributions only from 2020-2023 onwards.

4.4. Citation Analysis

Citation analysis is a valuable tool for studying academic communication, the interdisciplinary nature of a scientific field, and knowledge creation. Citations link documents, ideas, and arguments, allowing us to measure the influence of authors, institutions, and journals while tracking their impact over time.

4.4.1. Average Citation

Figure 7 shows that document citations fluctuated from 2015 to 2025, averaging 4.80 per article per year in 2015. The 2016-2020 period showed more variability, with citations declining in 2018 (1.83 citations per year). Citations increased significantly from 2019 to 2021, reaching 5.80 per year in 2021. High citation rates continued from 2015 to 2021, with a peak of 5.80 in 2021.

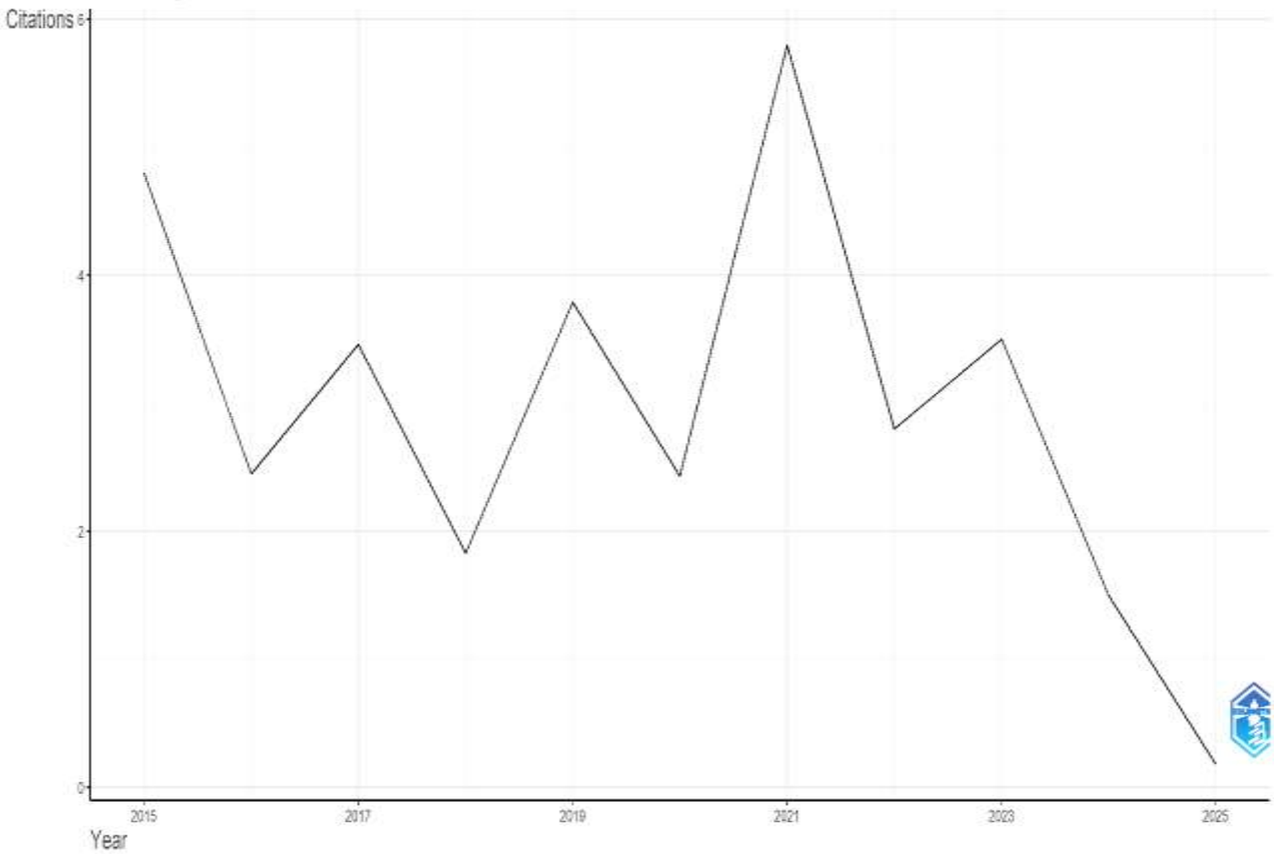

Figure 7: Average Citation Per Year From 2015-2025.
(This Temporal Analysis Displays Annual Citation Rates to Assess Research Impact Patterns and Identify Periods of High Scholarly Influence)

Our dataset reveals that the 318 articles show varying citation performance across publication years. The 6 documents from 2015 achieved the highest total citations per article (52.83), while the 18 documents from 2021 demonstrated the highest annual citation rate (5.80 per year). More recent publications show declining citation metrics, with 92 articles from 2024 averaging 3.00 total citations per article and 87 articles from 2025 averaging only 0.18 citations per article, reflecting insufficient time for citation accumulation.

4.4.2. Citation Based on Countries

Figure 8 presents the citation distribution across countries, revealing the global impact and influence of research contributions in AI and learning analytics for teacher decision-making.

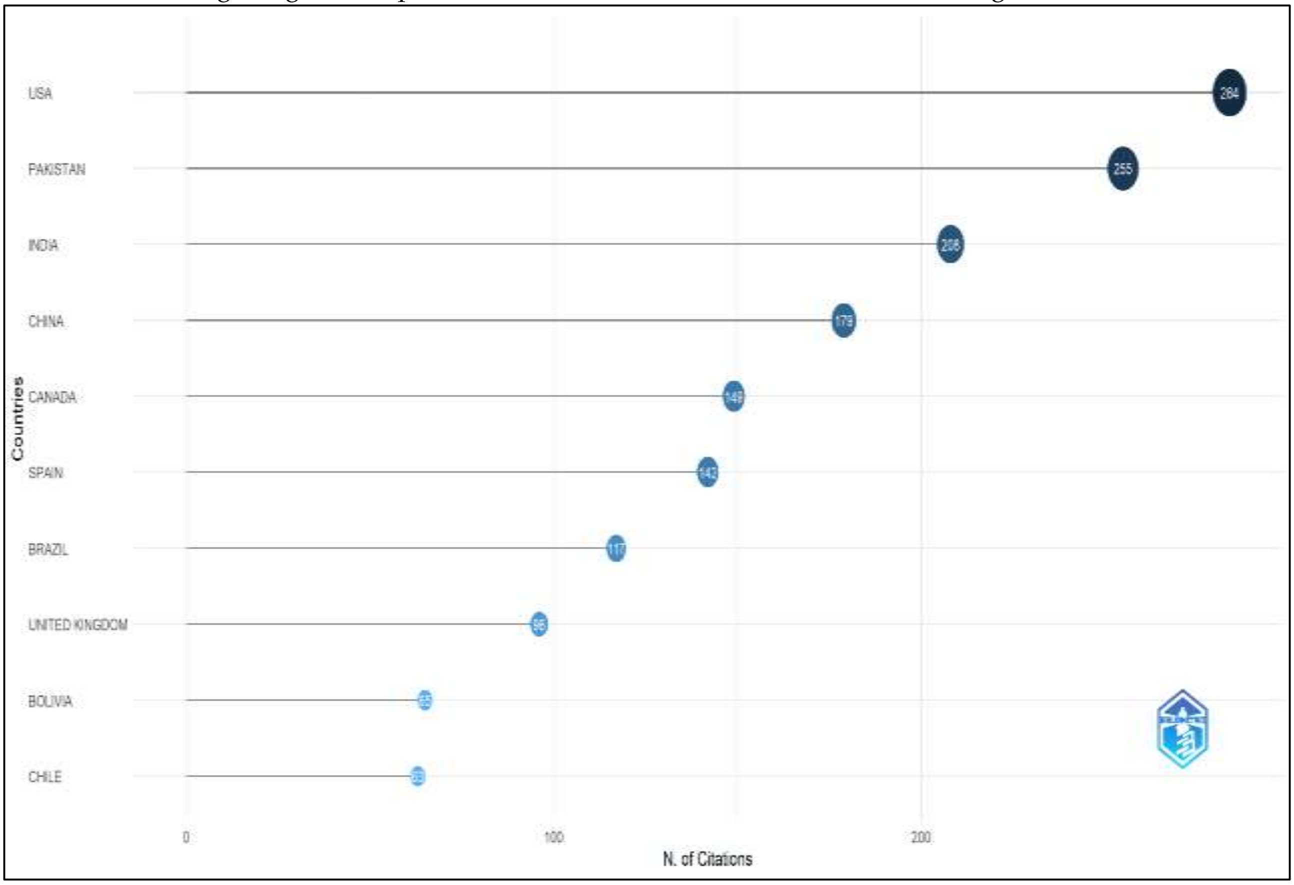

Figure 8: Top 10 Most Cited Countries From 2015-2025.
(This Ranking Shows Citation Impact by Country to Reveal Research Influence Patterns and Compare Scholarly Impact Across Nations)

Based on the total 1,831 citations across all countries, the United States demonstrates the highest citation impact with 284 total citations (15.5% of total citations), establishing its position as the most influential contributor to the field's scholarly discourse. Pakistan follows as the second most cited country with 255 citations (13.9%), indicating significant research influence despite having fewer total publications compared to other major producers. India ranks third with 208 citations (11.4%), while China accumulates 179 citations (9.8%), reflecting substantial scholarly impact from these Asian research contributors. The middle-tier countries show moderate but consistent citation levels, with Canada contributing 149 citations (8.1%), Spain with 142 citations (7.8%), Brazil with 117 citations (6.4%), and United Kingdom providing 96 citations (5.2%). Countries with emerging research presence include Bolivia (65 citations, 3.5%), Chile (63 citations, 3.4%), United Arab Emirates (51 citations, 2.8%), and Lithuania (45 citations, 2.5%). The remaining countries contribute between 1-43 citations each, representing less than 2.5% individually. The citation distribution pattern reveals that research influence does not directly correlate with publication volume, as demonstrated by Pakistan's high citation impact relative to its publication output. The data indicates that citation impact remains concentrated among a smaller number of countries, with the top ten countries (USA through Chile) accounting for 77.4% of total citations in the field, while the remaining 20 countries contribute only 22.6% of citations collectively.

4.4.3. Co-Citation

The co-citation network (Figure 9) reveals four distinct research communities that demonstrate varying approaches to integrating foundational educational theories within AI and learning analytics for teacher decision-making. The red cluster represents researchers focused on the technological knowledge component of TPACK, with tight citation patterns indicating collaborative development of computer algorithms and technical implementations that support educational applications. This community exemplifies the technological infrastructure necessary for effective TPACK integration while maintaining focus on educational rather than purely technical outcomes.

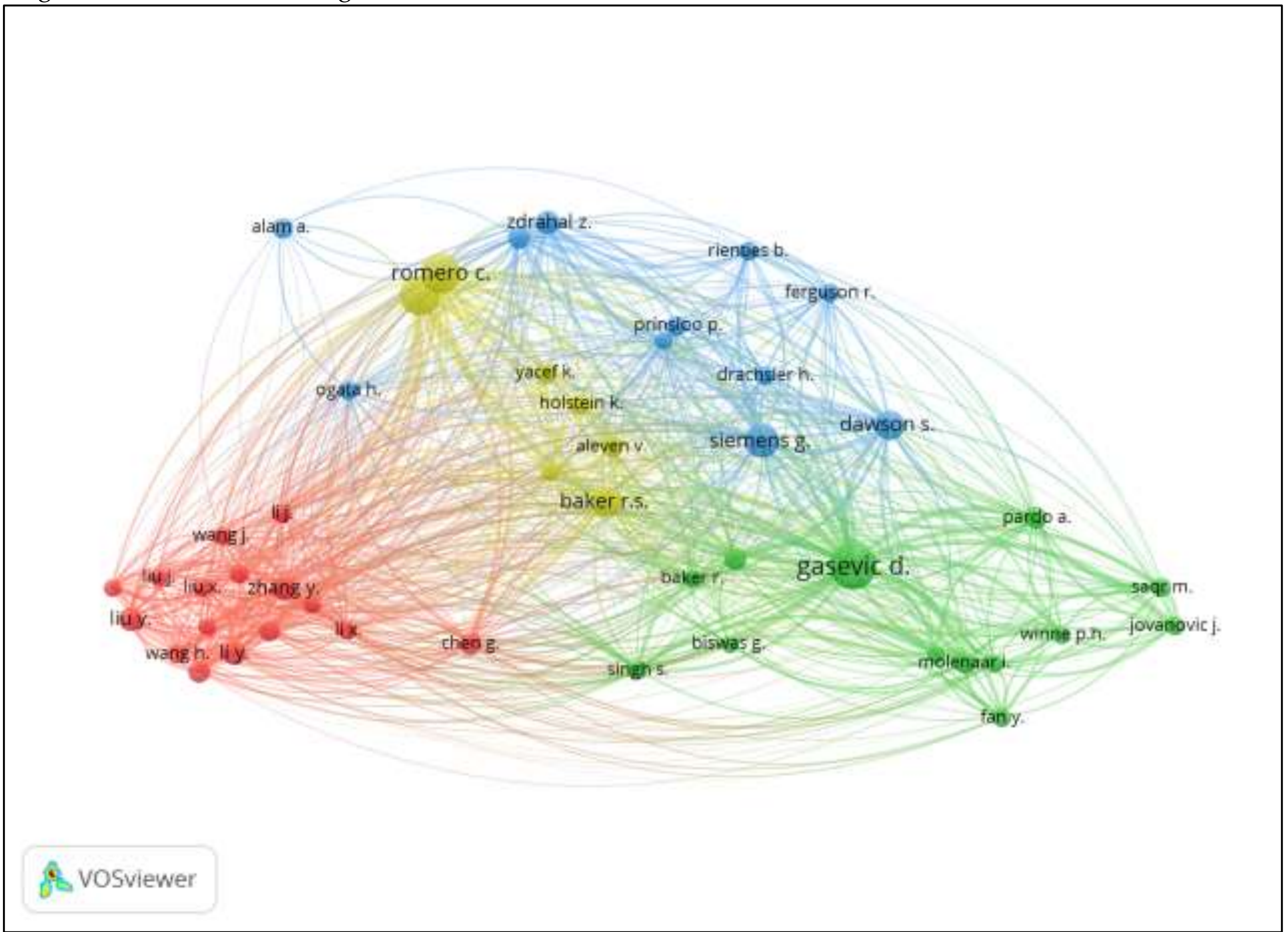

Figure 9: Co-Citation Network Analysis of Authors in Ai and Learning Analytics for Teacher Decision-Making From 2015-2025.
(This Network Visualization Maps Researcher Relationships Based on Co-Citation Patterns to Identify Collaborative Communities and Intellectual Connections)

The green cluster constitutes the most established research community with dense collaborative networks in learning analytics methods and educational data analysis, representing sophisticated integration of technological capabilities with pedagogical knowledge as envisioned in Intelligent-TPACK frameworks.

The blue cluster focuses on institutional applications and student support systems, demonstrating practical implementation of connectivism principles where AI systems function as institutional nodes connecting teachers to relevant student information and intervention strategies.

The yellow cluster bridges educational technology with teaching practice, embodying the critical synthesis between technological innovation and pedagogical reasoning model by ensuring AI tools support all phases from comprehension through reflection.

4.4.4. Global Cited Documents and Authors

Table 2 shows the top 10 most cited publications in our dataset, which include seven journal articles and three conference papers, organized into three distinct thematic areas.

The Predictive Analytics and Performance Modeling cluster, led by Xing et al. (2015) (246 citations), established TPACK integration principles by emphasizing AI systems must be "practical and understandable for users," while Adnan et al. (2021) (164 citations) demonstrated how machine learning supports Shulman's (1987) transformation and instruction phases through early intervention, exemplifying Siemens' (2005) connectivist vision of AI as specialized nodes enhancing teacher expertise.

The Educational Technology Integration cluster shows sophisticated theoretical synthesis, with Prieto et al. (2016) (94 citations) pioneering teacher-AI complementarity through multimodal analytics embodying Intelligent-TPACK framework, while Herodotou et al. (2019) (79 citations) advanced personalization frameworks supporting complete pedagogical reasoning cycles.

Table 1: Top 10 Global Cited Documents and Authors.

Authors	Title	Publishing Source	Total Citations
(Xing et al., 2015)	Building a student performance prediction model that is both practical and understandable for users	Computers in Human Behavior	246
(Adnan et al., 2021)	Predicting at-Risk Students at Different Percentages of Course Length for Early Intervention Using Machine Learning Models	IEEE Access	164
(D. H. Chang et al., 2023)	Sustainalism: An Integrated Socio-Economic-Environmental Model to Address Sustainable Development and Sustainability	Sustainability	141
(Alam, 2021)	Energy and Latency-Aware Computation Offloading and Resource Allocation for a Multi-Access Edge Computing-Enabled Heterogeneous Network	IEEE International Conference on Advanced Computing, Communication and Control, ICAC	125
(Prieto et al., 2016)	Multimodal Teaching Analytics: Automated Extraction of Orchestration Graphs from Wearable Sensor Data	ACM International Conference Proceeding Series	94
(Adnan et al., 2022)	Scaffolding computer programming languages learning with tailored English vocabulary based on learners' performance states	PeerJ Computer Science	91
(Prinsloo & Slade, 2017)	Exploring the role of power in data justice discourse in higher education	ACM International Conference Proceeding Series	88
(Herodotou et al., 2019)	Dimensions of personalisation in technology-enhanced learning: a framework and implications for design	British Journal of Educational Technology	79
(Bhutto et al., 2020)	Smart Wearable Devices for Primary Care Monitoring in Healthcare: Data Analysis and Teaching Model Construction	International Conference on Information Science and Communication Technology, ICISCT	67
(Cano & Leonard, 2019)	Early dropout prediction using data mining: a case study with high school students	IEEE Transactions on Learning Technologies	65

The Educational Data Ethics cluster addresses ethical framework integration through Prinsloo and Slade (2017) (88 citations) examining power dynamics challenging AI neutrality, Chang et al. (2023) (141 citations) developing sustainalism frameworks, and Alam (2021) (125 citations) addressing TPACK implementation prerequisites. Citation patterns reveal that sustained impact requires integrating multiple framework components rather than purely technical innovation, with temporal progression demonstrating systematic evolution toward comprehensive theoretical synthesis. However, few works achieve complete integration of TPACK principles with full pedagogical reasoning support and connectivist functionality, suggesting opportunities for deeper theoretical integration addressing geographic inequalities and cultural responsiveness challenges.

4.5. Conceptual And Intellectual Structure

This subsection investigates the impact and influence patterns within the research domain, examining citation metrics, geographic citation distribution, co-citation networks, and the most influential publications to understand knowledge flow and scholarly impact in the field.

4.5.1. Co-Occurrence Network

The VOSviewer analysis reveals five primary thematic clusters that demonstrate successful theoretical framework integration within AI and learning analytics for teacher decision-making (Figure 10). From 1,220 keywords appearing at least 137 times, the most frequently occurring terms with strongest link strength—"students" (199 occurrences, 1700 link strength), "teaching" (125 occurrences, 987 link strength), "decision making" (117 occurrences, 831 link strength), "machine learning" (77 occurrences, 681 link strength), and "data mining" (63 occurrences, 603 link strength)—reflect the field's evolution toward integrating technological capabilities with pedagogical expertise as envisioned in TPACK frameworks.

The red cluster (31 items) embodies the pedagogical knowledge component of TPACK, with "decision making," "teaching," and "data privacy" forming core nodes that connect to "distance learning," "collaborative learning," and "personalization." This cluster emphasis on the human-centered aspects of pedagogical reasoning, particularly the transformation and instruction phases where teachers adapt content for diverse learners while maintaining ethical considerations. The green cluster (31 items) represents the technological knowledge domain, featuring "data mining" alongside "student performance," "decision trees," and "predictive analytics," demonstrating how quantitative approaches support the evaluation and reflection phases of pedagogical reasoning cycle through systematic data analysis.

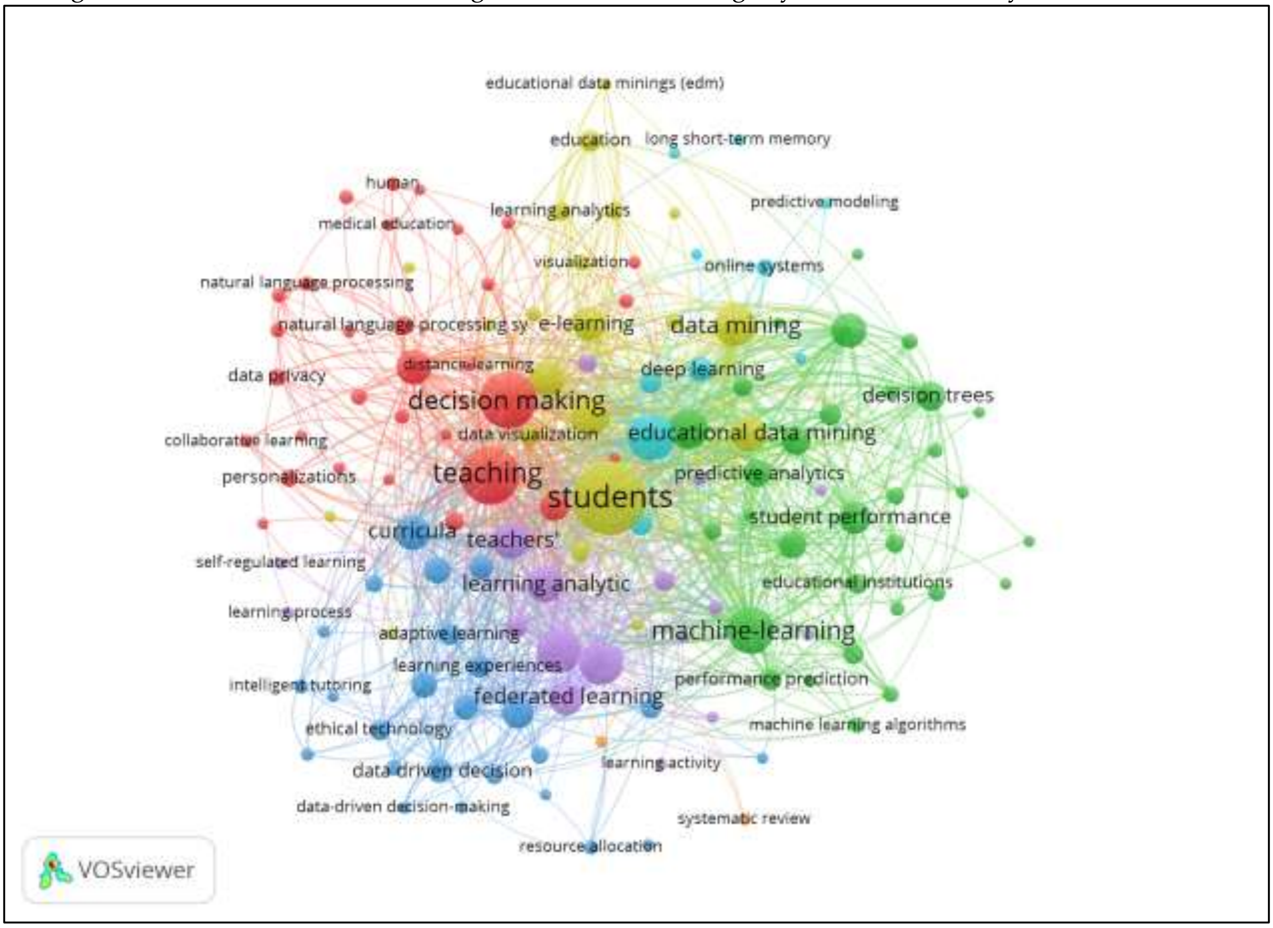

Figure 10: Co-Occurrence Network Analysis in AI And LA For Teacher Decision-Making From 2015-2025.
(This Keyword Network Reveals Five Thematic Clusters, Demonstrating Successful Integration of Technological Capabilities with Educational Theory Rather Than Disciplinary Separation)

The blue cluster (25 items) exemplifies Intelligent-TPACK integration through "federated learning," "adaptive learning," "intelligent tutoring," and "ethical technology," showing how advanced AI techniques are being ethically integrated with pedagogical practice. The yellow cluster (21 items) reflects connectivism principles through "students," "educational data mining," and "learning analytics," positioning learners as active nodes in distributed knowledge networks. The purple cluster (17 items) showcases sophisticated computational techniques supporting teacher decision-making, representing the successful synthesis of technological and pedagogical knowledge domains that characterizes mature TPACK implementation where AI systems function as augmentative tools enhancing rather than replacing human expertise in educational contexts.

4.5.2. Thematic Map

The thematic map classifies research themes based on centrality and density, revealing how different research areas align with theoretical framework development within AI and learning analytics for teacher decision-making (Figure 11).

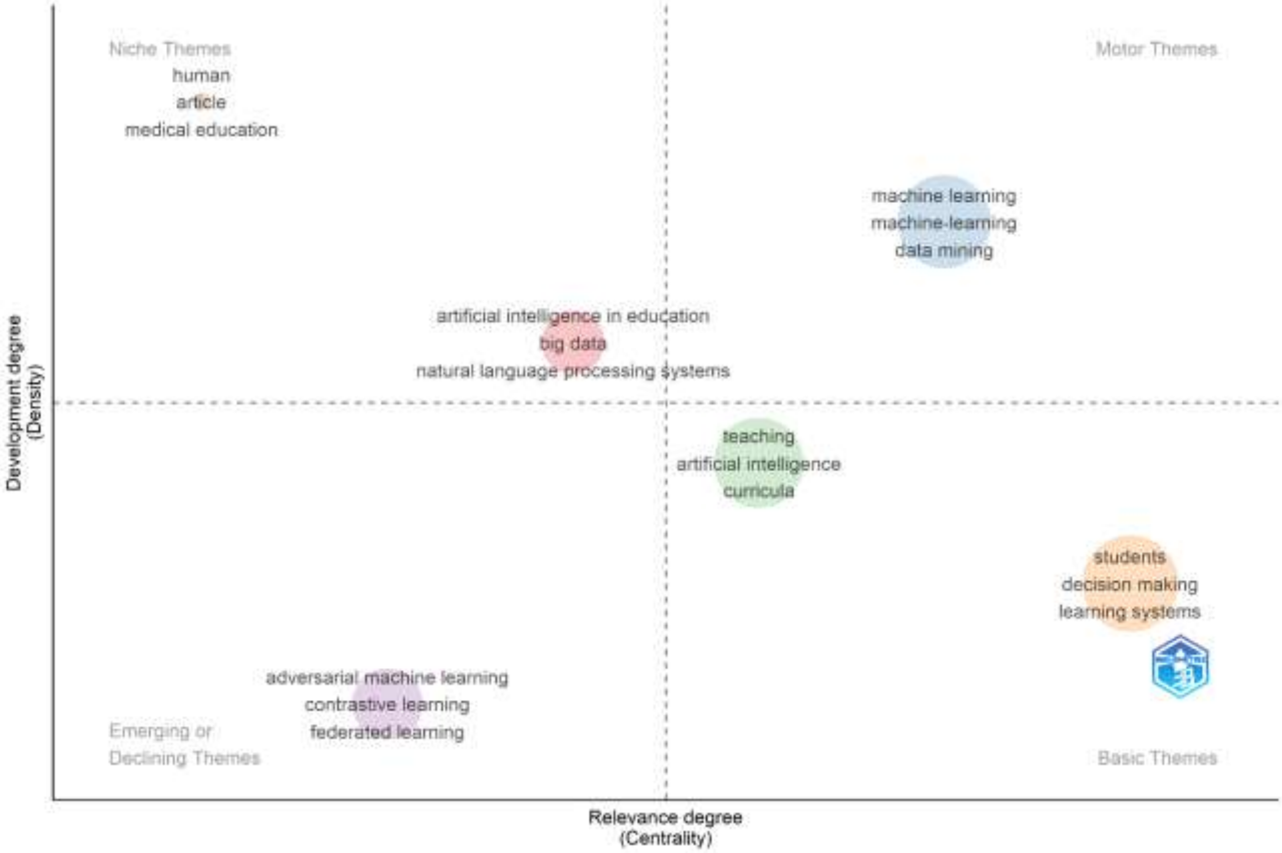

Figure 11: Thematic Map of Research Topics in AI And LA For Teacher Decision-Making From 2015-2025.
(This Strategic Diagram Positions Themes by Development Level, Identifying Mature Areas (Machine Learning), Basic Concepts Needing Development (Decision Making), And Emerging Opportunities (Federated Learning)

Motor Themes in the upper right quadrant represent mature technological knowledge components of TPACK that have achieved successful integration with pedagogical practices. Machine learning, and data mining demonstrate high centrality and density, indicating these technologies have evolved beyond isolated technical domains to become well-established tools supporting multiple phases of pedagogical reasoning cycle, particularly the evaluation and assessment phases where systematic data analysis enhances teacher decision-making capabilities.

Basic Themes including "students," "decision making," and "learning systems" reflect the enduring relevance of foundational recognition that decision-making constitutes "the basic teaching skill." Their high centrality but lower density suggests these fundamental concepts require deeper theoretical development to bridge technological capabilities with complete pedagogical reasoning framework. Niche Themes like "human" and "medical education" represent domain-specific applications of TPACK integration with high internal development but limited broader connections, while Emerging Themes such as "federated learning" and "adversarial machine learning" embody advanced connectivism principles where AI systems function as sophisticated nodes in distributed knowledge networks, though their low centrality indicates these approaches have not yet achieved mainstream integration within educational practice. The central positioning of "artificial intelligence in education," "teaching," and "curricula" demonstrates transitional areas bridging connectivisms' vision with practical TPACK implementation, serving as critical links between specialized AI technologies and mainstream pedagogical practice while supporting the evolution towardmIntelligent-TPACK framework that preserves human expertise in educational decision-making.

4.5.3. Factorial Analysis

The conceptual structure map (Figure 12) demonstrates successful theoretical framework integration within AI and learning analytics for teacher decision-making, with Dimension 1 and Dimension 2 explaining 44.43% and 26.64% of variation respectively. Rather than forming separate clusters, concepts appear as one interconnected group, validating the field's achievement of what Intelligent-TPACK framework envisioned where technological, pedagogical, and content knowledge domains are seamlessly woven together. This unified structure reflects successful implementation of connectivism principles, where diverse concepts function as interconnected nodes in a distributed knowledge network that enhances rather than fragments educational practice.

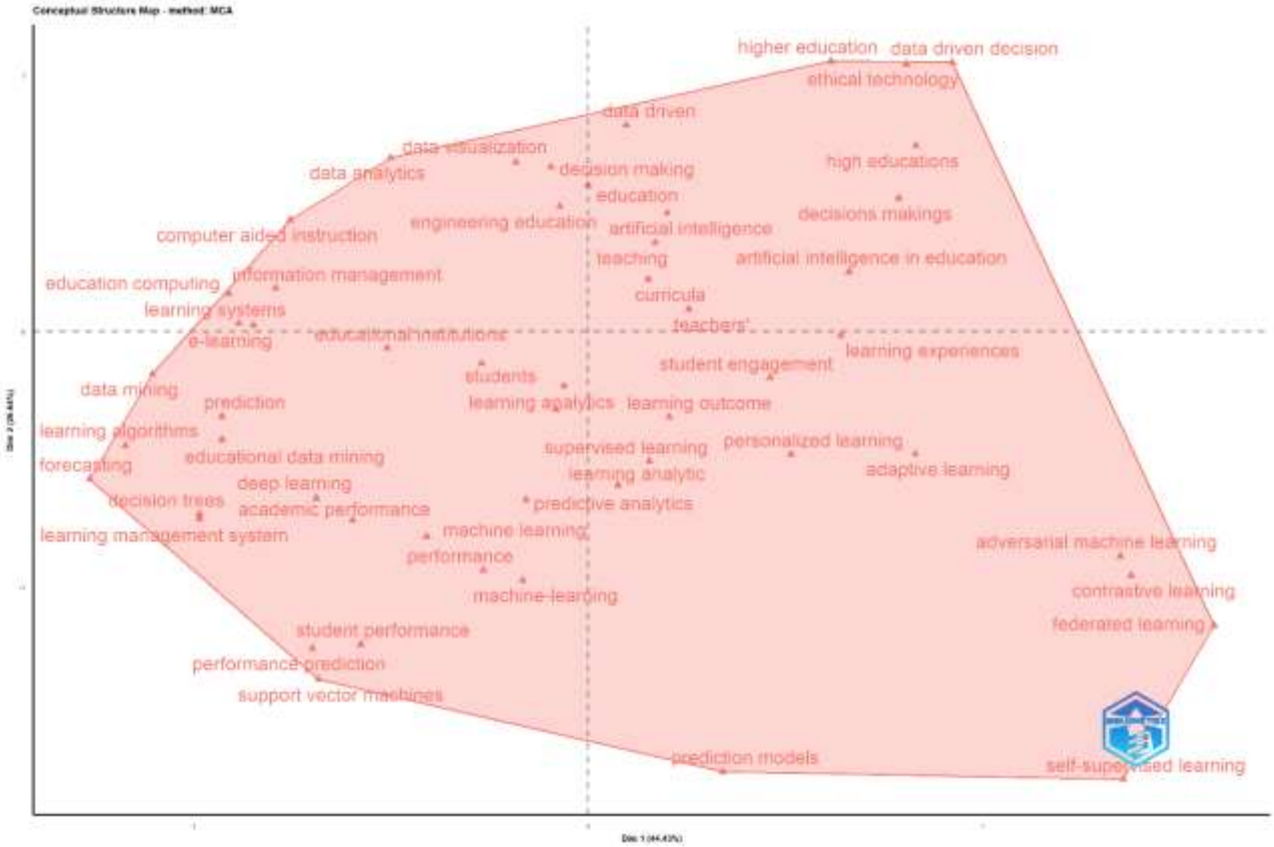

Figure 12: Conceptual Structure Map of AI And LA For Teacher Decision-Making (MCA Method) From 2015-2025.

(This Visualization Shows Concepts as One Interconnected Group Rather Than Separate Clusters, Demonstrating Successful Theoretical Framework Integration in The Field)

The positioning patterns reveal sophisticated theoretical synthesis supporting pedagogical reasoning model. Basic educational concepts—"students," "learning analytics," "education," and "teaching"—occupy the central position, representing the pedagogical knowledge core that connects all technological applications, validating that human-centered educational practice remains the organizing principle despite technological advancement. Technical terms like "machine learning," "data mining," and "predictive analytics" cluster near these educational foundations, demonstrating successful TPACK integration where technological knowledge serves pedagogical purposes rather than existing as separate technical domains. Advanced AI concepts like "federated learning" positioned at the periphery represent emerging connectivist applications that embody sophisticated distributed learning networks while maintaining focus on augmenting teacher capabilities. The bridging role of "ethical technology," "personalized learning," and "adaptive learning" exemplifies the field's evolution toward Intelligent-TPACK frameworks that preserve human expertise while leveraging technological capabilities to support all phases of pedagogical reasoning—from comprehension and transformation through instruction, evaluation, reflection, and renewed understanding.

5. DISCUSSION

This bibliometric analysis reveals how AI and learning analytics for teacher decision-making has evolved from Skeel's (1989) early vision of technology as a tool to develop teacher decision-making skills into a sophisticated domain that systematically operationalizes Shulman's (1987) Model of Pedagogical Reasoning and Action, Siemens' (2005) connectivism framework, and Celik's

(2023) Intelligent-TPACK model. The findings illuminate the field's theoretical transformation in addressing Sugar et al.'s (2004) challenges of moving beyond "personal decisions" toward systematic educational evaluation while preserving essential human expertise.

5.1. Research Landscape and Growth Dynamics

Our four-phase evolution pattern demonstrates progression from addressing Vanlommel and Schildkamp's (2019) observation that teachers frequently rely on instinctive judgment rather than systematic data analysis. The 2024 publication surge validates the critical intersection of AI and learning analytics for enhancing institutional performance, moving beyond Sugar et al.'s (2004) "personal decisions" toward systematic evaluation. However, this growth reveals concerning geographic inequality: USA, China, and India control 65% of research output, contradicting Mukkala et al. (2025) envision, as AI's democratizing potential for transformative education across diverse contexts.

The temporal evolution reflects successful implementation of Skeel's vision but extends toward comprehensive support for Shulman's six-step pedagogical reasoning process. Yet our findings reveal critical gaps in addressing Unciti (2023) identification as teaching's complexity requiring combination of different knowledges, attitudes, skills, and values. While research volume has grown exponentially, geographic concentration suggests limited progress in developing culturally responsive frameworks that Karakuş et al. (2025) emphasized as essential for ethical decision-making in diverse educational contexts. The conference predominance, while accelerating implementation of what Vorobyeva et al. (2025) described as personalized learning through AI approaches, may undermine the theoretical rigor necessary for addressing Lan and Zhou (2025) identified as dynamic interactions between AI technologies and self-regulated learning across different cultural contexts.

The geographic concentration contradicts the democratizing potential that multiple contemporary scholars identified for AI in education. While Alotaibi (2024) demonstrated AI and LMS integration's potential for higher education transformation, our findings suggest that current development patterns may exacerbate rather than address global educational inequalities by concentrating sophisticated capabilities in already-advantaged regions. This pattern undermines what Ahmad et al. (2024) described as data-driven artificial intelligence's comprehensive potential for educational improvement, and contradicts what Arya and Verma (2024) and Ajuwon et al. (2024) identified as AI's role in improving both efficiency and educational quality across diverse contexts.

The field has achieved technological sophistication but failed to address fundamental equity concerns. Contemporary research demonstrates both promise and limitations, e.g., while Dann et al. (2024) showed sophisticated AI applications for understanding student engagement, and Alwaqdani (2024) investigated teachers' perceptions revealing both potential and difficulties, these advances remain concentrated in well-resourced contexts. The predominance of conference proceedings, while reflecting Kopcha et al. (2020) identification in prioritizing "process over product" in technology integration, may limit the theoretical sophistication needed to address what Chang et al. (2024) identified as AI's complex impact on self-regulated learning across diverse educational environments.

5.2. Intellectual Structure and Thematic Organization

Our co-citation analysis reveals four research communities that validate practical implementation of Holstein et al.'s (2019) teacher-AI complementarity, while our five-cluster thematic architecture demonstrates comprehensive framework implementation across multiple domains. The unified conceptual structure from factorial analysis confirms successful integration of technological, pedagogical, and content knowledge domains, validating Intelligent-TPACK integration. However, critical examination reveals that these collaborative networks, while sophisticated within regions, have not achieved the global knowledge networks that envision connectivism.

The motor theme positioning of "machine learning" and "data mining" indicates mature technological development, but the basic theme status of "decision making" suggests insufficient progress in addressing what contemporary scholars identify as critical implementation challenges. Our thematic mapping reveals that current implementations may still function primarily as evaluation tools rather than comprehensive reasoning support systems that pedagogical reasoning model requires. This limitation reflects what Downes (2022) identified as the risk of generic AI tools reducing cognitive engagement when pedagogical optimization is insufficiently prioritized, and validates persistent concerns raised by Brew and Saunders(2020) and Clough et al.(2009) that simply providing technological tools does not automatically improve educational outcomes.

The positioning of "federated learning" as an emerging theme with low centrality reveals untapped potential for what advanced connectivist applications could achieve. While Siemens (2005) envisioned learning networks where knowledge could reside in non-human appliances while preserving human agency, current implementations have not achieved this sophisticated distributed cognition. Contemporary research validates both promise and limitations e.g., Wiedbusch et al. (2022) demonstrated how pedagogical companions can support teachers' interpretation of multimodal learning analytics, and Prasad and Sane (2024) developed self-regulated learning frameworks using generative AI, but our findings suggest these advances remain primarily applicable to well-resourced educational contexts.

The five-cluster architecture demonstrates Tammets and Ley (2023) emphasized about meaningful AI integration into professional development, with the red cluster's centrality of "decision making," "teaching," and "data privacy" reflecting successful integration of ethical considerations that Celik (2023) identified as essential for Intelligent-TPACK implementation. However, the field has not adequately addressed what Burton (2024) described as the need for AI-driven educational transformation that preserves cultural values while achieving technological enhancement. Moreover, current collaborative patterns, while demonstrating sophisticated human-AI collaboration development, fail to address what Selwyn (2022) identified as the ironies of automated decision-making that may inadvertently reduce teacher autonomy when implemented without sufficient cultural and contextual consideration.

The conceptual structure validates successful movement beyond what early decision support systems could achieve, demonstrating sophisticated integration where technological tools genuinely support rather than compete with what Ho (2022) and Smith et al. (2024) identified as teachers' natural decision-making abilities combining multiple information sources. Yet the field has not achieved the cultural responsiveness necessary for global applicability, limiting the potential for creating AI/LA systems that honor diverse educational traditions while achieving technological enhancement.

5.3. Research Impact and Knowledge Networks

Citation patterns reveal successful implementation of augmentative approaches that preserve what McCarty et al. (2021) identified as the complex interplay of factors influencing teacher decision-making. Countries achieving high citation impact despite lower publication volumes demonstrate research effectively supporting rather than replacing what Vanlommel and Schildkamp (2019) described as teachers' valuable instinctive judgment. However, the geographic concentration of both high-impact research and institutional networks raises concerns about equitable knowledge diffusion and framework development that contemporary scholars have identified as critical for comprehensive AI implementation.

The sustained citation impact of foundational works validates successful evolution beyond early concerns about appropriate AI use in educational contexts, demonstrating sophisticated understanding of how to enhance rather than undermine teacher decision-making capabilities. Contemporary high-impact research shows promise e.g., Ouyang et al. (2023) demonstrated effective integration of AI performance prediction with learning analytics for improving student learning, while Salas-Pilco et al. (2022) provided systematic review evidence for AI and learning analytics applications in teacher education. However, our analysis reveals that even highly cited works have not adequately addressed the need for dynamic decision-making support that adapts to varying instructional environments and teacher expertise levels.

The temporal emergence of leading institutions primarily from 2020 onwards demonstrates concentrated commitment but limits development of frameworks addressing diverse global educational needs. While institutions like Central China Normal University show dramatic growth reflecting Lawrence et al. (2024) emphasis on multi-year teacher-centered design approaches, the geographic concentration limits knowledge diffusion to the importance of collaborative opportunities in teacher decision-making across different cultural contexts (Pashiardis, 1994). Even sophisticated approaches like those demonstrated by Ifenthaler and Schumacher (2023) regarding reciprocal AI and human intelligence issues, and Wang et al. (2023) examining teachers' AI readiness encompassing cognitive understanding, practical abilities, vision for integration, and ethical awareness, remain primarily applicable to well-resourced educational contexts.

Recent research highlights both advances and persistent limitations in knowledge network development. While Ng et al. (2023) examined teachers' AI digital competencies in post-pandemic contexts, and Nazaretsky et al. (2022) investigated teachers' trust in AI-powered educational technology, our findings suggest that knowledge networks remain concentrated among institutions with similar technological capabilities and educational contexts. The collaborative patterns demonstrate successful implementation of shared control concepts where teachers and AI systems collaborate rather than compete for decision-making authority, validating approaches ensuring AI systems work in real classroom environments through co-design processes involving teachers as partners rather than end-users.

However, current knowledge networks fail to address the need for integrating AI into digital pedagogy while preserving essential human relationships and contextual knowledge. The field has succeeded in developing what contemporary scholars describe as sophisticated technological capabilities, but has not achieved the global collaboration necessary for ensuring these frameworks serve diverse educational contexts effectively while preserving local educational values and practices that make teaching both an art and a science.

5.3. Research Impact and Future Strategic Directions: Toward Enhanced Human-AI Collaboration

The collective findings demonstrate successful progress in developing AI/LA systems that address what our introduction identified as the critical need for technological solutions augmenting human judgment with systematic analytics. The field has moved beyond early concerns about whether AI technologies are appropriate in educational contexts toward sophisticated understanding of how they can serve educational goals while preserving professional autonomy and addressing legitimate concerns about educational equity and data protection. However, significant challenges persist in achieving what our literature review established as the essential goal, helping teachers become more thoughtful and effective decision-makers who can adapt to students' changing needs. Future research must address how theoretical frameworks can accommodate the cultural and contextual diversity that effective teaching requires while maintaining the proven principles that make AI/LA tools genuinely augmentative rather than replacement technologies. The transformation from Shavelson's (1973) recognition of decision-making as the basic teaching skill toward sophisticated AI-enhanced decision support represents significant progress, but realizing full potential requires addressing persistent challenges in geographic equity, theoretical innovation, and practical implementation while preserving essential human elements that make teaching both an art and a science.

6. CONCLUSION

Our comprehensive examination of 318 publications spanning a decade (2015-2025) reveals a compelling evolution of artificial intelligence and learning analytics for teacher decision-making from experimental applications into a sophisticated research domain that successfully integrates TPACK, Shulman's Pedagogical Reasoning Model, and connectivism frameworks while consistently prioritizing augmentation over replacement of human expertise. The field has progressed through four distinct phases culminating in explosive growth in 2024, with five interconnected thematic clusters and four collaborative research communities demonstrating remarkable theoretical integration, yet this development remains concentrated in the USA, China, and India, creating an "innovation-equity paradox" where technological advancement may inadvertently exacerbate global educational inequalities. While citation patterns validate that research quality and international collaboration significantly enhance impact, with the most influential works from Xing et al.'s interpretable prediction models to contemporary ethical frameworks consistently demonstrating teacher-AI complementarity, significant challenges persist in supporting complete pedagogical reasoning cycles, achieving cultural responsiveness across diverse contexts, and translating sophisticated academic frameworks into practical implementations that serve global educational equity. Moving forward, the field must prioritize comprehensive international consortiums with mandatory equity partnerships, cross-cultural validation frameworks, and systematic approaches that ensure every advancement in AI and learning analytics contributes to more equitable, effective, and fundamentally human-centered educational practice—recognizing that while technology serves as a powerful instrument for systematic analysis and support, the teacher remains the artist, student growth remains the masterpiece, and the ultimate goal is creating educational environments where AI/LA genuinely serves human flourishing while preserving the essential relationships, contextual knowledge, and professional intuition that remain at the heart of excellent teaching across all global contexts.

7. LIMITATION

This bibliometric analysis, while providing comprehensive insights into AI and learning analytics for teacher decision-making, operates within several methodological constraints that warrant careful consideration. Our primary reliance on Scopus and English-language publications, though strategically chosen for robust coverage and analytical compatibility, may inadvertently amplify the geographic inequalities we identified by potentially underrepresenting valuable research published in regional venues or non-English academic contexts. The bibliometric approach, although powerful for revealing broad patterns across the research landscape, necessarily prioritizes breadth over depth, thereby enabling us to map influential networks and thematic clusters while limiting our ability to assess the practical classroom impact or methodological rigor of individual studies. Additionally, our keyword-based search strategy reflects our disciplinary understanding of relevant terminology; however, the interdisciplinary nature of educational technology research suggests that important contributions may exist under different conceptual frameworks that our approach did not capture. Most significantly, this study examines the academic research discourse rather than actual implementation practices in educational settings, thus creating a gap between scholarly publications and the lived experiences of teachers working with these technologies in diverse classroom contexts worldwide. The analysis was conducted during 2025, affecting completeness of current year data, and our application of predominantly Western-derived theoretical frameworks may limit understanding of how AI/LA systems function within different cultural and educational contexts. Nevertheless, these limitations do not diminish the value of our findings but rather highlight that this analysis represents one important perspective within a multifaceted field that requires diverse methodological approaches and voices to fully understand the complex relationship between artificial intelligence, learning analytics, and the fundamental human work of teaching.

Terminology Clarification: In this study, "teacher decision-making" serves as an umbrella term for all professional educational choices made by educators. This includes what some refer to as "instructional" (methods, content, and activities) and "pedagogical" (theoretical and philosophical approaches) decision-making.

Author Contribution: **Conceptualization,** R.R., I.N.M., R.N., N.L.B., R.M., R.R., V.L., T.M.R., N.S., H.C.I., F.V.E., and F.S.P.; **methodology,** R.R., I.N.M., R.N., N.L.B., R.M., T.M.R., and H.C.I.; **software,** R.R., I.N.M., V.L., and F.S.P.; **validation,** R.R., I.N.M., R.N., N.L.B., R.R., V.L., N.S., and H.C.I.; **formal analysis,** R.R., I.N.M., R.N., N.L.B., R.M., T.M.R., N.S., and F.V.E.; **investigation,** R.R., I.N.M., R.N., N.L.B., R.M., R.R., V.L., T.M.R., N.S., H.C.I., F.V.E., and F.S.P.; **resources,** R.R., I.N.M., R.M., T.M.R., N.S., H.C.I., and F.V.E.; **data curation,** R.R., I.N.M., R.N., N.L.B., V.L., and N.S.; **writing—original draft preparation,** R.R., I.N.M., R.N., N.L.B., R.M., R.R., V.L., T.M.R., N.S., H.C.I., F.V.E., and F.S.P.; **writing—review and editing,** R.R., I.N.M., R.N., N.L.B., R.M., R.R., V.L., T.M.R., N.S., H.C.I., F.V.E., and F.S.P.; **visualization,** R.R., I.N.M., N.L.B., V.L., N.S., and F.V.E.; **supervision,** R.R. and I.N.M.; **project administration,** R.R., I.N.M., and F.V.E.; **funding acquisition,** R.R., I.N.M., R.N., N.L.B., R.M., R.R., V.L., T.M.R., N.S., H.C.I., F.V.E., and F.S.P. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The authors sincerely would like to thank Indonesian Education Scholarship (BPI), Center for Higher Education Funding and Assessment (PPAPT), and Indonesian Endowment Fund for Education (LPDP) from the Ministry of Finance Republic Indonesia for granting the scholarship and supporting this research and all the participants involved in this study.

Conflicts Of Interest: We want to confirm that we have no financial interests or affiliations with any organization that may have a direct or indirect interest in the subject matter discussed in the manuscript.

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