

Mapping Integration and Triangulation in AI-Enhanced Mixed Methods Research: A Bibliometric Analysis

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ABSTRACT

This study reviews the scholarly discourse at the intersection of mixed methods research (MMR) and artificial intelligence (AI), specifically examining how MMR's foundational commitments to methodological integration and evidence triangulation are represented across the literature while highlighting the continuing importance of human methodological judgment in AI-enabled research. A bibliometric analysis was conducted on 1,208 Scopus-indexed publications spanning 2016–2026, employing performance analysis, science mapping, and thematic mapping. Analytical tools included Bibliometrix and VOSviewer, with document selection following PRISMA-guided procedures. The findings reveal extraordinary growth, with an annual rate of 95.28% that accelerated after 2023. China ($n = 273$) and the United States ($n = 261$) emerge as leading contributors to the field. Thematic mapping demonstrates that AI occupies the conceptual core of the literature, whereas MMR functions primarily as a peripheral bridging construct. Integration and triangulation appear infrequently as distinct thematic clusters, suggesting limited explicit theorization of these foundational methodological principles. Collaboration is intensive (3.66 co-authors per publication) but modestly international (23.76%). The findings indicate that AI is currently positioned as a methodological catalyst that enhances research processes rather than a disruptive force that fundamentally redefines mixed methods inquiry. Despite increasing AI adoption, the robustness, credibility, and interpretive depth of MMR continue to depend on researchers' capacity for critical reasoning, contextual understanding, ethical reflection, and meaningful synthesis of diverse forms of evidence – competencies that remain distinctly human and indispensable for rigorous scientific inquiry.

Keywords: Mixed Methods Research; Artificial Intelligence; Bibliometric Analysis; Methodological Integration; Evidence Triangulation; Human–AI Collaboration

Introduction

The convergence of AI and MMR represents one of the most consequential yet undertheorized developments in contemporary social science methodology (Combrinck, 2024; Ramli & Yahya, 2025; Bista, 2026). While MMR has long been valued for its capacity to integrate quantitative precision with qualitative depth (Devkota & Mahapatra, 2025; Levitt et al., 2018; Timans et al., 2019; Sommer Harrits, 2011), the rapid proliferation of AI technologies – particularly generative AI tools such as ChatGPT and large language models – has introduced unprecedented opportunities and challenges for methodological practice (Christou, 2023; McIntosh et al., 2025; Borger et al., 2023; Costa et al., 2025; Devkota et al., 2026). Yet despite growing scholarly attention to this intersection, fundamental questions remain unanswered: How is AI actually reshaping the conduct of MMR? Are traditional practices of methodological integration and evidence triangulation being transformed, augmented, or undermined by AI-driven tools? And does the explosive growth in publications represent genuine methodological innovation or merely a discursive shift in how research is framed?

These questions are not merely academic. AI is now deployed across all stages of the research process (Madanchian & Taherdoost, 2025; Siddique et al., 2026) – from data collection and automated analysis to interpretation and dissemination (Rane et al., 2024; Xu et al., 2021) – while MMR has become increasingly prominent as a framework for addressing complex, multidimensional research problems (Taherdoost, 2022; Fieldhouse et al., 2025; Nashwan et al., 2023). However, these trajectories have largely developed in parallel, with limited systematic examination of their intersection (Fieldhouse et al., 2025; Altamirano et al., 2026). This gap is particularly concerning given that AI's opacity, potential for algorithmic bias, and tendency toward pattern recognition without causal explanation raise fundamental questions about validity and trustworthiness – questions that MMR's emphasis on triangulation and integration is uniquely positioned to address (Guenduez et al., 2026; Vivek et al., 2023).

To understand how AI may be reshaping MMR, it is necessary to first establish what MMR's core methodological commitments entail (Paudyal, 2026). At its foundation, MMR is distinguished not merely by the use of multiple methods, but by the systematic integration of qualitative and quantitative approaches to generate insights that neither method could achieve alone (Levitt et al., 2018; Moss et al., 2026). This integration operates across design, analytical, and interpretive dimensions (Fetters et al., 2013; Riazi, 2016). Evidence triangulation – a closely related but conceptually distinct principle – refers to the use of multiple data sources, methods, investigators, or theoretical perspectives to cross-validate findings and enhance research credibility (Vivek et al., 2023). While integration emphasizes combination for comprehensive understanding, triangulation emphasizes corroboration for validity. Both face new challenges and opportunities in the age of AI (Nair et al., 2024; Saheb & Saheb, 2024).

AI introduces several dynamics that could, in principle, reshape practices of integration and triangulation (Abramson et al., 2026). Its capacity for processing vast quantities of unstructured data is discussed in the literature as potentially expanding data triangulation beyond traditional sources (Rane et al., 2024). Machine learning algorithms may enable pattern identification across modalities that escape human detection (McIntosh et al., 2025; Mahadevkar et al., 2024). However, the extent to which these possibilities are being realized – or even critically examined – remains unclear. Automated tools for thematic analysis and topic modeling raise questions about whether AI supplements or supplants

human interpretation (Fieldhouse et al., 2025; Jafari-Koulaee & Bagheri-Nesami, 2026), while issues of algorithmic bias, lack of transparency, and AI-generated “hallucinations” threaten research validity (Guenduez et al., 2026; Devkota et al., 2026). Yet these challenges are not systematically theorized in the literature, and whether AI is transforming MMR’s foundational commitments or merely augmenting existing practices is an open empirical question (Costa et al., 2025).

Despite these profound implications, existing literature on AI and MMR remains fragmented and undertheorized. Current scholarship falls into three categories: (a) studies applying AI tools within mixed methods frameworks without systematically examining how AI changes integration and triangulation (Saheb & Saheb, 2024; Nair et al., 2024); (b) methodological commentaries speculating about AI’s potential to reshape MMR but lacking empirical grounding (Altamirano et al., 2026); and (c) bibliometric and scoping reviews mapping publication trends without probing the substance of methodological practice (Fieldhouse et al., 2025). What is missing is systematic, empirically grounded mapping of how integration and triangulation are represented – or not – in the discursive landscape of AI-MMR scholarship, and whether AI’s emergence has shifted the thematic prominence of these methodological commitments. Hence, this study aims to fill this unanswered gap.

Accordingly, this study also sought to address:

- RQ1: What are the temporal, geographical, and disciplinary patterns of publication in the AI-MMR literature, and who are the key contributors?
- RQ2: How frequently and in what thematic contexts do integration-related terms appear in the AI-MMR literature, and what does this pattern suggest about the explicit theorization of integration?
- RQ3: How frequently does triangulation appear as a thematic cluster in the AI-MMR literature, and to what extent is it connected to AI-related concepts?
- RQ4: How are AI-related keywords connected to integration and triangulation terms in the literature’s co-occurrence networks?
- RQ5: How do the thematic structures of the AI-MMR literature differ between the pre-generative AI period (2016–2022) and the post-generative AI period (2023–2026), and what shifts are observable?

To address these questions, this study employs bibliometric analysis – a systematic, quantitative approach to mapping large-scale publication patterns, citation networks, and keyword structures, which is commonly used in the existing literature, e.g., Donthu et al. (2021), Kumar (2025), and Siddique et al. (2026a). This method allows objective identification of: (a) whether integration and triangulation terms appear in proximity to AI terms (keyword co-occurrence); (b) which authors and institutions are driving the discourse (performance analysis); and (c) how thematic clusters have emerged and shifted over time (thematic mapping) (Passas, 2024). We acknowledge that bibliometric analysis alone identifies discursive patterns but cannot directly measure methodological practice. Therefore, our findings should be interpreted as a map of scholarly discourse about integration and triangulation, rather than a direct assessment of these as enacted practices. This distinction is both a limitation and a contribution: by identifying what is said about integration and triangulation, we can reveal gaps, inconsistencies, and unexamined assumptions warranting further investigation.

This study makes three contributions. First, it provides systematic, empirical mapping of the AI-MMR literature, synthesizing a rapidly growing but fragmented body of work. Second, it applies the specific lens of integration and triangulation – MMR’s core methodological commitments – to examine whether these principles appear as distinct thematic clusters in the discourse or remain peripheral to

the AI-centric conversation. Third, by identifying patterns of discourse rather than inferring practice, it provides a foundation for future research examining the gap between methodological claims and actual methodological conduct.

The remainder of this paper proceeds as follows. Section 2 details the methodology, including search strategy, inclusion criteria, and analytical tools. Section 3 presents bibliometric findings across performance analysis, science mapping, and thematic structure. Section 4 interprets these findings in relation to the research questions and outlines implications. Section 5 concludes with limitations, future research directions, and practical implications for methodologists, journal editors, and research funders.

Methodology

Research Design

This study adopts a descriptive-analytical bibliometric research design to systematically map the scholarly discourse at the intersection of MMR and AI, with particular attention to how methodological integration and evidence triangulation are represented in the literature (Passas, 2024; Donthu et al., 2021; Devkota et al., 2026). Bibliometric analysis was selected because it enables objective, quantitative, and replicable examination of large volumes of academic literature, allowing systematic identification of publication trends, citation patterns, collaboration networks, and thematic structures (Donthu et al., 2021).

The analytical strategy directly addresses each research question: RQ1 is examined through performance analysis (productivity and citation indicators); RQ2 and RQ3 through keyword co-occurrence and thematic mapping; RQ4 through proximity analysis of AI-related and methodological terms in co-occurrence networks; and RQ5 through temporal comparison of thematic structures between pre- and post-generative AI periods.

Critically, this study is positioned as an analysis of scholarly discourse about integration and triangulation, rather than a direct examination of these as enacted methodological practices. Bibliometric analysis can identify *what is said about these constructs but cannot measure how they are practiced* in research – a distinction that shapes both the interpretation of findings and the scope of claims made.

Search Strategy

A structured Boolean search strategy was developed to retrieve relevant literature from the Scopus database. The search was conducted in January 2026 and covered the publication period from 2016 to 2026. The start year of 2016 was selected based on established precedent identifying this as the onset of significant AI dissemination following widespread adoption of deep learning (and to enable comparison between pre-generative AI (2016–2022) and post-ChatGPT (2023–2026) periods. The following Boolean search string was applied to TITLE-ABS-KEY fields in Scopus:

TITLE-ABS-KEY(("mixed method" OR "mixed-method*" OR "multi-method*" OR "multimethod*" OR "qualitative and quantitative")) AND TITLE-ABS-KEY(("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network*" OR "natural language processing" OR "NLP" OR "generative AI" OR "large language model*" OR "LLM" OR "ChatGPT")) AND TITLE-ABS-KEY(("integration" OR "integrat*" OR "triangulation" OR "triangulat*" OR "methodological integration" OR "evidence triangulation" OR "data triangulation" OR "theory*

triangulation” OR “investigator triangulation”))

No geographical restrictions were applied. The search was restricted to peer-reviewed journal articles, conference papers, and book chapters published in English. Subject area limits were not applied to ensure comprehensive coverage across disciplines.

Database and Tools

The Scopus database was selected as the primary data source over alternatives such as Web of Science owing to its extensive and multidisciplinary coverage of high-quality scholarly publications and its superior coverage of social science and education journals (Baas et al., 2020). Scopus offers rich bibliometric information including citation data, author affiliations, abstracts, keywords, and references, which supports detailed performance evaluation and scientific mapping.

Analyses were conducted using R version 4.3.1 with Bibliometrix package version 4.1.0 (via Biblioshiny) to compute key indicators such as publication productivity, citation impact, thematic trends, and collaboration structures (Aria & Cuccurullo, 2017). For network visualization, VOSviewer version 1.6.20 was employed to generate maps of co-authorship, co-citation, keyword co-occurrence, and bibliographic coupling (van Eck & Waltman, 2014). Microsoft Excel was used for data preprocessing, including cleaning, normalization, and preparation of analytical tables.

To ensure analytical rigor and reproducibility, the following parameters were consistently applied: (a) a minimum threshold of 5 document occurrences for keyword inclusion; (b) a minimum of 2 co-occurrences for network construction; (c) full counting method for author and country co-authorship; and (d) fractional counting for documents with multiple affiliations to avoid overrepresentation of collaborative works (van Eck & Waltman, 2014; Perianes-Rodriguez et al., 2016).

Data Selection Process

The document selection process followed a structured and transparent approach based on the PRISMA 2020 framework, ensuring systematic identification, screening, eligibility assessment, and inclusion of relevant literature (Page et al., 2021). This framework was selected because it provides standardized reporting guidelines that enhance transparency and reproducibility in systematic reviews and bibliometric studies (Page et al., 2021; Moher et al., 2009).

As illustrated in Figure 1, the identification stage began with a comprehensive search in Scopus yielding 4,337 records, of which 1,786 were excluded due to duplication (n=124), publication outside the 2016-2026 timespan (n=287), non-English language (n=156), or irrelevance to the study's focus (n=1,219) – defined as publications that did not substantively address either AI applications in research contexts or mixed methods methodology. The screening stage reviewed 2,551 records based on titles, abstracts, and keywords, excluding 1,025 records for focusing exclusively on AI technical development without methodological application, mentioning AI or MMR only in passing, being corrigenda or editorials, or lacking discussion of integration or triangulation.

The eligibility stage critically evaluated 1,526 full-text articles against inclusion criteria requiring explicit MMR approach, substantive AI engagement, discussion of integration or triangulation, and applied research context, resulting in the exclusion of 318 records for insufficient empirical contribution, unclear methodology, or duplication. The final inclusion resulted in 1,208 documents for analysis. All inclusion decisions were documented with exclusion reasons to maintain a complete audit trail (Haddaway et al., 2022). Selection criteria are summarized in Table 1.

Table 1

Inclusion and Exclusion Criteria by PRISMA Stage

Stage	Inclusion Criteria	Exclusion Criteria
Identification	Published 2016-2026; English language; Journal articles, conference papers, book chapters	Duplicates; Outside timespan; Non-English; Irrelevant subject areas
Screening	Substantive discussion of AI or MMR; Original research; Mentions integration/triangulation	AI technical development only; Passing mention only; Corrigenda, editorials; No integration/triangulation discussion
Eligibility	Explicit MMR approach; Substantive AI engagement; Discussion of integration/triangulation; Social science/education/applied context	Insufficient empirical contribution; Unclear methodology; Duplication identified in full-text review
Inclusion	Meets all eligibility criteria; Full text available	Fails any eligibility criterion

Data Quality Assurance

To ensure reliability and reproducibility, several quality assurance procedures were implemented. The initial database search and record screening were conducted independently by two researchers to minimize selection bias. Inter-coder agreement was assessed using Cohen's Kappa: screening stage Kappa = 0.82 (agreement: 89.7%), eligibility stage Kappa = 0.87 (agreement: 92.3%). Disagreements were resolved through discussion and consensus. These agreement rates exceed the acceptable threshold of 80% commonly recommended in systematic review methodology (Belur et al., 2021).

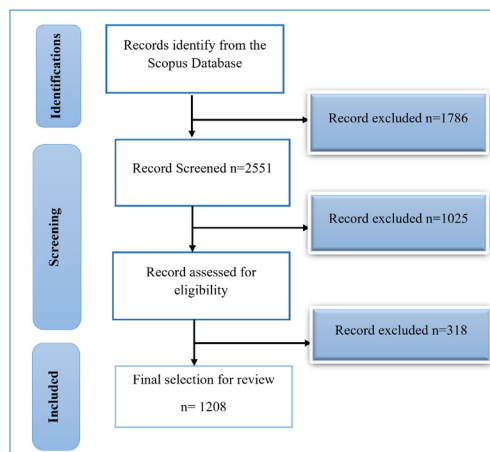
Duplicate records were identified using automated deduplication in Scopus supplemented by manual verification. Author name disambiguation was performed using Scopus's author identifier system, supplemented by manual verification to address name variations and institutional affiliations.

Keyword standardization was conducted to merge synonymous terms while preserving meaningful distinctions. This process involved consolidating variant forms (e.g., "mixed methods," "mixed-method," "mixed methods research" to "mixed methods research") and resolving hyphenation inconsistencies, following best practices for bibliometric keyword normalization. A full keyword normalization log was maintained for audit purposes.

Finally, the full dataset was validated against the PRISMA 2020 checklist to ensure complete reporting of the selection process.

Figure 1

Document Selection Process



Results

Main Information of the Dataset

The dataset's main descriptive indicators point to a field in an early, explosive growth phase rather than one of steady, mature accumulation. An annual growth rate of 95.28%, paired with a document average age of under one year, signals that critical mass in this research area has formed almost entirely within the last few publication cycles a pattern consistent with a topic whose momentum is being driven by a recent technological disruption (generative AI) rather than gradual, organic expansion of mixed methods scholarship over time (See Table 2). The average citation count of 8.97, despite such young document age, is notable and warrants cautious interpretation: it likely reflects a small, tightly interconnected early-adopter community citing one another rapidly, or citation behavior typical of preprint- and conference-driven AI-adjacent fields, rather than broad, field-wide impact accumulation. Structurally, the ratio of 4079 authors to 1208 documents, with 3.66 co-authors per document and only 164 single-authored works, indicates that this is fundamentally a collaborative, team-based research area likely reflecting the convergence of methodologists and AI/data science specialists. However, the relatively low international co-authorship rate of 23.76% suggests this collaboration remains largely institutional or domestic rather than globally distributed, pointing to a maturity gap that has not yet caught up with the field's rapid quantitative growth, and which is worth flagging explicitly as a limitation or future research direction in your discussion section.

Table 2

Main information of the Dataset

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2016:2026
Sources (Journals, Books, etc)	421
Documents	1208
Annual Growth Rate %	95.28
Document Average Age	0.991
Average citations per doc	8.97
References	122791
DOCUMENT CONTENTS	
Keywords Plus (ID)	1178
Author's Keywords (DE)	4183
AUTHORS	
Authors	4079
Authors of single-authored docs	164
AUTHORS COLLABORATION	
Single-authored docs	168
Co-Authors per Doc	3.66
International co-authorships %	23.76
DOCUMENT TYPES	
article	1208

Performance Analysis

Performance analysis focuses on the productivity and impact dimensions of the literature (Siddique et al., 2026b). It examines annual publication trends, the most productive and most cited authors, leading journals, and influential documents and countries. This groundwork precedes the science-

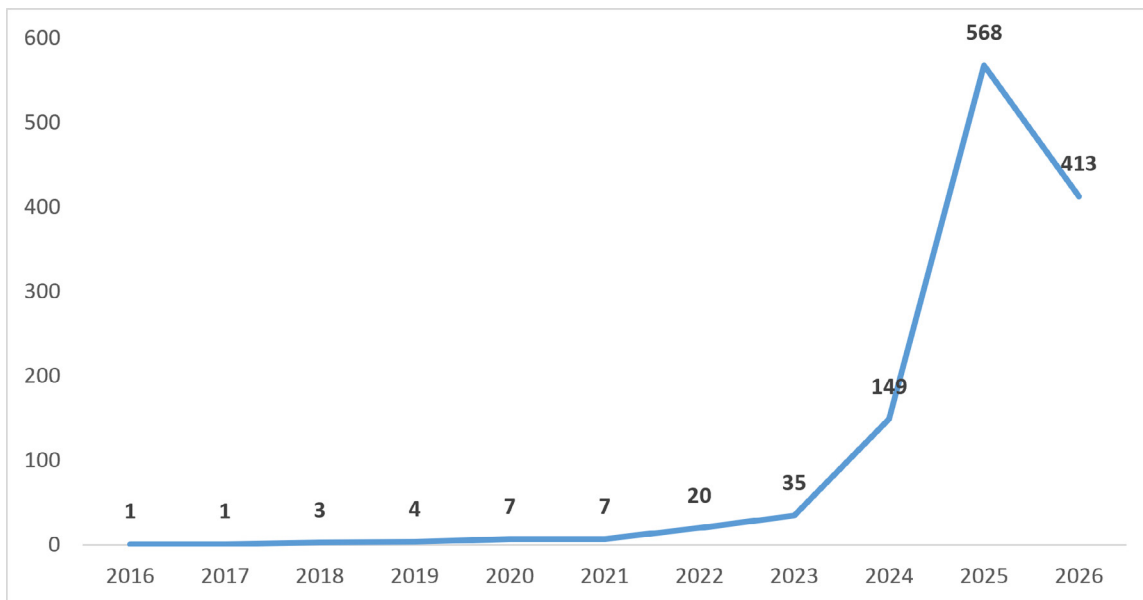
mapping stage, which explores the field's deeper intellectual structure.

Annual Scientific Production

Annual scientific production is the number of research publications generated within a specific field over a defined period, serving as a fundamental indicator of its growth, relevance, and developmental trajectory (Agbo et al., 2021). It allows scholars to assess how academic interest evolves and to identify whether a research area is emerging, expanding, or reaching maturity. Figure 2 shows annual output from 2016 to 2019 remains extremely low, increasing marginally from one to four publications, which indicates a nascent stage with limited scholarly attention. A gradual upward shift is observed between 2020 and 2022, where publications rise from 7 to 20, suggesting early recognition and growing academic engagement. This phase reflects the initial consolidation of the research theme within the scholarly community. A pronounced acceleration occurs from 2023 onward, marking a transition into a high-growth phase. The number of publications increases sharply from 35 in 2023 to 149 in 2024, followed by an exponential surge to 568 in 2025. Although there is a decline to 413 publications in 2026, this figure reflects only partial-year data, as the Scopus search was conducted in early 2026 and therefore does not capture a complete publication cycle for that year. Consequently, the output remains significantly higher than previous years, indicating sustained research intensity rather than a downturn. This pattern reflects an exponential growth trajectory typical of emerging and disruptive domains, likely driven by external catalysts such as advancements in AI and its integration into research methodologies.

Figure 2

Annual Scientific Production



Most Relevant Source Analysis

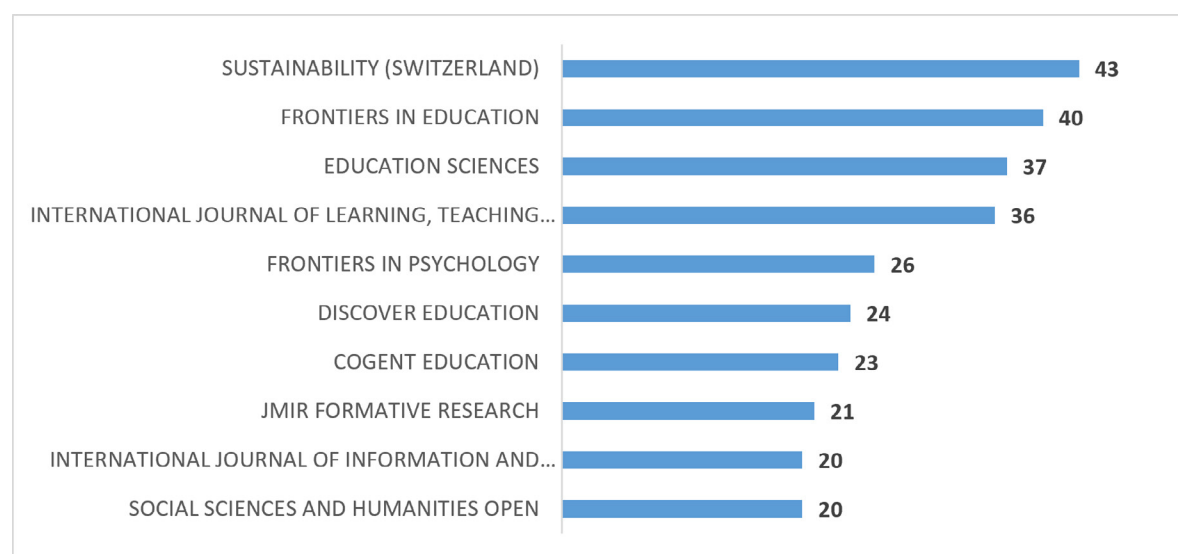
Most relevant sources in bibliometric analysis refer to the journals that contribute the highest number of publications within a specific research domain, indicating the primary outlets shaping knowledge production and dissemination (Lowar et al., 2025). These sources reflect not only publication

concentration but also the disciplinary orientation and intellectual structure of the field. In the context of MMR in the age of AI, the distribution of articles across leading journals provides insight into where scholarly conversations are most actively taking place.

The results in figure 3 reveal a strong dominance of interdisciplinary and education-oriented journals, with Sustainability (Switzerland) (43 articles) and Frontiers in Education (40 articles) leading the output. This suggests that the integration of AI into MMR is being widely explored within sustainability transitions and educational innovation contexts. Journals such as Education Sciences (37) and the International Journal of Learning, Teaching and Educational Research (36) further reinforce the centrality of education as a key application domain, indicating that methodological integration and evidence triangulation are particularly relevant for teaching, learning analytics, and digital pedagogy. The inclusion of Frontiers in Psychology (26) highlights the behavioral dimension, while outlets like JMIR Formative Research and International Journal of Information and Education Technology emphasize the technological and applied research orientation. It should be noted that Sustainability and Frontiers in Education are both open-access journals, a publishing model generally associated with faster review cycles and higher submission volumes, which may partly contribute to their leading publication counts. However, the consistent presence of multiple education-focused journals from different publishers – including subscription-based outlets suggests that this disciplinary concentration reflects a substantive research orientation rather than an artifact of open-access publishing patterns alone. Notably, the concentration of publications within applied, education-oriented outlets – rather than methodology-focused journals indicates that integration and triangulation are being actively enacted as practical research tools within disciplinary application settings, even where they remain less explicitly theorized as standalone methodological constructs. This distribution provides early evidence of the very discourse-practice relationship this study sets out to examine: methodological integration and triangulation appear to be operating robustly at the level of practice, ahead of their formal articulation within the broader AI-mixed methods discourse.

Figure 3

Most relevance Source Analysis



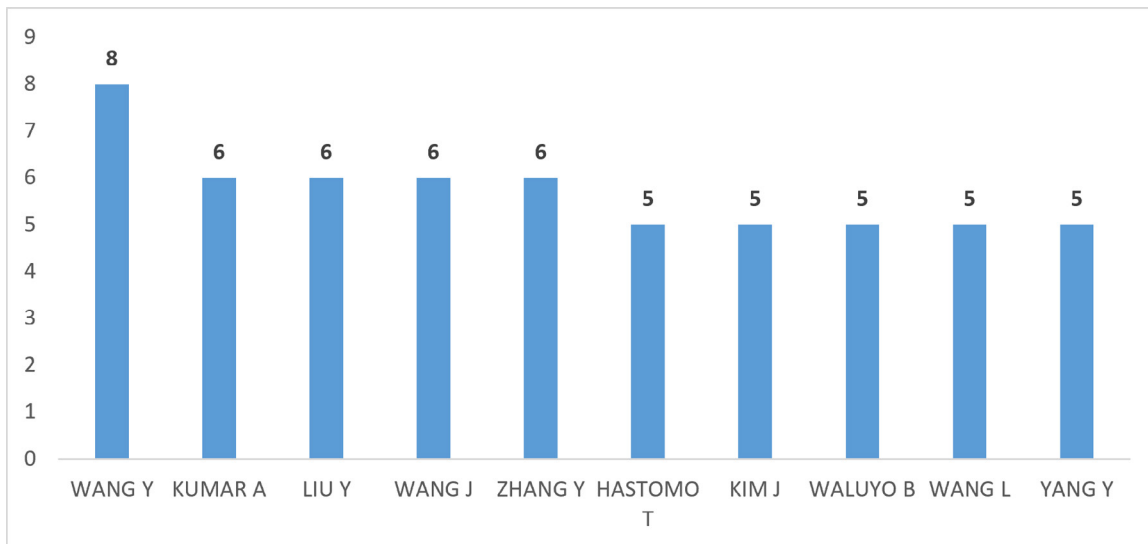
Most Relevance Authors

Most relevant authors in bibliometric analysis are those who contribute the highest number of publications within a specific research domain, reflecting their productivity, visibility, and influence in shaping the field's intellectual development (Siddique et al., 2026b). These authors often act as knowledge drivers, setting research agendas, advancing methodological approaches, and fostering collaboration networks. In emerging domains such as MMR in the age of AI, identifying leading authors helps to understand where core expertise and innovation are concentrated.

The results in figure 4 indicate a relatively dispersed authorship structure, with no single dominant contributor, suggesting that the field is still evolving and lacks a highly centralized intellectual leadership. *Wang Y* leads with 8 publications, followed by *Kumar A*, *Liu Y*, *Wang J*, and *Zhang Y* with 6 publications each, while several others contribute 5 articles. This narrow difference in publication counts reflects a balanced distribution of scholarly output rather than concentration among a few elite researchers. Additionally, the recurrence of common surnames such as Wang, Liu, Zhang, and Yang suggests a strong contribution from Asian research communities, particularly China, indicating regional leadership in this domain. However, the moderate publication counts also imply that even the most productive authors are not yet highly prolific, reinforcing the idea that the field is in a rapid growth phase with expanding participation. The moderate publication counts across even the most productive authors further imply that the field has not yet consolidated around a small set of prolific contributors; rather, this dispersed productivity pattern is consistent with a domain in which integration and triangulation practices are still being distributed across a broad, expanding base of researchers rather than being advanced and codified by a concentrated group of methodological specialists.

Figure 4

Most Relevance Authors



Countries Scientific Production and citation analysis

Countries' scientific production in bibliometric analysis refers to the distribution of research output across different nations, indicating geographical contributions, research capacity, and global knowledge diffusion within a specific domain (Lowar et al., 2025). It helps identify leading countries, emerging contributors, and the overall internationalization of the research field. In rapidly evolving

domains such as AI-integrated MMR, country-level analysis reveals how technological readiness, policy support, and academic infrastructure influence scholarly productivity.

The results demonstrate a highly competitive and globally distributed research landscape, with China (273) and the USA (261) emerging as the leading contributors. This near parity suggests a dual leadership structure, where both countries play a central role in advancing the field, likely driven by strong investments in AI and research innovation. India (231) and Indonesia (208) follow closely, indicating the significant rise of developing economies in global research production, particularly in technology-enabled education and applied research contexts. European representation is led by the UK (147) and Spain (91), reflecting steady but comparatively moderate contributions. Meanwhile, countries such as Saudi Arabia (138), Malaysia (114), Thailand (79), and Kazakhstan (71) highlight the growing involvement of emerging and middle-income nations. Overall, the distribution suggests a shift toward a more multipolar research ecosystem, where both developed and developing countries actively contribute. This pattern reflects the democratization of knowledge production, supported by digital technologies and AI, enabling wider global participation in the field – a geographic breadth that is analytically significant for this study, since it indicates that questions of methodological integration and triangulation in AI-enhanced MMR are not confined to a narrow set of Western research traditions, but are being engaged with across a structurally diverse set of national research systems.

“Most Cited Countries” (TC) is a bibliometric indicator measuring the total citations received by documents affiliated with each country, reflecting research impact rather than mere publication volume. As shown in figure 5, China leads decisively with 1,534 citations, followed by the United Kingdom (1,226) and the United States (1,028), forming a clear top tier ahead of Spain (469), Indonesia (365), Saudi Arabia (359), Romania (342), India (315), Thailand (277), and Malaysia (269). Analytically, China’s dominance likely reflects substantial investment in AI-in-education research combined with strong collaboration networks, generating early and frequently cited work (See Figure 6). The UK and USA’s strong citation counts, even without necessarily leading in output volume, suggest these countries are producing agenda-setting, foundational papers that other researchers cite when framing their own studies – a “quality over quantity” pattern that may indicate a concentration of conceptually foundational work on integration and triangulation specifically, rather than broad-based applied output. Meanwhile, the notable presence of Indonesia, Saudi Arabia, Malaysia, and Thailand signals emerging research strength from Southeast Asia and the Gulf region, likely tied to national digital-education transformation initiatives, despite these regions being historically underrepresented in Western-centric methodology literature.

Figure 5

Most Cited Countries

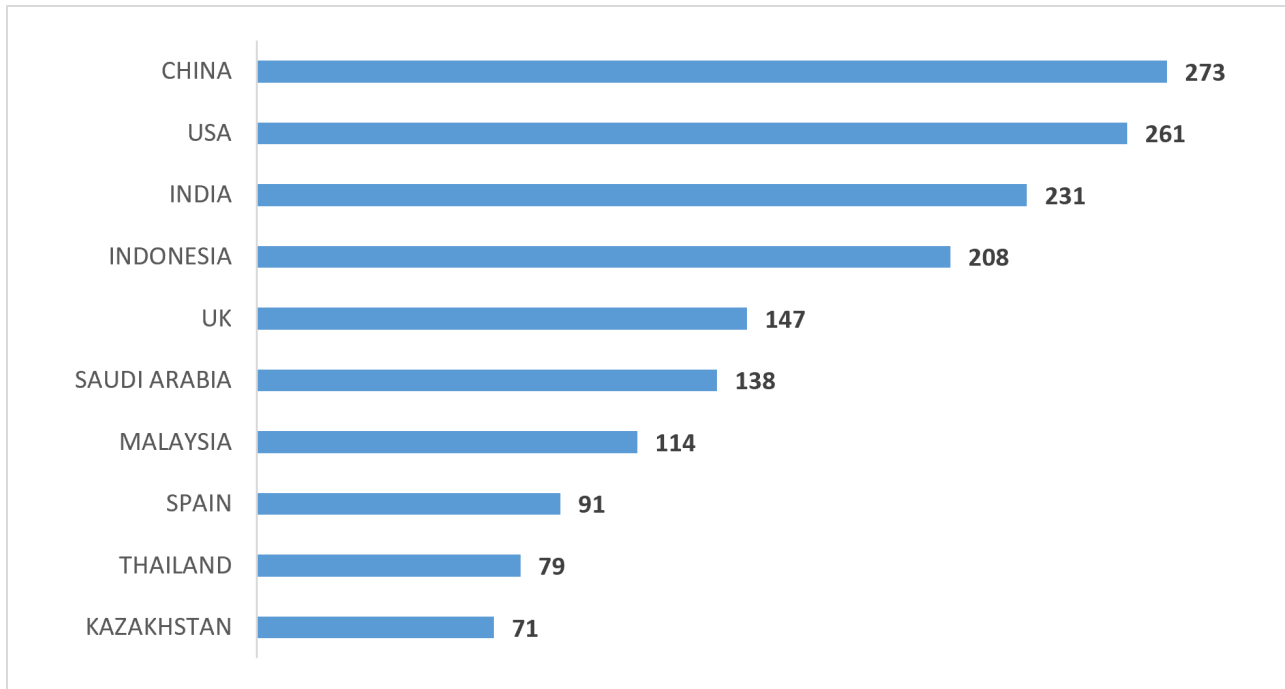
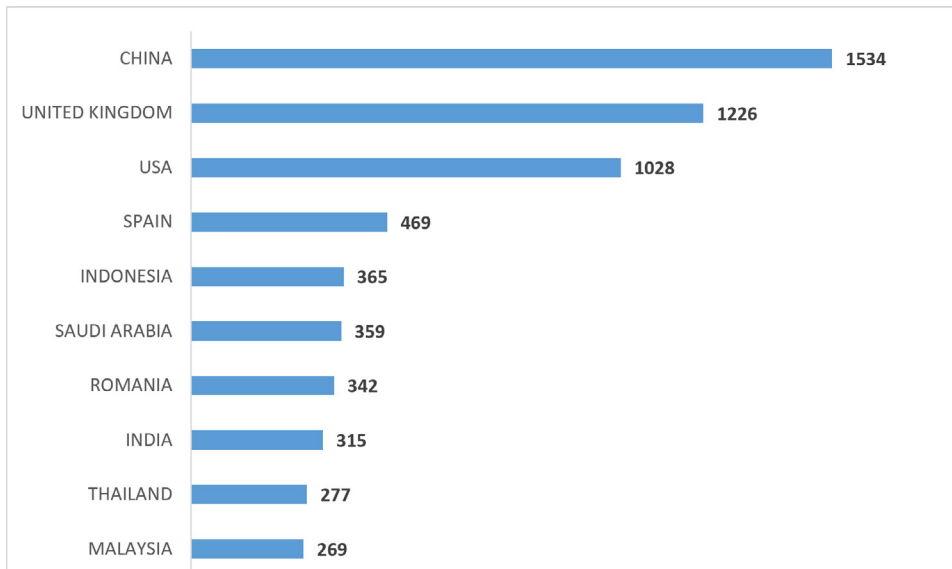


Figure 6

Most Impactful Countries



Science Mapping

Science mapping is employed as an analytical technique to systematically examine the intellectual structure of the research domain. Through bibliometric indicators citation analysis, co-authorship networks, and keyword co-occurrence it quantitatively identifies thematic clusters, research trends, and knowledge gaps, enabling a rigorous, data-driven assessment of scholarly development and

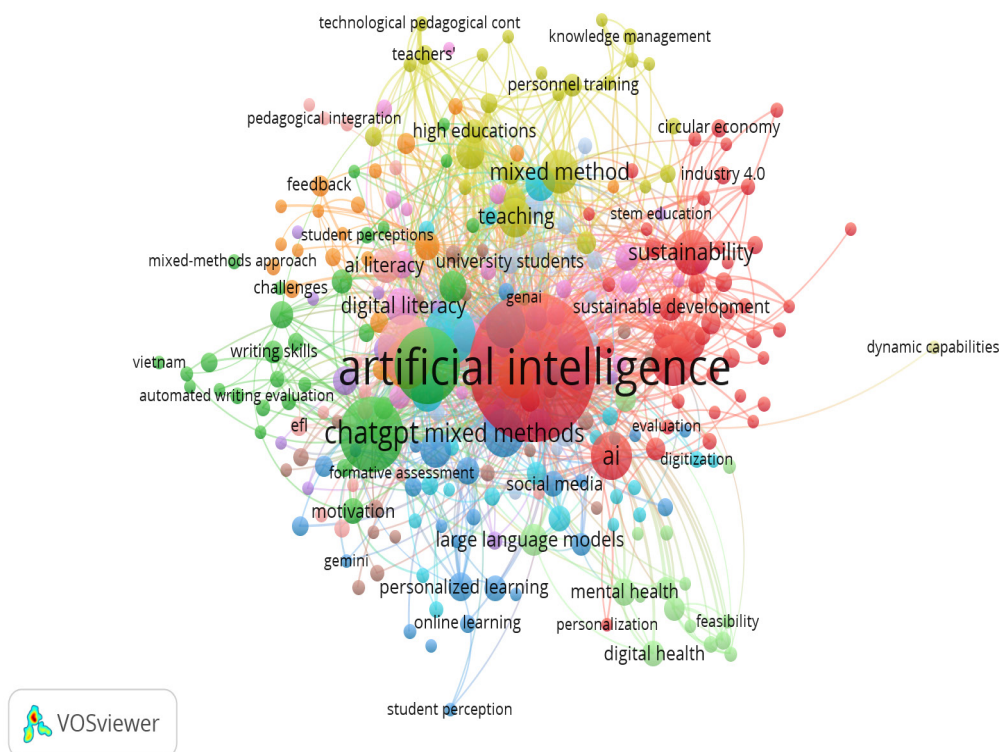
guiding strategic directions for future research within the field.

Co-occurrence network Based on all Keywords

The keyword co-occurrence analysis provides strong support for the study by clearly demonstrating a well-structured and evolving research landscape centered on AI. The dominance of AI in both frequency and connectivity confirms its role as the core driver of scholarly activity, while its close association with terms such as higher education, ChatGPT, and generative AI highlights the rapid and meaningful integration of advanced technologies into educational and applied contexts. The presence of complementary themes such as machine learning, digital literacy, teaching, and sustainability further reflects the interdisciplinary and application-oriented nature of the field (See Figure 7). Importantly, methodological terms like mixed methods and mixed method exhibit notable link strength, indicating that they play a valuable bridging role by connecting technological innovations with educational practices and empirical inquiry. Although explicit keywords related to integration and triangulation appear less frequently, their implicit presence within strongly connected clusters suggests that these methodological principles are embedded within research practices, even if not always explicitly labeled. Furthermore, the connections between AI-related terms and mixed methods concepts, though often mediated through application domains, demonstrate that researchers are increasingly adopting comprehensive approaches to study complex AI-driven phenomena. Overall, the network structure positively reinforces the study's premise by showing that the field is not only technologically robust but also methodologically supported, with significant potential for further strengthening the explicit articulation of integration and triangulation in future research.

Figure 7

Co-occurrence network based on all Keywords

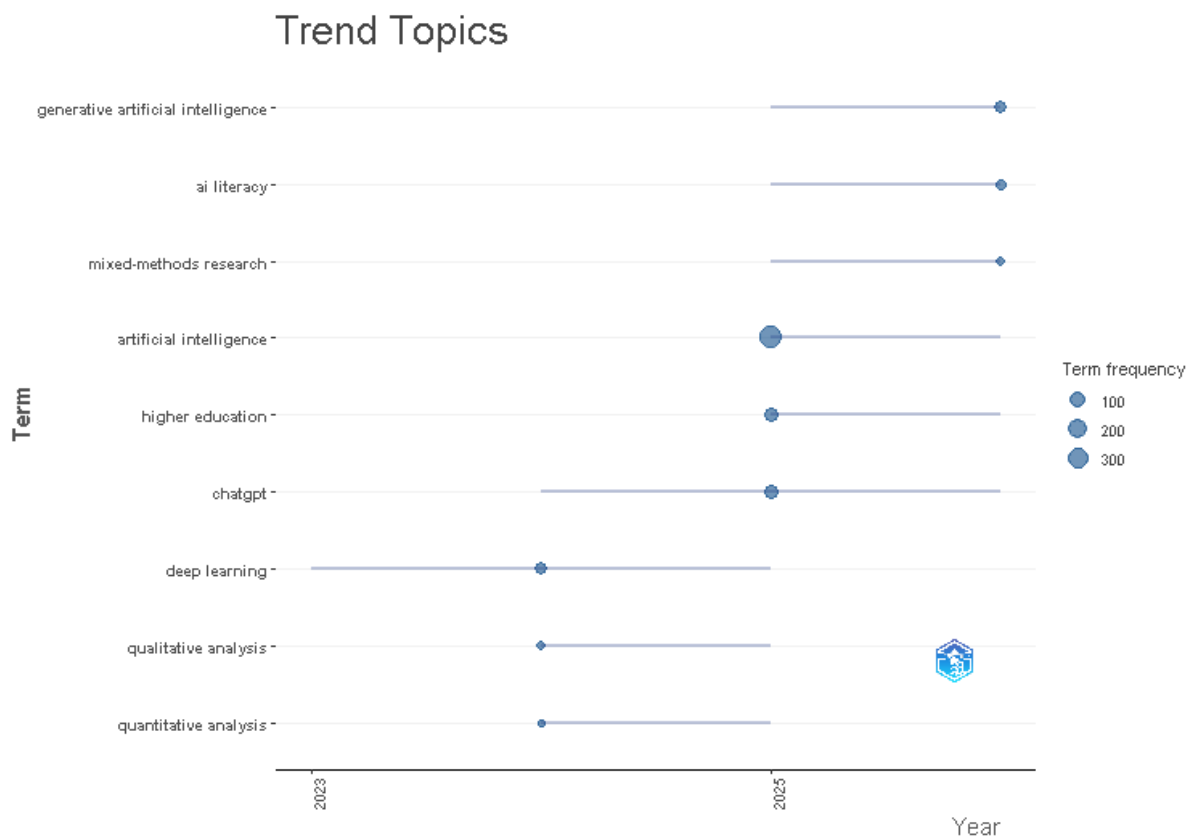


Trend Topic Analysis

This trend topics plot tracks the temporal emergence, persistence, and relative frequency of key terms across the dataset, with the x-axis marking years and bubble size representing term frequency; the horizontal line for each term shows its active timespan. The plot reveals three distinct temporal layers (See Figure 8). The earliest cluster quantitative analysis, qualitative analysis, and deep learning centers around 2023–2024, with comparatively small bubble sizes, reflecting the field’s initial grounding in established methodological and technical vocabulary. Chatgpt spans a wider range but peaks closer to 2025, marking the point at which generative AI tools entered mainstream discourse. AI stands out as the dominant term, with by far the largest bubble (frequency exceeding 300) centered at 2025, confirming its position as the field’s most frequent and persistent core concept. Higher education appears at a similar point in time but with a much smaller bubble, indicating a supporting rather than central role. The most recent and still-emerging terms generative AI, ai literacy, and mixed-methods research appear furthest to the right, with activity concentrated from 2025 onward and comparatively small bubble sizes. Their late appearance and low frequency indicate these are still-developing themes rather than established ones. Notably, mixed-methods research appears only in this most recent cluster, rather than earlier alongside qualitative and quantitative analysis, suggesting that MMR as an explicitly named construct is a late-arriving term relative to the field’s core methodological vocabulary – reinforcing the broader pattern that the field’s technological growth around AI has outpaced the explicit theorization and naming of its methodological integration practices.

Figure 8

Trend Topic



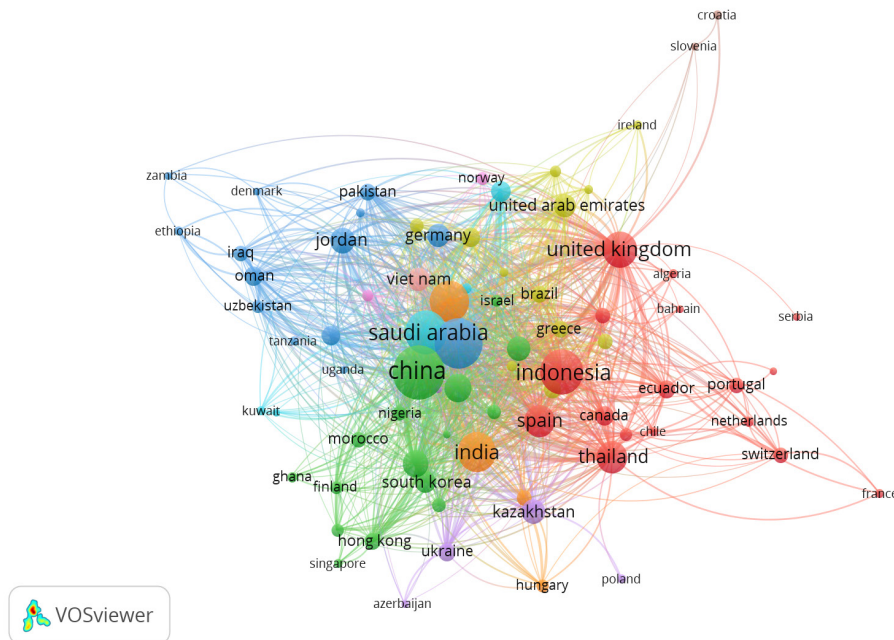
Bibliographic Coupling Based on countries

Bibliographic coupling based on countries links nations according to the extent to which their publications cite the same underlying references (Farrukh et al., 2020). It reflects similarity in research focus, shared intellectual foundations, and collaboration potential, rather than mere productivity or citation impact. Total Link Strength (TLS) is the key indicator here, measuring how strongly a country's research base is intellectually connected to others within the global knowledge network.

The results reveal that China dominates not only in documents (142) and citations (1,534) but especially in TLS (28,957), indicating its central and highly integrated position within the global research network (See Figure 9). This suggests that Chinese research is not only prolific and impactful but also strongly aligned with the reference base of global scholarship in this domain. The United States (TLS 15,795) and United Kingdom (14,839) also demonstrate strong coupling, reflecting deep integration and continued influence in shaping the field's intellectual structure. Countries such as Saudi Arabia (TLS 18,160) and Malaysia (16,598) show exceptionally high link strengths relative to their document counts, indicating strong alignment and collaboration within global research streams even where citation impact remains moderate; this pattern suggests that these countries' publications draw substantially on the same core reference base as leading contributors, positioning them as intellectually integrated rather than peripheral participants in the field. Similarly, Indonesia (TLS 14,609) exhibits high connectivity, reinforcing its active participation in shared research agendas. In contrast, India shows high citations (1,367) but relatively lower TLS (8,189), suggesting research that is impactful in isolation but less structurally embedded within the network's shared referential foundations an indication that citation-based impact and network-based integration are distinct properties that do not necessarily move together. Lower-ranked countries such as Kazakhstan and Jordan display modest TLS, reflecting emerging rather than established participation in this global network. Overall, this pattern indicates that intellectual influence within the AI-mixed methods domain is shaped not solely by publication volume or citation counts, but by the degree to which a country's research draws upon and reinforces a shared, cumulative reference base a distinction that matters for this study's focus on integration and triangulation, since strong bibliographic coupling suggests that certain countries, regardless of output size, are converging on common methodological and technological reference points, while others remain comparatively isolated in their citation practices.

Figure 9

Bibliographic Coupling Based on countries



Co-Authorship analysis based on authors

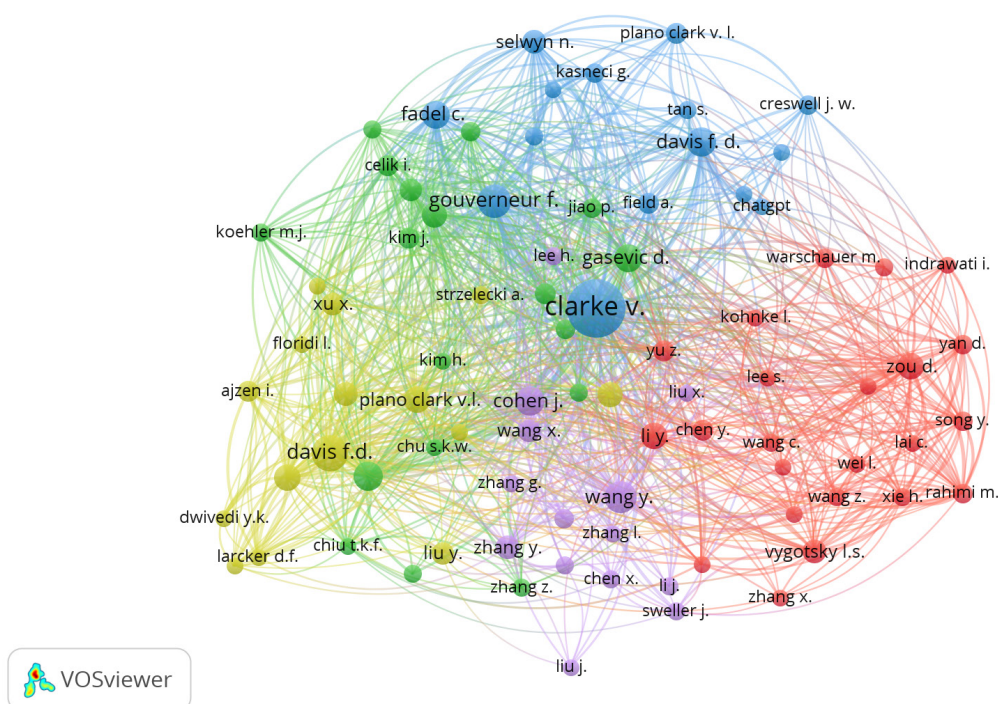
Co-authorship analysis based on authors examines the collaborative structure of a research field, identifying influential scholars and the strength of their collaboration networks (Razzaq et al., 2022). It uses two key indicators: citations, reflecting academic impact, and Total Link Strength (TLS), indicating the intensity of an author's collaborative ties with others. Together, these metrics reveal not only who is influential but also who is well-connected within the knowledge network.

The results highlight a mix of methodological pioneers and technology-oriented scholars shaping the field (See Figure 10). Clarke V. stands out with the highest citations (322) and an exceptionally strong TLS (1,663), indicating both high intellectual impact and extensive collaboration, likely linked to foundational methodological contributions relevant to qualitative and mixed methods design. Davis F.D. (125 citations; TLS 738), known for the Technology Acceptance Model, shows strong relevance in AI adoption studies, bridging behavioral theory and technological application. Similarly, Creswell J.W. and Plano Clark V.L., key figures in MMR, demonstrate moderate citations but solid TLS, confirming their enduring methodological influence in structuring research designs that rely on integrating qualitative and quantitative evidence. Authors like Gasevic D., Sarstedt M., and Wang Y. reflect the integration of analytics, AI, and advanced statistical modeling, with relatively balanced citation and network strength values. Notably, the co-authorship network is populated predominantly by two distinct author profiles: methodologists whose foundational work underpins mixed methods design and triangulation practice (Clarke, Creswell, Plano Clark ??), and technology- or analytics-oriented scholars whose work centers on AI application rather than methodological theorization. The absence of a visible sub-cluster of authors bridging both profiles – that is, scholars simultaneously prominent in citation and collaboration terms for explicitly theorizing AI-driven integration or triangulation suggests that, at the level of individual scholarly influence, the

practices of methodological integration and evidence triangulation have not yet produced a distinct, identifiable community of specialist authors within this literature. Influence in this network instead appears divided along disciplinary lines, with methodological authority and technological authority remaining largely separate rather than converging around a shared integration-triangulation research agenda. Interestingly, the presence of duplicate naming formats (e.g., Davis F.D. and Davis F. D.) suggests potential data normalization issues, which may slightly fragment true influence and should be addressed through author disambiguation in future analyses. Overall, the network reflects a hybrid intellectual structure in which foundational methodologists and emerging AI-focused researchers remain interconnected but functionally distinct, indicating that the convergence of methodological rigor and technological innovation central to this study's concern with integration and triangulation is still occurring at the level of shared discourse rather than through a consolidated community of authors working explicitly at that intersection.

Figure 10

Co-Authorship analysis based on authors



Thematic Evolution

Thematic evolution analysis examines how key research themes develop, transform, and persist over time by tracking the flow of keywords across different time periods. Rather than providing a static snapshot, it reveals the dynamic progression of a research field, identifying which themes remain stable, which emerge, and how concepts become interconnected. In this study, the time periods are divided into three phases (2018–2024, 2025, and 2026), allowing for a longitudinal understanding of how AI (AI) and MMR have evolved together.

In the first phase (2016–2024), structure is relatively broad and foundational. The dominant themes include AI, machine learning, digital technologies, deep learning, and mixed methods (See Figure

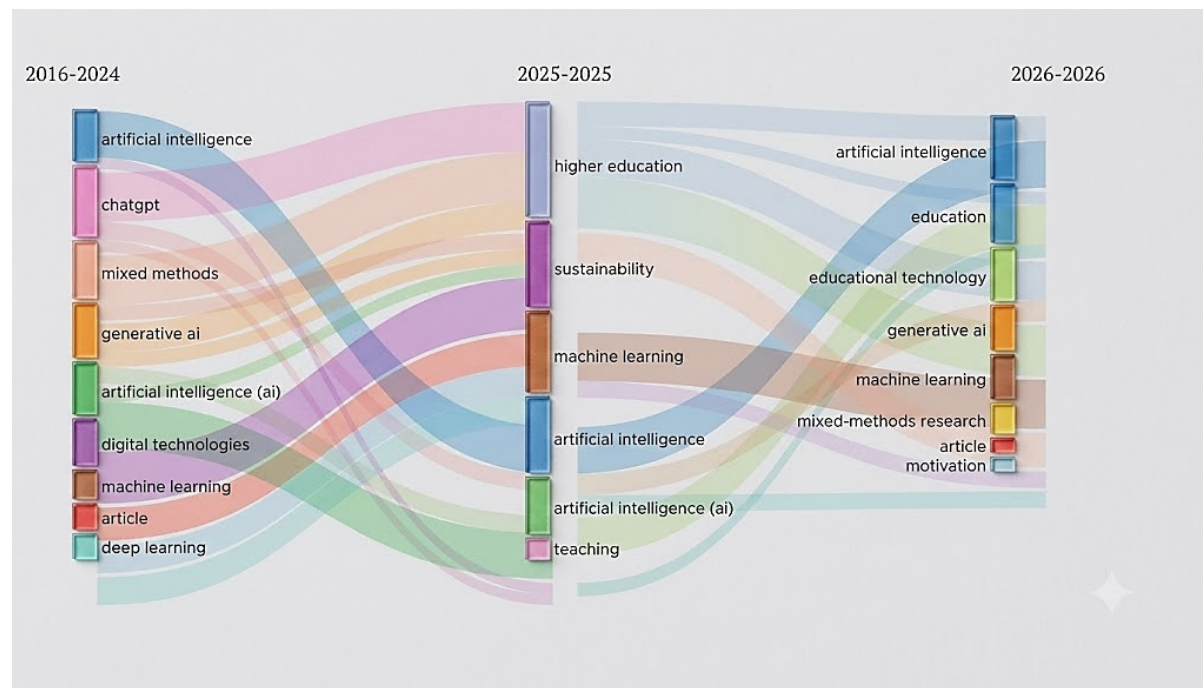
11). This indicates that the field was initially grounded in establishing technological capabilities alongside methodological approaches. The presence of mixed methods at this early stage is particularly important, as it shows that methodological considerations were already integrated into the study of AI, even when the technological focus was still developing. At the same time, emerging concepts such as ChatGPT and generative AI begin to appear, signaling the early introduction of advanced AI systems toward the later part of this period. Moving into the second phase (2025), the thematic structure becomes more application-oriented and consolidated. Core technological themes such as AI and machine learning persist, demonstrating strong continuity. However, these are now increasingly connected to applied domains such as higher education, teaching, and sustainability. This shift reflects a transition from purely technological exploration to contextual implementation, particularly within educational and societal frameworks.

The continuation of AI (AI) as a central node, along with its strong linkage to applied themes, indicates that AI is not only evolving technically but is also becoming embedded in real-world problem-solving contexts. Importantly, the presence of teaching-related themes suggests that mixed methods approaches are being utilized to understand complex human–technology interactions. In the final phase (2026), the thematic structure becomes more focused, refined, and specialized. Core themes such as AI, education, educational technology, generative AI, and machine learning remain dominant, indicating strong thematic stability. Notably, mixed-methods research reappears more explicitly in this stage, suggesting a growing recognition of the importance of rigorous methodological frameworks in studying AI applications. The stronger linkage between AI and education demonstrates that the field has matured into a well-defined interdisciplinary domain, where technological innovation and applied research are closely integrated. Emerging themes such as motivation indicate a deeper exploration of user experience and behavioral outcomes, further emphasizing the need for comprehensive research designs. Across all three phases, one of the most significant observations is the continuity of AI as the central theme, acting as a stable backbone throughout the evolution process.

At the same time, the gradual strengthening of connections between AI, application domains (especially education), and methodological approaches reflects an increasing conceptual and methodological convergence. While mixed methods terminology is not always consistently visible in every phase, its re-emergence and linkage in later stages suggest that it plays a crucial supporting role in addressing complex, multidimensional research problems associated with AI. Overall, the thematic evolution analysis strongly supports the study's central argument by demonstrating that the field is moving from technological emergence → applied integration → methodological consolidation. This progression indicates that research on AI is becoming more mature, interdisciplinary, and methodologically grounded. The findings highlight that the integration of AI and MMR is not static but is evolving toward a more cohesive and sophisticated framework, reinforcing the growing importance of combining advanced technologies with robust methodological approaches to address complex real-world challenges.

Figure 11

Thematic Evolutions



Thematic Map Analysis

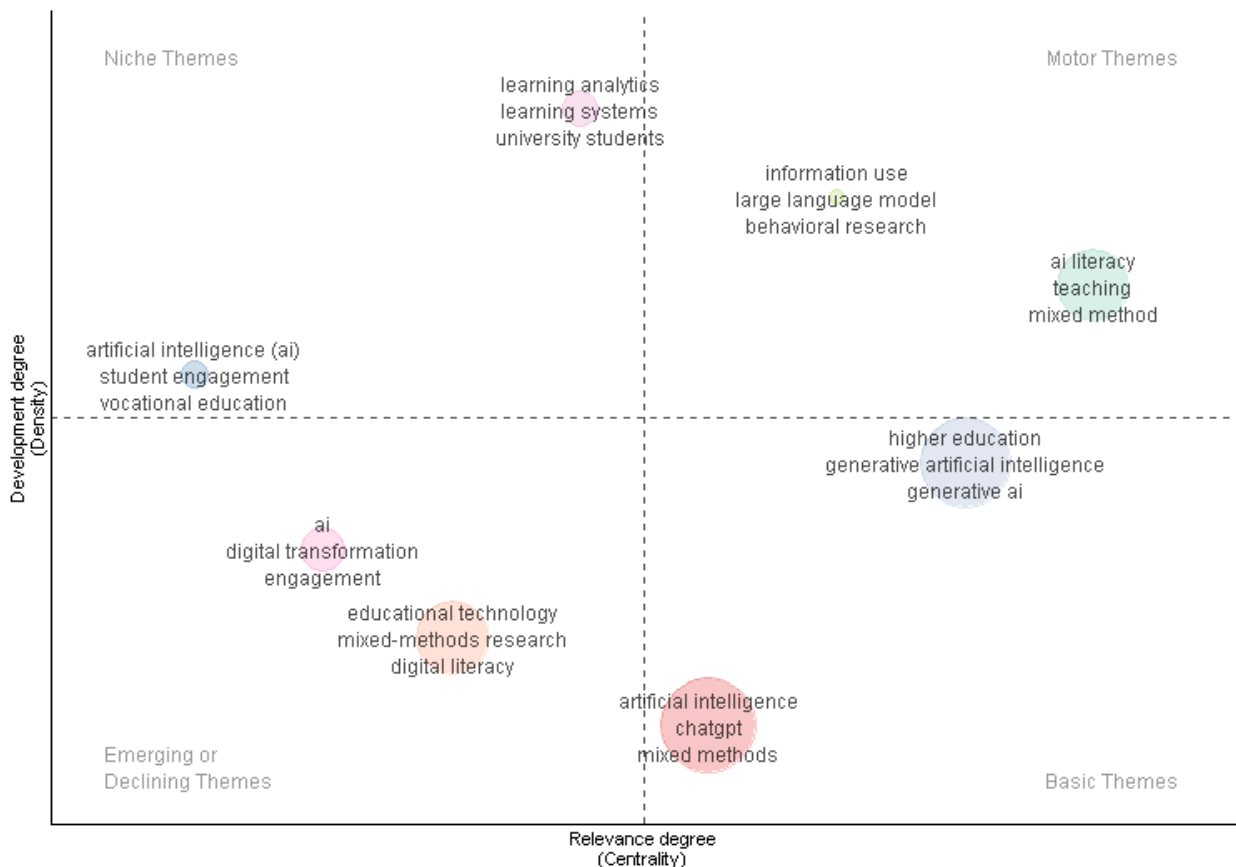
A thematic map is a bibliometric visualization that categorizes research themes based on two key dimensions: centrality (relevance) on the x-axis and density (development) on the y-axis. Centrality indicates how important or connected a theme is to the overall research field, while density reflects how well-developed and internally cohesive that theme is (Lowar et al., 2025). The map is divided into four quadrants, each representing a different stage of thematic evolution.

Upper-right quadrant (Motor Themes) includes highly developed and highly relevant topics. In this figure, themes such as AI literacy, teaching, mixed method, and large language models fall here (See Figure 12). These are the driving forces of the field, showing both strong conceptual development and high integration with other topics. Their presence suggests that research is actively advancing toward AI-driven education and methodological integration, making them central to future studies. Upper-left quadrant (Niche Themes) contains well-developed but less connected topics. Here, learning analytics, learning systems, and university students appear. These themes are specialized and mature, but relatively isolated. They contribute depth rather than breadth, indicating focused research areas that may not yet be fully integrated into the broader AI–education discourse. Lower-right quadrant (Basic Themes) represents highly relevant but underdeveloped topics. Themes such as higher education, generative AI, and AI are positioned here. These are foundational and widely connected, yet still evolving conceptually. Their placement indicates that although they are central to the field, more theoretical and empirical development is needed. This is critical for discussion, as it highlights where future research should focus. Lower-left quadrant (Emerging or Declining Themes) includes digital transformation, engagement, educational technology, and mixed-methods research. These themes have low centrality and low density, suggesting they are either emerging areas gaining attention or declining topics losing relevance. Given current trends, these are more likely emerging themes transitioning toward greater importance. Overall, the thematic map shows a dynamic and

evolving research landscape, where AI-related themes (especially generative AI and ChatGPT) are moving from basic to motor themes. This transition reflects a shift toward integration of advanced AI tools in education using mixed methods approaches, providing strong implications for future research direction and theoretical development.

Figure 12

Thematic Map



Discussion

A central contribution of this study is the empirical identification of what we term a “discourse-practice gap” in AI-MMR scholarship. Although integration and triangulation are foundational to MMR (Clark, 2019; Fetters et al., 2013; Costa et al., 2025), they do not emerge as distinct, mature themes within the literature’s keyword structure. Integration-related terms appear with moderate frequency but remain embedded within larger clusters, suggesting that integration is treated as an assumed feature of mixed methods work rather than as a process requiring explicit articulation in AI contexts. Triangulation, despite its recognized importance for validity and credibility (Vivek et al., 2023), receives even less visible attention.

This pattern warrants careful interpretation. The absence of integration and triangulation as dominant themes does not necessarily mean these practices are absent from AI-MMR research; it may indicate that they are being practiced without being thematized or reported in ways captured by keyword analysis (Cevik et al., 2025; Costa et al., 2025). However, the consistent gap between the prominence of AI-related terms and the marginality of methodological terms suggests that the discourse is

technology-led rather than methodologically-driven (Khoza and Van Der Walt, 2025; Pérez-Urbina, 2026). Researchers appear to be applying mixed methods frameworks to AI-related questions while devoting limited attention to examining how AI might challenge, extend, or reconfigure established understandings of what integration and triangulation entail (Nashwan et al., 2023; Hooshyar et al., 2025; Costa et al., 2025a). More importantly, this finding suggests that methodological rigor may increasingly be assumed rather than explicitly demonstrated. As AI becomes embedded within research workflows, the absence of explicit discussion surrounding integration and triangulation may hinder transparency, reproducibility, and the assessment of research quality.

This finding has implications for how we understand the relationship between AI and methodology. AI introduces several dynamics that could transform integration and triangulation practices: its capacity for processing vast quantities of unstructured data expands the scope of data triangulation (Rane et al., 2024; Coombs & Bagley, 2026); machine learning algorithms enable pattern identification across modalities that might escape human detection (McIntosh et al., 2025; Yamada, 2026); and generative AI can produce synthetic findings that complicate traditional notions of interpretive authority (Borger et al., 2023; Prianikov, 2025). Yet these possibilities are not being systematically theorized. The methodological implications of AI – including challenges related to algorithmic bias, transparency, explainability, and the reliability of AI-generated outputs (Guenduez et al., 2026) – remain underexplored in the literature we analyzed. This silence is concerning because very few studies have thus far proposed methodological frameworks capable of critically evaluating AI-assisted MMR. Without such frameworks, researchers risk adopting AI-enhanced analytical procedures faster than the field develops the methodological safeguards necessary to ensure validity, credibility, and accountability.

The findings further indicate that AI currently operates more as a methodological catalyst than as a methodological disruptor. The co-occurrence networks and thematic structures suggest that AI is being used to extend existing research practices – enhancing data processing, pattern recognition, and analytical capacity – rather than to fundamentally challenge or reconfigure MMR’s foundational principles. This observation is consistent with the notion of “methodological augmentation,” where new technologies supplement rather than replace established approaches (Fieldhouse et al., 2025; Altamirano et al., 2026). In this sense, AI presently appears to amplify methodological capabilities rather than redefine methodological logic. The core principles through which researchers establish validity, generate meaning, and integrate evidence remain largely unchanged despite substantial advances in computational capacity.

However, we caution against concluding that AI will remain a mere catalyst. The field is in a rapid growth phase, and the structures we observe represent a snapshot of scholarly discourse rather than a stable equilibrium. The positioning of generative AI and ChatGPT as basic themes – highly relevant but still developing – suggests that these concepts may move toward motor themes as theoretical consolidation occurs. Whether this consolidation will include explicit engagement with integration and triangulation, or whether it will proceed along purely technology-focused pathways, remains an open question. This uncertainty underscores the need for proactive theoretical work that anticipates how AI might ultimately function not just as a catalyst but as a disruptor – a force that compels fundamental rethinking of methodological assumptions. Accordingly, the catalyst-disruptor distinction proposed in this study should be viewed as a dynamic continuum rather than a fixed categorization, reflecting the evolving relationship between AI and MMR.

The collaboration patterns we observed reveal both strengths and limitations of the current research ecosystem. The average of 3.66 co-authors per document and the predominance of multi-authored

works indicate that this is fundamentally a collaborative and interdisciplinary field. However, the limited international co-authorship rate of 23.76% suggests that collaboration remains largely institutional or domestic. Given that AI development and research applications are shaped by diverse educational, cultural, and policy contexts, broader international collaboration may facilitate more inclusive methodological innovation and theoretical development.

The geographic distribution of publications shows China and the United States as leading contributors, with emerging contributions from India, Indonesia, and Malaysia. While this pattern reflects the growing global diffusion of AI-MMR scholarship, it also raises questions regarding whose methodological assumptions and epistemological perspectives shape the field. Future research should examine whether the discourse-practice gap identified in this study varies across geographic contexts and disciplinary traditions.

An important implication of our findings is that the increasing adoption of AI should not be interpreted as reducing the importance of human methodological judgment. The findings indicate that AI is being used primarily to support existing research practices rather than to replace researcher decision-making. This suggests that the robustness of MMR continues to depend on researchers' abilities to make informed judgments regarding research design, interpretation, integration, and validation. As Devkota et al. (2026) human expertise remains essential for planning research, understanding context, evaluating the credibility of evidence, recognizing biases, and ensuring meaningful synthesis between qualitative and quantitative findings.

This observation highlights a critical distinction between computational intelligence and methodological intelligence. While computational intelligence excels at processing information, detecting patterns, and generating outputs at scale, methodological intelligence involves contextual reasoning, theoretical sensitivity, ethical reflection, reflexivity, and the capacity to interpret evidence within broader social and disciplinary contexts. The enduring value of MMR lies not simply in combining multiple forms of data but in the human ability to integrate diverse sources of evidence into coherent, contextually grounded, and theoretically meaningful explanations. Consequently, methodological rigor in AI-enhanced MMR should be evaluated not only by the sophistication of AI tools employed but also by the transparency and quality of human interpretive decisions.

This observation has practical implications for training and practice. As AI tools become more integrated into research workflows, there is a risk that researchers may treat AI-generated outputs as authoritative without adequate critical scrutiny. Our findings suggest that such risks have not yet been systematically addressed in the literature. We argue that the most promising pathway for methodological advancement lies not in replacing human researchers with AI systems but in fostering human-AI collaborative approaches that combine computational capability with critical reasoning, reflexivity, and methodological expertise (Guenduez et al., 2026; Altamirano et al., 2026). From this perspective, the future of AI-enhanced MMR should be understood as a process of human-AI complementarity rather than technological substitution. AI can augment analytical efficiency and expand researchers' capacity to engage with complex datasets, but the ultimate responsibility for interpretation, validation, integration, and ethical decision-making remains fundamentally human (Branda et al., 2025; Devkota et al., 2026).

This study makes several contributions. It provides the first systematic bibliometric mapping of the AI-MMR literature with explicit attention to integration and triangulation, addressing a gap in the existing literature that has predominantly focused on educational applications or general bibliometric trends (Fieldhouse et al., 2025; Altamirano et al., 2026). By identifying the discourse-practice

gap, it shifts the conversation from documenting growth to critically examining the substance of methodological discourse. And by proposing the catalyst-disruptor distinction, it offers a framework for conceptualizing the relationship between AI and MMR methodology that can guide future theoretical and empirical work.

Conclusion

This bibliometric study provides a comprehensive assessment of the rapidly expanding literature at the intersection of AI (AI) and MMR (MMR) between 2016 and 2026. The findings reveal an exceptionally dynamic field characterized by accelerated publication growth, increasing interdisciplinary collaboration, and the emergence of AI as the dominant conceptual driver of scholarly discourse. However, despite the growing integration of AI into research processes, the foundational methodological principles of MMR – namely integration and evidence triangulation – remain only weakly theorized and insufficiently visible within the literature’s thematic structure.

The analysis demonstrates that the current body of academic research, publications, and scholarly discussions is largely technology-driven, emphasizing AI applications and capabilities while devoting comparatively limited attention to how AI reshapes methodological reasoning, integration processes, and validity frameworks. This imbalance suggests the existence of a discourse–practice gap in which methodological commitments are frequently assumed rather than explicitly examined. The study further indicates that AI currently functions primarily as a methodological catalyst that enhances existing research practices rather than as a disruptive force that fundamentally redefines them.

Ultimately, the future robustness of AI-enhanced MMR will depend not on technological sophistication alone but on researchers’ ability to exercise critical judgment, contextual interpretation, and rigorous methodological integration. While AI can substantially enhance data processing, analytical efficiency, and pattern recognition, it cannot replace the uniquely human capacities required for methodological reasoning, contextual understanding, ethical reflection, reflexivity, and meaningful interpretation. The enduring strength of MMR lies in researchers’ ability to critically integrate diverse forms of evidence, evaluate validity, and construct contextually grounded explanations that transcend algorithmic outputs. Taken together, the findings suggest that the central challenge facing AI-enhanced MMR is no longer whether AI can support research activities, but whether sufficiently robust methodological frameworks can be developed to ensure that technological advancement remains anchored in the principles of integration, triangulation, transparency, and human judgment. Advancing this field therefore requires stronger theoretical engagement with these foundational principles and a commitment to human–AI collaboration that augments rather than substitutes human expertise. Ultimately, the long-term value of AI in MMR will depend not on the sophistication of algorithms alone, but on researchers’ ability to combine technological innovation with critical reflection, contextual interpretation, ethical responsibility, and meaningful knowledge synthesis.

Limitations and Future Research Directions

This bibliometric analysis maps scholarly discourse rather than actual research practices; consequently, absent keywords indicate under-thematization of integration and triangulation, though these practices may occur without being explicitly labeled. Therefore, the findings should be interpreted as evidence of how integration and triangulation are represented in the literature rather than how they are enacted in practice. Moreover, reliance on Scopus may underrepresent non-English and regional literature, thereby introducing geographic and linguistic bias. Additionally, the search strategy may have omitted relevant studies due to rapidly evolving AI terminology, while the exclusive focus on integration

and triangulation excludes other important MMR dimensions such as philosophical paradigms and researcher reflexivity. Finally, citation-based indicators remain inherently unstable in this young field; thus, interpretations of scholarly influence require caution, and the partial 2026 data may affect recent trend analysis.

Building on these limitations, scholars should develop theoretical frameworks for AI-assisted integration and triangulation that explicitly address algorithmic bias, transparency, explainability, and hallucination risks. Furthermore, content analyses and qualitative case studies should complement bibliometric evidence by examining how integration and triangulation are actually enacted in practice. Future research should also investigate how human methodological judgment and human–AI collaboration influences the validity, credibility, and interpretive depth of MMR. Likewise, cross-national comparative studies would reveal whether the discourse–practice gap is universal or context-specific. Finally, extending analysis beyond education into healthcare, policy, and other applied domains would provide deeper insight into how AI is reshaping methodological practice over time.

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