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Data Visualization Literacy Frameworks: A Systematic Review of Models, Evaluation Approaches and Research Gaps

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Abstract

In the era of big data, automated visualization and advanced analytics, robust data visualization literacy frameworks are increasingly essential for supporting effective decision-making and the interpretation of complex information. Data visualization literacy refers to the ability to read, interpret, evaluate and communicate meaningful insights from visual representations of data. Despite its growing importance across domains such as healthcare, manufacturing, tourism, education and immersive analytics, research on structured frameworks remains fragmented and lacks standardization. This study presents a systematic literature review of data visualization literacy frameworks to synthesize current knowledge, examine evaluation approaches and identify research gaps. A total of 43 peer-reviewed studies published between 2013 and 2024 were analyzed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. The review examines framework objectives, theoretical foundations, usability considerations, educational validation, empirical effectiveness and assessment methods. The findings indicate that many frameworks emphasize usability and cognitive support, but their empirical effectiveness is often weakly validated through limited samples, short-term testing, or prototype-based evaluation. The review also highlights emerging literacy concerns related to generative artificial intelligence and automated visualization systems, including transparency, interpretability and user trust. Overall, this study emphasizes the need for standardized, empirically validated and domain-adaptable frameworks that support cognitive effectiveness, educational application and responsible visualization practice.

Keywords: Data Visualization Frameworks, Data Visualization Literacy, Evaluation Methods, Systematic Literature Review, Visual Analytics.

Introduction

Data visualization plays a crucial role in supporting analytics, monitoring and decision-making across various fields such as manufacturing, healthcare, tourism and immersive analytics. Numerous frameworks have been developed, but research shows that each framework has significant limitations. Therefore, it is important to conduct a Systematic Literature Review that identifies and compares the gaps in data visualization frameworks across different domains. This review aims to synthesize existing knowledge on data visualization frameworks, critically assessing their applications and identifying areas requiring further research. Data visualization in the context of big data analytics provides essential tools for transforming large-scale datasets into comprehensible insights, supporting decision-making across diverse domains (1). This systematic review will employ a rigorous methodology to ensure comprehensive coverage and unbiased analysis of the selected literature, thereby illuminating the current state-of-the-art and pinpointing underexplored facets within data visualization research (2). Furthermore, it will categorize existing visualization techniques and their associated challenges, offering insights into design requirements for future visual analytics tools (3). This endeavor seeks to provide a foundational reference for both researchers and practitioners, fostering advancements in the theoretical underpinnings and practical implementations of data visualization, including visual analytics approaches that enhance transparency and interpretability in AI-driven systems (4). This paper addresses the need for a comprehensive overview of existing data visualization frameworks, detailing their strengths and weaknesses in diverse application contexts. Specifically, this review aims to identify common architectural patterns, underlying theoretical

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models and empirical evaluations of these frameworks to ascertain their efficacy and generalizability across disparate domains. Moreover, it endeavors to highlight prevalent research gaps concerning the adaptability, scalability and cognitive load associated with current visualization paradigms (5). A significant portion of existing research focuses on recommendation systems that suggest visualization designs to users, though these often enumerate only a limited set of options (6). The sheer volume of digital news platforms necessitates sophisticated tools to filter, analyze and extract meaningful insights efficiently (7). However, the integration of visual analytics, which combines visualization, data mining and statistics, holds considerable promise for overcoming these limitations by offering more sophisticated and interactive exploratory capabilities (8).

In this review, data visualization literacy is defined as the capability to read, interpret, evaluate and communicate information from visual data representations in ways that support accurate reasoning and informed decision-making. It includes the ability to understand visual encodings, recognize patterns and anomalies, assess the appropriateness of chart types and critically evaluate whether a visualization supports or distorts the underlying data. This definition is important because the reviewed frameworks do not merely provide technical visualization tools; they also shape how users learn, interpret and apply visual information across educational, clinical, industrial, tourism, immersive and cross-domain settings.

The review is further contextualized within several theoretical traditions that explain why visualization frameworks differ in design and effectiveness. Cognitive load theory emphasizes the need to reduce unnecessary mental effort when users process complex visual information, while visual cognition explains how perception, attention and pattern recognition influence interpretation. Human-computer interaction theory highlights usability, interaction design and user experience as essential dimensions of framework evaluation. Learning sciences provide a basis for understanding how visualization literacy can be developed through instruction, feedback and assessment, whereas information visualization theory explains the role of visual encoding, abstraction and interaction in transforming data into interpretable knowledge. These perspectives provide a theoretical foundation for evaluating whether a framework is not only technically functional but also cognitively effective and educationally meaningful.

This systematic review also explores the pitfalls and challenges associated with the design and interpretation of visual representations, acknowledging that not all visualizations are inherently beneficial and can sometimes lead to misinterpretations or cognitive overload (9). Principles of effective data visualization emphasize that adhering to clear design guidelines such as appropriate chart selection, accurate scaling and minimizing clutter is essential to avoid misleading representations in visual data communication (10). Studies specifically examining visualization pitfalls in published scientific literature further confirm that poor design choices frequently distort data interpretation (11). Moreover, the rapid proliferation of data necessitates advanced visual analytics to derive meaningful insights, yet current frameworks often struggle with the sheer volume, velocity and variety of modern datasets, leading to a significant gap between data generation and effective analysis (8). Therefore, this article aims to address the aforementioned research gaps by answering the following questions: identifying data visualization frameworks used in academic literature, analyzing the gaps and limitations of these frameworks across various studies, comparing gaps across multiple domains including manufacturing, healthcare, tourism and immersive analytics and providing recommendations for future research to advance data visualization frameworks.

This systematic review synthesizes findings from various studies, providing a comprehensive understanding of the current state of data visualization frameworks and identifying key areas for future development, including immersive and collaborative visualization environments that enable multi-user analytical reasoning. Data visualization transforms abstract data into interpretable graphical representations, enabling users to identify patterns, trends and anomalies more intuitively (12). This process is integral to visual analytics, which integrates automated analytical methods such as machine learning with interactive visualizations to facilitate complex problem-solving (13). The synergy between machine learning and data visualization is particularly crucial in the current data-driven era, as it enables the interpretation of large and complex datasets (14). This integration enhances analytical model refinement through iterative visual feedback (15). The effectiveness of data visualization depends on its ability to leverage human perception and cognitive processes, thereby minimizing cognitive load (16). However, achieving this requires adaptable visualization approaches that consider user cognitive capabilities and contextual data requirements (17). This bridge between quantitative data and human intuition is essential for transforming raw data into actionable knowledge (18).

Data visualization frameworks provide structured methodologies and tools for developing effective visual representations. These frameworks range from grammar-based toolkits to comprehensive platforms that support the entire visualization pipeline, including data preparation, visual encoding, interaction design, evaluation and interpretation (19). The DNA framework of information design provides a structured vocabulary for classifying visual encoding elements and their relationships in charts and diagrams (20). Visual encoding frameworks such as the DNA Framework provide structured approaches to representing data through graphical elements (21). They help researchers and practitioners select suitable visualization techniques, align visual design with user needs and assess the usefulness of visual outputs across different domains (22). Domain-specific applications, such as financial news analytics, illustrate how visualization frameworks can be adapted to support decision-making in specialized contexts (23). Challenges in data visualization education further underscore the need for frameworks that are pedagogically grounded and accessible to diverse user groups (24). Practical implementation of these frameworks enables researchers to produce clearer and more effective visual representations of complex datasets (25). In media and social platforms, visualization frameworks that support data-driven content analysis contribute to more transparent and interpretable reporting (26). Their importance has increased as data-intensive environments require tools that are scalable, interpretable, interactive and adaptable to different users and contexts.

Methodology

This systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a comprehensive and transparent approach to identifying, selecting and critically appraising relevant studies. A comprehensive search strategy was developed to identify relevant publications across multiple scientific databases, focusing on keywords related to data visualization frameworks, evaluation methodologies and emergent trends. The selection criteria prioritized peer-reviewed articles, conference papers and book chapters published within the last decade to capture the most current developments and advancements in the field. PRISMA guidelines were strictly adhered to during the screening and data extraction phases, ensuring methodological rigor and minimizing bias. Data extraction forms were designed to capture essential information, including framework characteristics, evaluation methodologies employed and identified research gaps, ensuring consistency and completeness. Figure 1 showed the PRISMA Flow Diagram.

All retrieved studies underwent a rigorous quality assessment using established criteria to evaluate their methodological soundness and the reliability of their findings (27). The study selection and reporting process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 guideline (28).

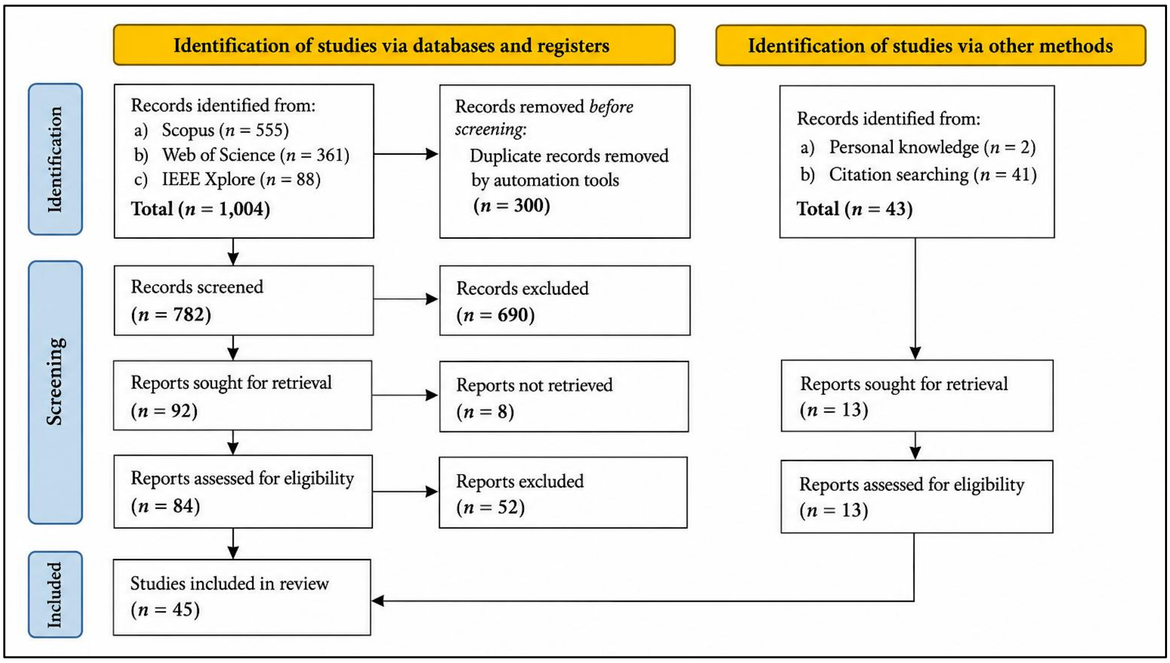

Figure 1: PRISMA Flow Diagram (Adapted from PRISMA 2020 guidelines (24))

Therefore, this article addresses the previously identified research gaps by examining several key questions concerning data visualization frameworks. Specifically, the review investigates which data visualization frameworks have been applied in academic literature, analyzes the reported gaps and limitations of these frame-works, compares their shortcomings across different domains such as manufacturing, healthcare, tourism and immersive analytics and formulates recommendations to guide future research in advancing the development of data visualization frameworks. These guiding questions structure the systematic literature review process to ensure a focused and comprehensive exploration of the topic while synthesizing findings from selected studies. This systematic review integrates evidence from a wide range of publications to provide a comprehensive understanding of the current state of data visualization frameworks and to identify critical areas requiring further development. By adopting this approach, the review not only catalogs existing frameworks but also critically evaluates their weaknesses and potential for improvement, thereby contributing to the development of more effective, adaptable and versatile visualization tools.

To identify relevant studies, a multi-database search strategy was implemented across prominent academic platforms, including Scopus, Web of Science, ScienceDirect and Google Scholar (14). Search terms were carefully constructed using Boolean operators and included keywords such as “data visualization framework,” “visualization toolkit,” “interactive visualization,” “visual analytics,” and “evaluation methodologies,” together with their related synonyms to ensure comprehensive coverage. The search process was refined iteratively by reviewing preliminary results and adjusting search strings to enhance relevance while minimizing unrelated articles. During the identification phase guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology, specific inclusion criteria were established, including publication year between 2013 and 2024 and restriction to journal articles only. Additional searches were conducted using major academic databases such as Scopus, IEEE Xplore and ACM Digital Library to ensure completeness of the retrieved literature. The search query template, formulated using Scopus syntax, was designed to systematically capture studies related to data visualization frameworks.

The search query template (using Scopus syntax) for identifying studies related to data visualization frameworks was as shown in Table 1. To ensure the rigor and relevance of this systematic review, specific inclusion and exclusion criteria were established, meticulously guiding the selection of studies for in-depth analysis.

Table 1: Search Query and Record Inclusion Criteria

ABS("data visualization framework" OR "data visualization tools" OR "framework for visualization" OR "visual analytics framework" OR "big data visualization" OR "interactive data visualization") OR TITLE("data visualization framework" OR "data visualization tools" OR "framework for visualization" OR "visual analytics framework" OR "big data visualization" OR "interactive data visualization") OR TITLE("framework for visualization" OR "visual analytics" OR "interactive data visualization" OR "visualization tools")

Table 2: Chart Review Exclusion Query

information literacy" OR "information visualization literacy" OR "data visualization literacy" OR "chart literacy" OR "information visualization" OR "data visualization framework" OR "chart") AND "review") AND NOT TITLE("chart review") AND DOCTYPE(ar) AND SRCTYPE(j) AND PUBYEAR > 2013

We realized that the term "Chart Review" was a keyword of the medical domain regarding specific medical studies, which were not relevant for our research, hence we have explicitly asked not to include this term in the papers title as shown in Table 2. As a second step, we have merged the results of the above three search queries by discarding duplicated records through the DOI field. We have added manual sources to the records retrieved by the query, where not present, which were part of the personal knowledge and expertise of the authors and of snowballing procedures of either queried or manually retrieved works. The total number of records retrieved after the above procedures was of 675 from queries and 43 from manual search plus snowballing. Ultimately, this refined search strategy yielded a comprehensive dataset for analysis, enabling a thorough examination of the current landscape of data visualization frameworks and their associated challenges (18). This rigorous selection process ensures that the review is grounded in high-quality, pertinent research, providing a robust foundation for identifying trends, gaps and future directions in the field (15).

The paper selection process began with an initial identification phase that yielded 7,168 potentially relevant scientific contributions, which were systematically exported into Zotero for efficient reference management (1). The data retrieved from the query and merge operations, together with records identified through manual searches, were exported to a shared Google Sheet for detailed manual inspection. For each record, the following information was documented: the databases searched, journal title, publisher, authors' names, paper title, abstract, keywords, publication year, DOI, citation count, source link and a notes field for shared comments among the authors. All four authors reviewed the inclusion and exclusion of records based on the predefined criteria presented in Table 1. To ensure consistency in the selection process, a calibration phase was conducted. In the first round, each author independently classified the first five records, resulting in disagreements on three records, which were subsequently resolved through discussion. In the second round, the next five records were independently classified, with only one disagreement requiring group discussion. Following calibration, the remaining records were divided equally among the four authors for individual classification into three categories: keep, discard and discuss. The discuss category was applied when uncertainty existed regarding inclusion or exclusion and required further deliberation. A group meeting was held to finalize decisions on all records categorized as discuss. Initially, approximately one-third of the records were placed in this category, although most were eventually discarded after group review. As an additional validation step, each author re-examined one-quarter of the discarded records and had the opportunity to reclassify them into the discuss category for further consideration. Only a small number of records were reassessed and approximately half of these were ultimately promoted to the keep category. In the final stage, all records classified as keep were comprehensively reviewed for data extraction.

Results

This section presents the findings related to the terms and definitions of data visualization frameworks identified in the reviewed studies. The analysis shows that definitions vary across the literature. Some studies describe these frameworks as structured methodological approaches for developing and evaluating visual representations, while others define them as integrated toolsets supporting the visualization pipeline, including data transformation and interaction design. These variations indicate a lack of a unified definition and reflect the multidisciplinary nature of data visualization research.

Table 3: Identified Data Visualization Frameworks.

Framework	Description	Domain	References
DVL-EDU Framework	Framework to enhance Data Visualization Literacy in education, including classification and difficulty ranking of visualizations.	Education	(12, 23)
EHR-IVT Framework	Interactive Visualization Tools for Electronic Health Records, focusing on interpreting and monitoring patients.	Healthcare	(15, 24)
Immersive Analytics Framework	Framework for data visualization using VR/AR, focusing on exploratory analytics and immersive interaction.	Immersive Analytics	(16, 18)
Tourism BI Framework	Business Intelligence framework for the tourism sector, integrating big data and dashboard reporting.	Tourism / Hospitality	(1)
PdM Visual Analytics Framework	Framework for predictive maintenance in Industry 4.0, combining data-driven and knowledge-driven approaches.	Manufacturing / Industry 4.0	(3)
DVL-Assessment Framework	Framework to assess Data Visualization Literacy through quizzes and visual tests.	Education / General	(12, 23)
Visual Analytics Health Framework	Visualization framework for patient data analysis, combining prediction and interactive monitoring.	Healthcare	(15, 24)
Tourism Dashboard Framework	Interactive dashboard for the tourism sector, focusing on tourist trends and economic data visualization.	Tourism / Hospitality	(1)
Immersive Education Visualization	VR/AR framework for educational data literacy, focusing on interactive visual exploration.	Education / Immersive	(12, 23)
PdM VR Analytics	VR-based framework for predictive maintenance visualization and immersive interaction.	Manufacturing / Industry 4.0	(3)
Healthcare Dashboard Framework	Interactive dashboard framework for real-time patient monitoring.	Healthcare	(15, 24)
Education BI Framework	Business Intelligence framework for education, analyzing student performance via visualization.	Education	(12, 23)
DataViz Literacy Framework	Framework measuring data visualization literacy through a combination of models and quizzes.	General / Education	(12, 23)
Healthcare Predictive Analytics	Framework for patient condition prediction using interactive visualizations.	Healthcare	(15, 24)
Immersive Tourism Analytics	VR/AR framework for tourism data analysis with immersive visualization.	Tourism / Immersive Analytics	(16, 18)
Education Interactive Visualization	Framework for educational data visualization, focusing on interactivity and student engagement.	Education	(12, 23)
Manufacturing Visual Analytics	Framework for production process visualization, supporting predictive maintenance and quality monitoring.	Manufacturing	(3)
Tourism Big Data Framework	Framework for visualizing tourism sector big data to support management decision-making.	Tourism / Hospitality	(1)
VR Education Analytics	VR framework for analyzing student data literacy in interactive education.	Education / Immersive	(12, 23)
PdM Interactive Dashboard	Interactive dashboard for predictive maintenance in Industry 4.0 with real-time visualization.	Manufacturing / Industry 4.0	(3)
Smart City Visualization Framework	Framework for urban data visualization, integrating IoT and traffic data for smart city analytics.	Smart City	(1)
Industrial IoT Visual Analytics	Visualization framework for industrial IoT data, monitoring sensors and predictive maintenance.	Manufacturing / Industry 4.0	(3)
Healthcare AI Visualization	Framework integrating AI predictions with patient visualization dashboards.	Healthcare	(15, 24)
Tourism Experience Analytics	Framework for analyzing tourist experiences with interactive dashboards.	Tourism / Hospitality	(1)
Education VR Learning Framework	VR framework to enhance data literacy and learning outcomes in education.	Education / Immersive	(12, 23)
Manufacturing Digital Twin Visualization	Visualization framework for digital twin in manufacturing, focusing on predictive maintenance and process monitoring.	Manufacturing	(3)

Immersive Healthcare Analytics	Framework VR/AR for healthcare data literacy, training medical staff in interactive analytics.	Healthcare / Immersive	(15, 24)
Education Interactive Analytics	Framework for student engagement in interactive data visualization dashboards.	Education	(12, 23)
Portal News for Visualization	Framework for analyzing news	Portal News	(7)
Portal News for Visualization	Framework for analyzing Portal news	News	(29)
Tourism Smart Analytics	Framework integrating real-time big data dashboards for tourism decision-making.	Tourism / Hospitality	(1)

Table 3 summarizes the identified data visualization frameworks according to their purpose, domain of application and source. The table shows that education-oriented frameworks mainly focus on improving data visualization literacy through classification, quizzes and interactive learning activities. Healthcare frameworks primarily support patient monitoring, clinical interpretation and predictive analytics, whereas manufacturing frameworks emphasize predictive maintenance, anomaly detection and process monitoring. Tourism frameworks are commonly implemented through business intelligence dashboards, while immersive analytics frameworks apply virtual and augmented reality to support exploratory interaction. This distribution indicates that data visualization frameworks are highly domain-dependent and differ substantially in their goals, technological requirements and evaluation priorities. This section examines the terms and definitions of data visualization frameworks identified in the literature. The findings show varying conceptualizations, reflecting the absence of a unified definition and the multidisciplinary nature of the field (30).

Table 4: Gaps and Limitations of Identified Frameworks

Framework	**Gap / Limitations**	**Domain**	**References**
DVL-EDU Framework	Concept-focused, limited empirical validation, restricted to education scenarios, limited interactivity	Education	(10, 19)
EHR-IVT Framework	Limited prediction and monitoring, constrained for multimodal data, lacks real-time support	Healthcare	(15, 24)
Immersive Analytics Framework	No standard evaluation, unclear when/why to use, interactivity depends on device	Immersive Analytics	(16, 18)
Tourism BI Framework	Fragmented research, simple dashboards, limited empirical evaluation	Tourism / Hospitality	(1)
PdM Visual Analytics Framework	Focused only on anomaly detection, limited knowledge-driven integration, minimal explainable AI	Manufacturing / Industry 4.0	(3)
DVL-Assessment Framework	Small sample sizes, limited cross-domain testing, incomplete coverage of DVL aspects	Education / General	(12, 23)
Visual Analytics Health Framework	Limited data integration, minimal user feedback, lack of empirical evaluation	Healthcare	(15, 24)
Tourism Dashboard Framework	Limited flexibility, low interactivity for predictive analytics, insufficient empirical validation	Tourism / Hospitality	(1)
Immersive Education Visualization	Validation only on small groups, limited longitudinal studies, VR device limitations	Education / Immersive	(12, 23)
PdM VR Analytics	Limited enterprise integration, interactivity evaluation limited	Manufacturing / Industry 4.0	(3)
Healthcare Dashboard Framework	Limited predictive analytics, restricted interactivity	Healthcare	(15, 24)
Education BI Framework	Simple dashboards, limited in-depth analysis, scarce quantitative evaluation	Education	(12, 23)
DataViz Literacy Framework	Quiz-based only, limited interactivity, minimal cross-domain validation	General / Education	(12, 23)
Healthcare Predictive Analytics	Limited real-time support, not all clinical variables covered, insufficient empirical evaluation	Healthcare	(15, 24)
Immersive Tourism Analytics	Limited validation, VR interactivity restricted, small user testing	Tourism / Immersive Analytics	(16, 18)
Education Interactive Visualization	Limited empirical studies, small sample sizes, partial DVL coverage	Education	(12, 23)
Manufacturing Visual Analytics	Limited interactivity, infrequent system evaluation, restricted real-time integration	Manufacturing	(3)
Tourism Big Data Framework	Limited validation, simple predictive analysis, low dashboard interactivity	Tourism / Hospitality	(1)

VR Education Analytics	Limited VR devices, small validation sample, not all DVL aspects covered	Education / Immersive	(12, 23)
PdM Interactive Dashboard	Limited interactivity, real-time integration restricted, few user evaluations	Manufacturing / Industry 4.0	(3)
Smart City Visualization Framework	Limited integration of IoT streams, few user studies, scarce validation	Smart City	(1)
Industrial IoT Visual Analytics	Limited scalability, minimal real-time analysis, sparse empirical evaluation	Manufacturing / Industry 4.0	(3)
Healthcare AI Visualization	Limited generalizability, incomplete variable coverage, few user tests	Healthcare	(15, 24)
Tourism Experience Analytics	Limited empirical validation, interactivity low, small user groups	Tourism / Hospitality	(1)
Education VR Learning Framework	Small validation groups, VR device limitations, partial DVL coverage	Education / Immersive	(12, 23)
Manufacturing Digital Twin Visualization	Limited real-time performance, partial coverage of manufacturing metrics	Manufacturing	(3)
Immersive Healthcare Analytics	Limited VR/AR devices, few user studies, not all tasks validated	Healthcare / Immersive	(15, 24)
Education Interactive Analytics	Limited empirical evaluation, small sample sizes, partial DVL coverage	Education	(12, 23)
Portal News for Visualization	Framework for analyzing news	Portal News	(7)
Portal News for Visualization	Framework for analyzing Portal news	News	(29)
Tourism Smart Analytics	Limited real-time analysis, small validation sample, low interactivity	Tourism / Hospitality	(1)

Table 4 presents the major gaps and limitations reported across the reviewed frameworks. The most frequent limitations include insufficient empirical validation, limited sample sizes, weak real-time integration, restricted interactivity and limited support for predictive or explainable analytics. Education frameworks tend to lack real-world testing and broader validation, while healthcare and manufacturing frameworks often require stronger real-time data integration and more transparent decision-support mechanisms. Tourism frameworks are frequently limited by simple dashboard design and low predictive capability, whereas immersive analytics frameworks face device dependency and the absence of standardized evaluation procedures. These findings suggest that many existing frameworks remain useful at the conceptual or prototype level but require stronger validation before they can be generalized across operational settings.

Figure 2 visualizes the frequency of gaps and limitations in data visualization frameworks across different domains. The figure indicates that education frameworks are most frequently associated with limited empirical validation and small sample sizes. Healthcare frameworks show recurring limitations in real-time support and predictive analytics, while tourism frameworks are commonly affected by fragmented research and reliance on simple dashboards. Manufacturing frameworks emphasize anomaly detection but often lack comprehensive real-time integration and systematic evaluation. Immersive analytics frameworks show gaps related to device limitations and the absence of standardized evaluation methods. Across domains, partial coverage of data visualization literacy competencies and limited scalability remain recurring issues.

This section compares the gaps in data visualization frameworks across different domains, including manufacturing, healthcare, tourism and immersive analytics, highlighting both domain-specific limitations and shared challenges such as limited validation, scalability issues and the lack of standardized evaluation methods.

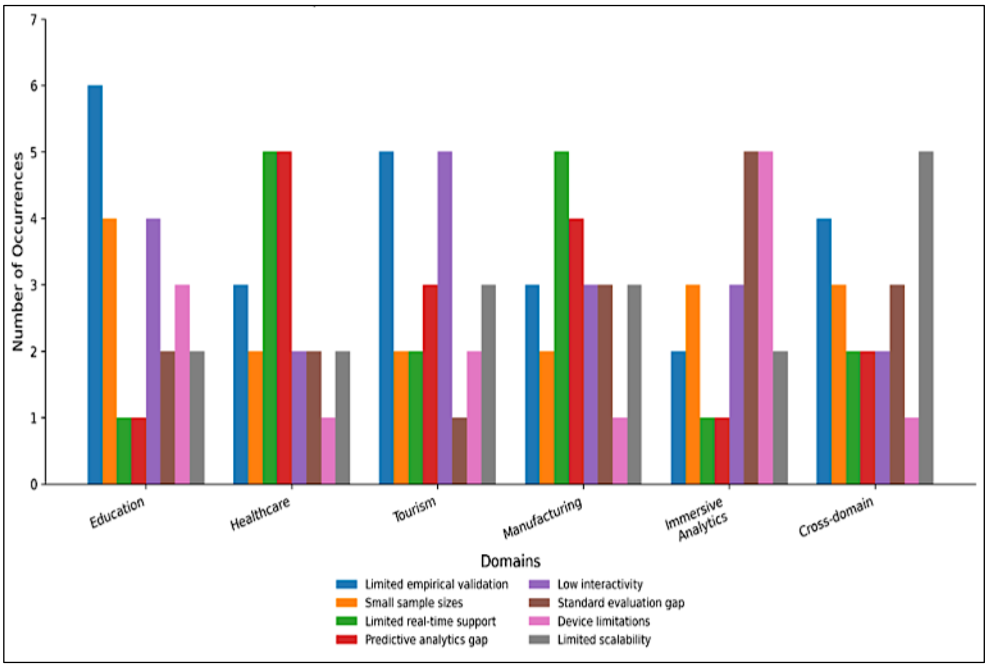

Figure 2: Gaps/Limitation in Data Visualization Framework (1, 10, 12-14, 16, 19)

Table 5: Cross-Domain Comparison of Framework Gaps.

Domain	Key Gaps / Limitations	Observations / Examples from Literature	References
Education	a) Limited empirical validation; small sample sizes; partial coverage of DVL skills b) Limited interactivity	Frameworks often focus on conceptual models or quizzes. VR/AR frameworks are emerging but evaluation is limited (DVL-EDU Framework, Immersive Education Visualization).	(12, 23)
Healthcare	a) Limited real-time support; minimal integration of multimodal clinical data b) Restricted predictive analytics c) Lack of explainable AI	Most frameworks focus on dashboards (EHR-IVT Framework, Visual Analytics Health Framework), but usability and predictive features remain gaps.	(15, 24)
Tourism / Hospitality	a) Fragmented research; dashboards are simple b) Low interactivity c) Limited predictive and big data integration	Tourism BI Framework and Tourism Dashboard Framework show initial BI adoption; immersive analytics frameworks still limited.	(1)
Manufacturing / Industry 4.0	a) Focus on anomaly detection only; limited integration of knowledge-driven methods b) Limited real-time interactivity c) Sparse evaluation	PdM Visual Analytics Framework and PdM Interactive Dashboard focus on predictive maintenance; interactivity and comprehensive monitoring are gaps.	(3)
Immersive Analytics / VR/AR	a) No standard evaluation methodology; difficult to determine when/why to use b) Device dependency limits adoption c) Small sample sizes	Immersive Analytics Frameworks (VR/AR for education or tourism) are promising but early-stage and collaborative immersive systems such as CAVE-style and HMD platforms highlight the challenge of establishing consistent evaluation benchmarks.	(16, 18)
Portal News	a) Evaluation Methodology: There is no standard methodology to measure the impact of immersive news experiences (VR/AR), focusing only on traditional pageview metrics. b) Usage Analysis: It's difficult to determine when and why to use immersive formats; analytics fail	Limited Evaluation: Literature shows the evaluation of Immersive (VR/AR) content for journalism is extremely limited and not yet standardized; similarly, data mining approaches for detecting misleading news content on social media remain difficult to evaluate systematically. Conceptual Focus: Existing analytical frameworks are often conceptual or use only simple testing (e.g., quizzes), not deep experience analytics.	(26)

	to measure qualitative comprehension levels.		
General / Cross-domain	a) Partial coverage of DVL competencies; limited scalability b) Small validation samples	Cross-domain frameworks (DataViz Literacy Framework, DVL-Assessment Framework) attempt to cover multiple sectors but often lack depth or empirical support.	(12, 24)

Table 5 compares framework gaps across domains and demonstrates that some limitations are shared, while others are context-specific. Limited empirical validation appears across education, tourism, immersive analytics and cross-domain frameworks, suggesting a broad methodological weakness in the field. Real-time integration is particularly critical in healthcare and manufacturing because these domains depend on continuous and timely data streams. In contrast, tourism frameworks show weaker predictive and big-data integration, while immersive analytics frameworks are constrained by hardware limitations and inconsistent usability assessment. The comparison clarifies that future framework development should not rely on a single generic solution but should balance cross-domain standards with domain-sensitive implementation requirements.

This section outlines recommendations for future research to advance the development of data visualization frameworks. Future studies should focus on developing standardized and scalable frameworks that can be applied across multiple domains while incorporating rigorous empirical validation. Greater integration of emerging technologies and consistent evaluation methodologies is also needed to enhance usability and effectiveness.

Table 6: Recommendations for Future Research

Recommendation	Supporting Literature	References
Standardization of Evaluation Methods	Evaluation of data visualization frameworks remains inconsistent. Developing standardized evaluation methodologies — grounded in structured visual encoding principles such as the DNA framework of information design — would improve the comparability and effectiveness of visualizations.	(20, 22)
Real-time Data Integration	Many frameworks fail to integrate real-time data processing, especially in fields like healthcare and manufacturing. Future research should focus on improving the scalability and responsiveness of frameworks.	(3, 14)
User-Centered Design	More emphasis is needed on user experience in data visualization frameworks. Research should incorporate user feedback to refine designs and improve usability.	(13, 17)
Integration of Explainable AI (XAI)	Many frameworks lack integration with explainable AI, which could enhance understanding and trust in automated data insights, particularly in healthcare and financial services.	(6, 31)
Cross-Domain Frameworks	There's a need for frameworks that can be generalized across different domains, combining industry-specific tools with cross-domain applicability. Understanding the inherent value of visualization — its cognitive utility and communicative power for analysts — is fundamental to building frameworks that transcend specific application contexts.	(24, 31)
Enhancing Predictive Capabilities	Many frameworks, especially in predictive maintenance, lack predictive analytics integration. Research could focus on enhancing the predictive capabilities of these frameworks.	(13, 14)
Immersive Visualization Standards	Immersive collaborative visualization (VR/AR) frameworks lack consistency in their evaluation methods and usability standards. Research should standardize these frameworks — particularly for multi-user CAVE-style and HMD environments — to enhance their practical utility.	(16, 18)
Multimodal Data Representation	With the explosion of big data, multimodal visualization frameworks could allow users to process various data types simultaneously. Research on such frameworks could be expanded.	(14, 31)
Addressing Cognitive Bias in Visual Analytics	Frameworks should incorporate strategies to reduce cognitive biases in decision-making processes through better design and interaction mechanisms.	(9, 12)
Develop hybrid evaluation methods to measure the qualitative impact of immersive news	Explainable AI (XAI): Ensures that predictive analytical models for content success are transparent and actionable for news editors.	(7, 26, 29)

Real-world Testing and Validation	Many proposed frameworks remain theoretical. Future research should focus on real-world case studies to validate their practical applicability, using structured encoding principles to bridge conceptual design and operational deployment.	(20, 30)

Table 6 translates the identified gaps into future research recommendations. Standardized evaluation methods are needed to improve comparability across studies, while real-time data integration should be prioritized in domains where timely decision-making is essential. User-centered design is also necessary because framework effectiveness depends not only on technical performance but also on whether users can interpret and act upon visual outputs. The integration of explainable analytical approaches is particularly important in high-stakes domains such as healthcare, where transparency and trust are central to decision-making. These recommendations directly respond to the limitations identified in the reviewed studies and provide a practical direction for developing more robust and adaptable visualization frameworks.

These recommendations provide a direction for future research to address the limitations found in existing frameworks as shown in Figure 3. By focusing on standardization, user-centered design, real-time data integration and advanced artificial intelligence applications, the next generation of data visualization frameworks could greatly enhance their utility and impact across various industries.

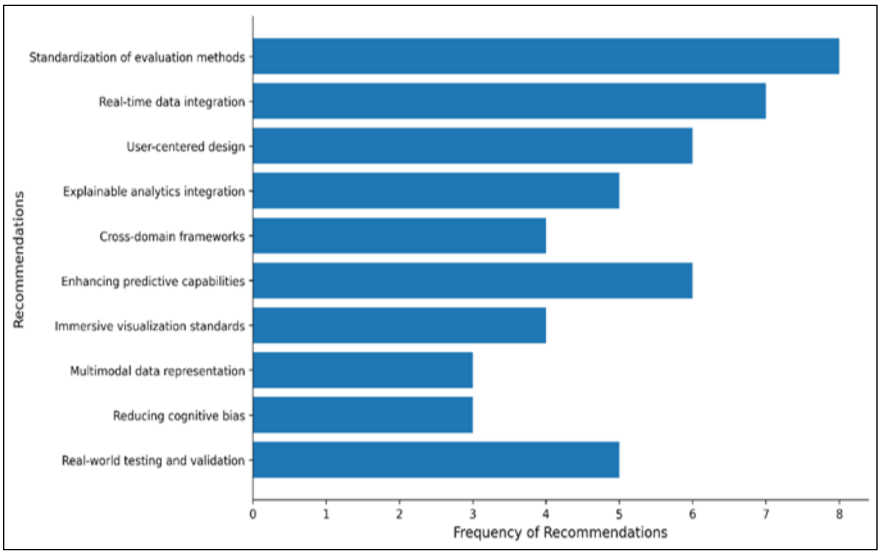

Figure 3: Recommendations for Future Research to Advance Data Visualization Frameworks (11, 20, 22)

Discussion

The systematic literature review provides critical insights into the state of data visualization literacy frameworks by examining their design purposes, domain applications, limitations and future development needs. The findings are discussed in relation to prior work on visual analytics, empirical evaluation, cognitive effectiveness and visualization education. This approach enables the review to move beyond cataloging frameworks and to critically interpret how existing models contribute to, or fall short of, the broader goals of data visualization literacy.

The findings are consistent with prior studies emphasizing that effective visualization requires more than graphical representation; it must also support perception, reasoning and interaction (8, 12, 24). The recurring lack of empirical validation aligns with earlier concerns that visualization systems are often evaluated through limited usability tests or prototype demonstrations rather than long-term operational studies (32). Challenges in sustaining long-term integration of visual analytics in real-world settings further underscore the gap between prototype evaluation and operational deployment (32, 33). Similarly, the need for adaptable and user-sensitive frameworks corresponds with research highlighting the importance of cognitive fit, interaction design and human-centered machine learning in visual analytics (13, 17). These connections suggest that future frameworks should combine technical functionality with theoretically grounded evaluation methods.

In addition, the rapid growth of automated visualization systems and generative artificial intelligence introduces new literacy challenges that extend beyond traditional chart interpretation. Users increasingly need to evaluate whether automatically generated visualizations are accurate, explainable and appropriate for the intended analytical task. This finding is consistent with recent visualization research emphasizing that artificial intelligence can support visualization recommendation and generation, but it also requires transparent design, critical interpretation and careful human oversight (6, 27).

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The findings related to Research Question 1 indicate that a diverse range of data visualization frameworks has been developed across six primary domains, namely education, healthcare, tourism, manufacturing, immersive analytics and cross-domain applications. In the education domain, most frameworks are conceptual in nature and are designed to enhance Data Visualization Literacy by providing structured models that support teaching and learning processes. However, these frameworks often lack empirical validation and real-time interactivity features. In healthcare, frameworks are generally developed to assist professionals in interpreting complex patient data and supporting clinical decision-making. While they demonstrate practical relevance, many of them are limited in terms of real-time integration, predictive analytics capabilities and transparent decision-support mechanisms. In tourism, visualization frameworks are typically implemented through dashboard-based systems that monitor trends and tourist behavior, yet they frequently remain descriptive rather than predictive in nature. In manufacturing, frameworks focus primarily on predictive maintenance and anomaly detection through visual analytics, although integration of knowledge-driven insights and real-time data handling remains limited. Immersive analytics frameworks leverage virtual and augmented reality technologies to enhance data exploration experiences, but their broader application is constrained by hardware limitations and the absence of standardized evaluation methods. Cross-domain frameworks attempt to provide generalized models applicable across sectors; however, their broad scope often reduces contextual depth and domain-specific adaptability. Overall, the review demonstrates that although numerous frameworks exist, they vary significantly in structure, purpose and application and no unified or standardized framework is consistently adopted across disciplines.

The findings related to Research Question 2 highlight several recurring gaps and limitations in existing data visualization frameworks across different domains. One of the most significant limitations is the lack of empirical validation, as many frameworks, particularly in education, healthcare and tourism, are grounded in conceptual models and theoretical foundations but have not undergone rigorous testing in real-world settings. Although frameworks such as the DVL-EDU Framework aim to classify visualization types and improve Data Visualization Literacy, their practical effectiveness in authentic educational environments remains insufficiently evaluated. Another common limitation involves small sample sizes, especially in healthcare and manufacturing studies, which restricts the generalizability of findings and limits the applicability of these frameworks across diverse contexts. Limited real-time data integration is also frequently observed, particularly in healthcare and manufacturing domains, where frameworks require real-time data streams to generate accurate and actionable insights but often lack full implementation capability. Additionally, many frameworks do not incorporate robust predictive analytics or explainable mechanisms, reducing their effectiveness for advanced decision support and limiting user trust in automated outputs. In tourism, frameworks tend to rely on simple dashboard designs with low interactivity, constraining their ability to support higher-level strategic analysis. Overall, these findings indicate that while numerous frameworks have been developed, significant methodological and technical limitations continue to hinder their scalability, reliability and practical impact.

The findings related to Research Question 3 reveal both recurring and domain-specific gaps in data visualization frameworks. Healthcare and manufacturing exhibit similar limitations, particularly in the integration of real-time data and the implementation of predictive analytics, despite both sectors relying heavily on continuous data streams for decision-making. In contrast, education and tourism face challenges associated with conceptual frameworks that lack sufficient empirical validation, as educational models often remain theoretical while tourism frameworks tend to rely on relatively simple dashboard systems that do not address the complexity of large-scale data analysis. Immersive analytics presents distinct challenges, including the absence of standardized evaluation methods and the technical limitations of virtual and augmented reality devices, reflecting the early developmental stage of these frameworks. Overall, the comparison demonstrates that while certain structural limitations are shared across domains, each field also encounters unique constraints shaped by its contextual and technological requirements

These domain comparisons also reflect broader theoretical expectations from information visualization and human-computer interaction research. Domains with time-sensitive decisions, such as healthcare and manufacturing, require real-time monitoring and reliable interaction mechanisms, while domains focused on learning or public communication require stronger support for interpretation and literacy development (3, 15, 25). The contrast between domain-specific and cross-domain frameworks indicates that general models can provide conceptual breadth, but they may lose practical depth when applied to specialized contexts. This reinforces the need for modular frameworks that preserve common evaluation standards while allowing customization for user needs and domain constraints.

The findings related to Research Question 4 provide several recommendations to advance the development of data visualization frameworks. Future research should prioritize the standardization of evaluation methods to enable consistent comparison and validation across domains. Improving real-time data integration and scalability is also essential, particularly in sectors that rely on continuous data streams for timely decision-making. The adoption of user-centered design principles is strongly recommended to ensure that frameworks are intuitive, functional and aligned with end-user needs. Additionally, integrating explainable analytical approaches can enhance transparency and trust in decision-support systems, especially in high-stakes environments. Cross-domain frameworks should be further refined to balance generalizability with domain-specific depth. Finally, longitudinal studies and real-world testing are necessary to validate the long-term effectiveness and operational applicability of these frameworks.

One of the key research directions emerging from this systematic review is the need to address the proliferation of terms and semantic heterogeneity in the definitions of Data Visualization Literacy. Across the examined frameworks, terms such as visual literacy, data visualization literacy and visual analytics are frequently used interchangeably or without clear conceptual boundaries. This inconsistency creates confusion within the academic community and hinders the establishment of standardized approaches for teaching, assessing and applying Data Visualization Literacy. The variation in definitions across domains, including education, healthcare, manufacturing and tourism, further highlights the absence of a coherent conceptual foundation. Developing a unifying construct for Data Visualization Literacy would provide clarity and consistency, facilitating improved communication among researchers and practitioners. A standardized definition would support cross-domain applicability while maintaining contextual relevance, enhance curriculum development by promoting a shared understanding of visualization competencies and enable the creation of reliable and comparable assessment tools. As data visualization continues to play an increasingly critical role across sectors, establishing a unified conceptual framework becomes essential to ensure coherent implementation and evaluation practices. Therefore, the development of a unifying construct for Data Visualization Literacy represents a significant research priority that can strengthen theoretical alignment, educational practices and applied framework development across disciplines (34).

This systematic literature review, while comprehensive, does have several limitations that should be acknowledged. One significant limitation is the temporal scope of the review, which focuses on literature from 2014 onwards. This decision was made for several key reasons. Over the past decade, there have been significant advancements in data visualization technologies and frameworks, driven by the rapid growth of big data, interactive visualization tools and the rise of immersive technologies like VR and AR. These developments have fundamentally transformed how data is visualized and interacted with, making earlier studies less relevant in reflecting the current state of the field. Additionally, recent innovations such as AI-driven visualizations and real-time data processing have become more prominent in the last ten years and these aspects are crucial for understanding modern frameworks, which older studies may not address.

Furthermore, focusing on recent literature ensures that the review captures frameworks that are still active and relevant today. Many older frameworks may no longer be in widespread use or have been replaced by more robust and tested models. By focusing on the last decade, the review reflects frameworks that are more likely to have practical applications today, thus offering a more accurate and timely analysis of the state of data visualization frameworks.

Another limitation stems from the selection of databases and journals. While prominent databases such as Scopus, IEEE Xplore and ACM Digital Library were included, there may be valuable frameworks and insights published in smaller journals or conference proceedings that were not captured in this review. The exclusion of such sources means that the study may have missed frameworks that are either newer or more niche, thus limiting the breadth of the review.

Additionally, domain-specific biases may affect the results. Some domains, particularly education, have a wealth of established research, leading to more robust frameworks, while other fields, such as tourism, may have fewer frameworks and research. This discrepancy can affect the comparability and generalizability of the findings, as frameworks in some domains may have more extensive research backing them, while others may be underdeveloped or still in the exploratory phase.

Furthermore, while the frameworks examined in this study are often valuable in theory, many are still theoretical or in the early stages of development and may not have been empirically validated in real-world settings. Frameworks that have not been tested in practical environments are subject to the risk of being ineffective or impractical in real-world applications, limiting the full utility of the study (35).

Finally, the review primarily focuses on published academic literature, which may not fully reflect the latest frameworks used in industry practice. Frameworks developed outside the academic domain or those still in prototyping stages in private industries may not be included. This gap limits the study's ability to provide a complete picture of the current landscape of data visualization frameworks, especially as they are applied outside the academic context.

In conclusion, while the review offers valuable insights into the development of data visualization frameworks, it is important to recognize the limitations of focusing on literature from the last decade, the choice of databases, the biases across domains and the focus on academic literature. Future research could address these gaps by expanding the review to include frameworks from emerging technologies, industry-specific applications and frameworks developed in earlier periods that may still have significant relevance.

Conclusion

This systematic review demonstrates that data visualization literacy frameworks have developed across multiple domains, including education, healthcare, tourism, manufacturing, immersive analytics, portal news and cross-domain applications. The reviewed frameworks provide useful conceptual, technical and evaluative contributions, but their maturity varies considerably across domains. The major findings show that many frameworks support usability, visual interpretation and decision-making, yet they remain limited by insufficient empirical validation, small validation samples, weak real-time data integration, inconsistent assessment methods, limited predictive capability and inadequate explainability in decision-support contexts. The review also shows that emerging automated visualization and generative artificial intelligence systems introduce new literacy requirements, particularly related to transparency, interpretability and user trust. This study is limited by its dependence on published academic literature, possible domain imbalance and the exclusion of some industry-based frameworks that may not be documented in scholarly databases. Future research should therefore prioritize standardized evaluation methods, longitudinal and real-world validation, stronger educational assessment, explainable and predictive analytics and scalable frameworks that remain sensitive to domain-specific needs. Addressing these directions will help develop more reliable, interpretable and practical data visualization literacy frameworks for research, education and professional decision-making (35).

The systematic review of 36 journals reveals that while there are promising data visualization frameworks in multiple domains, there are significant gaps that need to be addressed. These include empirical validation, real-time data integration, predictive analytics and explainable AI. By following the recommendations for future research, such as standardizing evaluation methods, enhancing real-time capabilities and focusing on user-centered design, the development of more robust, scalable and effective data visualization frameworks can be achieved.

Abbreviations

AR: Augmented Reality, BI: Business Intelligence, DVL: Data Visualization Literacy, EHR: Electronic Health Records, PdM: Predictive Maintenance, PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses, SLR: Systematic Literature Review, VR: Virtual Reality, XAI: Explainable Artificial Intelligence.

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Author Contributions

Muhamad Dody Firmansyah: Material Preparation, Data Collection, Testing and Analysis, Manuscript Preparation, Subsequent Revisions, Zurina Saaya: Conceptualization, Study Design, Supervision, Validation, Nurul Izrin Md Saleh: Conceptualization, Study Design, Supervision, Validation. All the authors have read and approved the final manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study are derived from publicly available journal articles included in this systematic literature review. All analyzed sources are cited in the reference section. The data supporting the findings of this study are derived from publicly available journal articles included in this systematic literature review. All analyzed sources are cited in the reference section.

Declaration of Artificial Intelligence (AI) Assistance

Generative AI tools were used only to assist with language refinement, grammar checking, formatting support and improvement of clarity during manuscript revision. The authors take full responsibility for the content, originality, accuracy and scientific integrity of this manuscript.

Ethics Approval

This study does not involve human participants, animals, or personal data and therefore does not require ethical approval. This study does not involve human participants, animals, or personal data and therefore does not require ethical approval.

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