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Systematic Review

Mapping the AI Landscape in Project Management Context: A Systematic Literature Review

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Abstract

The purpose of this research is to systematically map and analyze the use of AI technologies in project management, identifying themes, research gaps, and practical implications. This study conducts a systematic literature review (SLR) that combines bibliometric analysis with qualitative content evaluation to explore the present landscape of AI in project management. The search covered literature published until November 2024, ensuring inclusion of the most recent developments. Studies were included if they examined AI methods applied to project management contexts and were published in peer-reviewed English journals as articles, review articles, or early access publications; studies unrelated to project management or lacking methodological clarity were excluded. It follows a structured coding protocol informed by inductive and deductive reasoning, using NVivo (version 12) and Biblioshiny (version 4.3.0) software. From the entire set of 1064 records retrieved from Scopus and Web of Science, 27 publications met the final inclusion criteria for qualitative synthesis. Bibliometric clusters were derived from the entire set of 885 screened records, while thematic coding was applied to the 27 included studies. This review highlights the use of Artificial Neural Networks (ANN), Case-Based Reasoning (CBR), Digital Twins (DTs), and Large Language Models (LLMs) as central to recent progress. Bibliometric mapping identified several major thematic clusters. For this study, we chose those that show a clear link between artificial intelligence (AI) and project management (PM), such as expert systems, intelligent systems, and optimization algorithms. These clusters highlight the increasing influence of AI in improving project planning, decision-making, and resource management. Further studies investigate generative AI and the convergence of AI with blockchain and Internet of Things (IoT) systems, suggesting changes in project delivery approaches. Although adoption is increasing, key implementation issues persist. These include limited empirical evidence, inadequate attention to later project stages, and concerns about data quality, transparency, and workforce adaptation. This review improves understanding of AI's role in project contexts and outlines areas for further research. For practitioners, the findings emphasize AI's ability in cost prediction, scheduling, and risk assessment, while also emphasizing the importance of strong data governance and workforce training. This review is limited to English-language, peer-reviewed research indexed in Scopus and Web of Science, potentially excluding relevant grey literature or non-English contributions. This review was not registered and received no external funding.

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1. Introduction

Project management constitutes a structured discipline concerned with the coordination of resources, schedules, and stakeholders to achieve defined objectives. While it remains essential across various sectors, traditional approaches often face difficulties in managing the complexity and unpredictability of modern project environments [1]. These challenges include navigating cost constraints, adhering to timelines, and maintaining quality standards under conditions of uncertainty and limited early-stage information, which together constrain accurate forecasting and decision-making [2]. These limitations reinforce the need to explore alternative approaches and tools that enable more effective management of project dynamics. Despite growing interest, there is still a lack of collected evidence on how AI technologies address the entire project lifecycle, particularly beyond the planning and execution phases. Unlike prior systematic literature reviews (SLRs) such as that of Reznikov [3], which focuses on AI adoption issues, and of Adamantiadou & Tsironis [4], which focuses on AI's impact on project success measures, our review employs a combination of methods. We use a comprehensive bibliometric analysis to map the entire research framework, followed by a qualitative synthesis that traces the progress of AI applications throughout the project lifecycle. This dual methodology enables us to find and synthesize developing theme clusters that were not the subject of previous, more narrowly scoped assessments, resulting in a more comprehensive and current view of the field. The nature of projects includes complex systems, which consist of dependent components together with various stakeholders and changing environmental factors [3,4]. The interactions between people, processes, technology, and environmental factors create complex systems that traditional linear approaches struggle to handle effectively. The inherent complexity of projects becomes manageable through Artificial Intelligence (AI) because it provides predictive analytics, real-time monitoring and adaptive decision-making capabilities [5,6]. The adaptive role of AI can be better understood via the perspective of Contingency Theory, which emphasizes the need for organizations to modify strategy in response to environmental uncertainty. Similarly, the Dynamic Capabilities framework emphasizes the ability to detect, seize, and reorganize resources in response to rapid change. In project contexts, AI-powered predictive analytics and real-time monitoring improve these adaptive processes, allowing project managers to match responses with shifting environmental and organizational demands.

Thus, AI emerges as a potential ally for project managers, supporting decision-making, risk management, and cost optimization in the complex environments of contemporary projects [7]. AI offers a suite of methods that address such structural limitations. Through techniques including predictive analytics, real-time data processing, and algorithmic decision-making, AI supports more informed planning and execution. Technologies such as Machine Learning (ML), Natural Language Processing (NLP), and Digital Twins (DTs) have enabled the automation of repetitive activities, improvements in forecasting capabilities, and integration of heterogeneous project information [8]. These functions assist project managers in anticipating risks, allocating resources, and coordinating tasks more efficiently. On the other hand, the integration of AI into project management introduces new layers of complexity [9,10]. The application of AI spans multiple domains. Although sectors like IT and aerospace are also highly dependent on AI, they were not highlighted here since they did not appear prominently in the final list of included studies. We deliberately chose construction, healthcare, and manufacturing as examples of AI-PM applications that had been empirically validated in the reviewed literature. Examples from construction, healthcare, and manufacturing are included to demonstrate transferable AI capabilities; nonetheless, the primary focus of this research remains AI applications in project management. In construction, AI supports compliance verification, risk assessment, and dispute analysis [11]. In healthcare, AI-enabled Internet of Things (IoT) devices enhance operational control through continuous patient monitoring [12]. In manufacturing, Function Modeling (FM) supported by AI contributes to both product design and lifecycle maintenance [13]. These examples demonstrate how AI tools facilitate task automation and knowledge integration across sectors.

A principal area of AI's contribution involves managing the interdependencies between time, cost, and quality. Historical data is used in predictive models to improve the accuracy of project forecasts. ML methods such as Artificial Neural Networks (ANN) and Case-Based Reasoning (CBR) generate decision-support insights based on patterns in past data [14]. DTs provide dynamic simulations of physical systems that allow real-time monitoring and timely adjustments [15]. These developments enhance responsiveness and reduce performance deviations during project execution.

Recent systematic reviews reinforce these findings and extend them. For instance, Reznikov [3] identified the role of AI, ML, and Large Language Models (LLMs) in supporting decision-making across all knowledge areas defined by the PMBOK® Guide. Adamantiadou and Tsironis [4] noted that although AI has been widely applied in the planning and execution phases, research remains limited concerning its use in project closure. Kozhakmetova et al. [16] observed thematic clusters of AI application in decision-making, cost optimization, and performance analysis, while also identifying underexplored integrations with blockchain and IoT systems. Similarly, Hashimzai and Mohammadi [17] confirmed that although AI improves risk anticipation and resource allocation, high implementation costs and organizational resistance present critical barriers. Hossain et al. [18] highlighted the lack of empirical validation in real-world projects, raising concerns about the generalizability and reproducibility of AI outcomes.

While AI holds considerable promise, its integration into project environments is not without challenges. Many AI applications depend on the availability of high-quality, standardized data, which is frequently lacking. Alignment with traditional management frameworks requires cross-disciplinary competencies and often involves organizational restructuring. Furthermore, ethical considerations such as transparency, data governance, and accountability raise concerns about responsible deployment [2,19]. These constraints underscore the need for further research into the scalability and reliability of AI-enabled project tools. Accordingly, the purpose of this review is to comprehensively synthesize recent research on AI in project management, map thematic developments and identify methodological and practical gaps for future research. This study combines bibliometric analysis with qualitative coding to provide an in-depth theme interpretation as well as a quantitative mapping of research activity. We considered only peer-reviewed journal publications in English that expressly explored AI applications in project management; works without methodological detail or outside the project management context were removed. To maintain methodological rigor and reproducibility, we excluded grey literature and industry reports. To ensure quality and comparability across included studies, we limited our scope to peer-reviewed journals that were written in English. This SLR investigates the role of AI in project management by examining recent applications, emerging trends, and persistent limitations. This study aims to clarify the contributions of AI technologies and to identify areas where further empirical and theoretical development is required. Understanding these dynamics is important not only for advancing academic research but also for guiding practitioners and policymakers on secure AI adoption. The remainder of this paper is structured as follows: Section 2 describes the research methodology; Section 3 details the results; Section 4 discusses the implications; and Section 5 concludes this study.

2. Materials and Methods

This study examines the role of AI in project management through a systematic literature review (SLR). This systematic literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. The PRISMA-ScR checklist and flow diagram are included in the Supplementary Materials. The review protocol was not prospectively registered in a public repository however; the methodology was defined a priori and strictly adhered to throughout this study. The review was conducted using the multi-method approach proposed by Carvalho et al. [20], in alignment with the PRISMA 2020 framework [21]. In contrast to previous studies, which relied exclusively on qualitative synthesis, this study combines bibliometric mapping and qualitative coding, allowing for both macro-level trend analysis and in-depth thematic exploration. Figure 1 presents the SLR process flow, outlining its sequential stages in accordance with PRISMA guidelines. The search terms contained both 'Artificial Intelligence' and 'Project Management', but it is important to note that project management itself is inherently complex because it involves managing projects that have interrelated systems, dynamic interactions and multiple sources of uncertainty. The dataset was predetermined and comprehensive, consisting exclusively of peer-reviewed academic publications in English that directly addressed AI in project management and provided adequate methodological details. Aside from the basic eligibility criteria, no further studies were included or excluded. There were no restrictions on the country of study or the specific project management framework.

This review draws on a comprehensive search conducted in the Scopus and Web of Science databases, covering literature available up to November 2024. We excluded AI-specific repositories such as arXiv and IEEE Xplore. We focused on peer-reviewed, indexed journals to ensure methodological clarity and quality. However, this exclusion may have limited coverage of emerging, pre-publication AI trends, which is acknowledged as a limitation. The search terms "Artificial Intelligence" and "Project Management" returned 696 and 368 results, respectively. Screening was carried out in two stages: first, two independent reviewers assessed the titles and abstracts for relevance, and then the full text was checked to validate eligibility. Discrepancies were handled through debate until a consensus was established.

After merging the datasets and removing 179 duplicates using R, 885 documents remained. Bibliometric mapping was conducted on the entire set of 885-screened records, which revealed several thematic clusters. We chose clusters that demonstrated a clear conceptual link between AI and project management (PM), such as expert systems, intelligent systems, and optimization algorithms. Within these clusters, we applied a citation threshold of at least three citations per year to focus the qualitative synthesis on impactful and widely recognized contributions, resulting in 27 documents for detailed examination. This threshold was not applied to the entire dataset, but rather to the documents within the selected clusters. As a sensitivity check, the dataset was examined without applying this criterion, and the findings showed no significant variations in the detected theme clusters, despite the inclusion of extra low-impact articles. This suggests that the citation filter helped focus the synthesis without significantly influencing the main thematic findings. Bibliometric analysis was performed on the 885 screened records, however qualitative synthesis and classification were limited to the 27 included studies. This final sample supported an analytical process combining inductive and deductive coding to identify key

AI techniques, including applications of DTs. From the initial 1064 records, the selected studies offer a representative basis for understanding current AI applications in project management. The exact search queries used to ensure the reproducibility of the literature search across both databases were as follows:

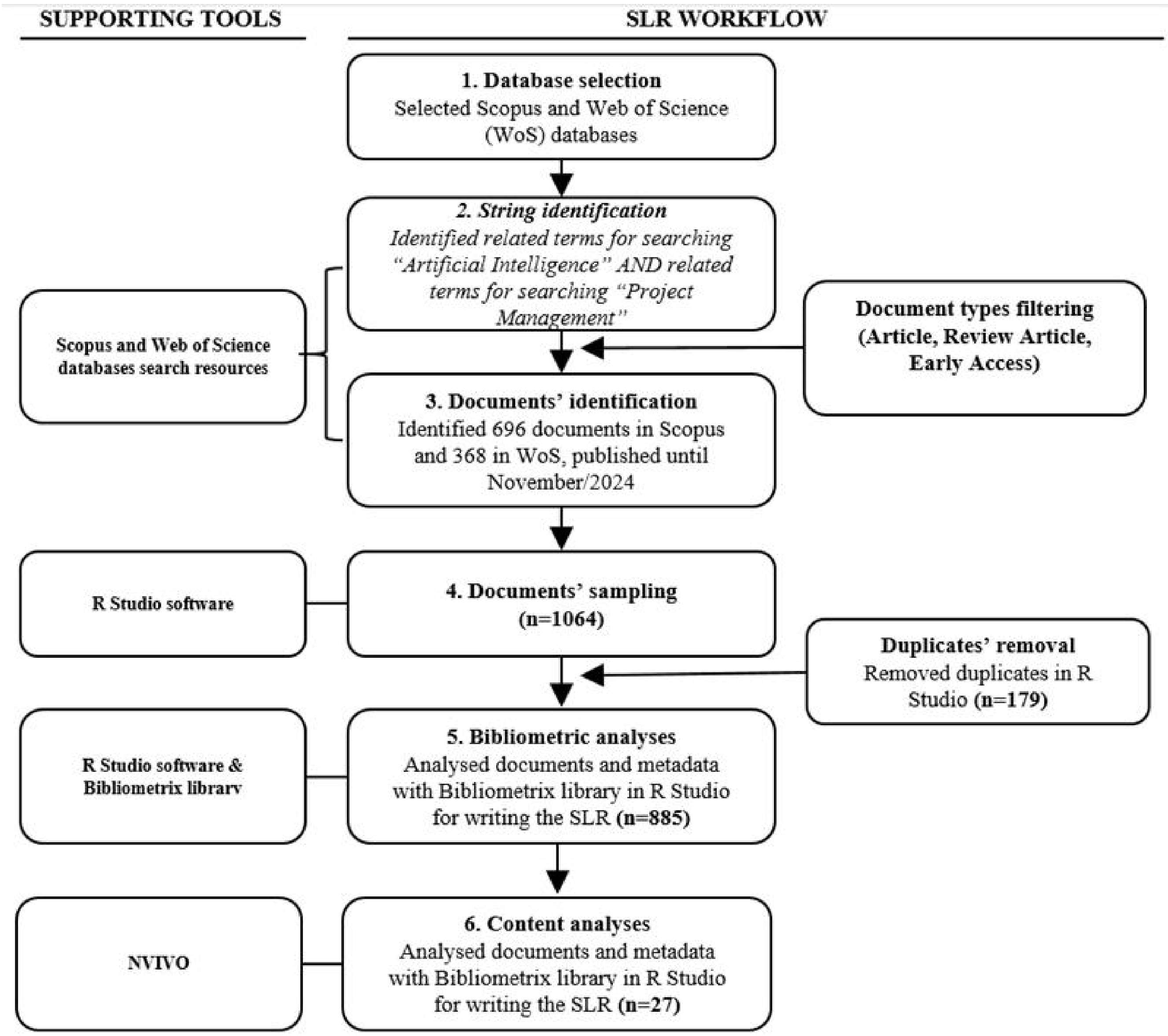

Figure 1. SLR process flow.

Scopus: (TITLE-ABS-KEY (“artificial intelligence”) AND TITLE-ABS-KEY (“project management”)) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “re”)) AND (LIMIT-TO (LANGUAGE, “English”))

Web of science: Refine results for “artificial intelligence” (Topic) AND “project management” (All Fields) and Article or Review Article or Early Access (Document Types) and English (Languages)

Terms like 'Agile' and 'Scrum' were deliberately excluded from our core search query. We chose this option to prevent a methodological bias toward specific frameworks. Our goal was to conduct a wide, fundamental review of AI's application across the entire field of project management. By focusing on the essential themes of 'artificial intelligence' and 'project management,' we ensured that our search included studies relevant to various methodologies, not only Agile or Scrum. This approach allows for a more comprehensive and unbiased analysis of the literature.

Data Analysis

Bibliometric and content analysis were combined to provide both a quantitative overview of the research activity and a qualitative assessment of thematic trends. In the data analysis, we employed the multi-method SLR approach proposed by Carvalho et al. [20], integrating bibliometric and content analysis to combine quantitative and qualitative techniques. This amalgamation facilitated the extraction of meaningful insights and patterns from the selected body of literature.

Bibliometrics was instrumental in identifying dominant themes, prolific authors, and key publication metrics within a short timeframe [22]. For the bibliometric analysis, we utilized the Biblioshiny tool [23], owing to its robust interface and advanced visualization capabilities. This study applied a range of widely recognized bibliometric indicators to assess research productivity and impact, including total publications (TP), total citations (TC), author productivity over time, co-citation networks, most locally cited references, thematic mapping using Keywords Plus, and a three-field plot. Co-citation analyses of references, sources, and authors proved particularly valuable for uncovering research trends and assessing intellectual proximity. In addition, keyword co-occurrence analysis measured the frequency with which terms appeared together across publications, highlighting conceptual relationships within the field [24].

Content analysis was conducted to enable a deeper qualitative examination of the literature, identifying key latent research variables and their interrelations, following the guidelines of Webber's protocol [25]. NVivo software was employed to support the coding process [26], incorporating both deductive and inductive coding strategies. The deductive approach was grounded in existing theories and frameworks, guiding hypothesis development and verification, while the inductive approach allowed for the identification of emergent themes and patterns not constrained by predefined categories. This dual approach provided both theoretical validation and the opportunity to generate novel insights. To improve validity, two independent coders performed qualitative coding using NVivo. Although Cohen's kappa values for most coded themes indicated moderate to strong agreement, a few themes yielded poor values. Furthermore, the advanced analytical features available in NVivo ensured precision and depth in the qualitative analysis. Together, these complementary methods established a rigorous and comprehensive analytical framework, enabling a robust response to the research questions.

3. Results and Findings

3.1. Author's Production over Time

Figure 2 shows the top authors' production over time, revealing not only the productivity of authors but also the impact of their contributions. It illustrates the scholarly output of leading authors within the field of AI and project management. Each horizontal line represents an individual author's publication timeline, with bubble size indicating the number of publications in a given year and color intensity reflecting the TC per year.

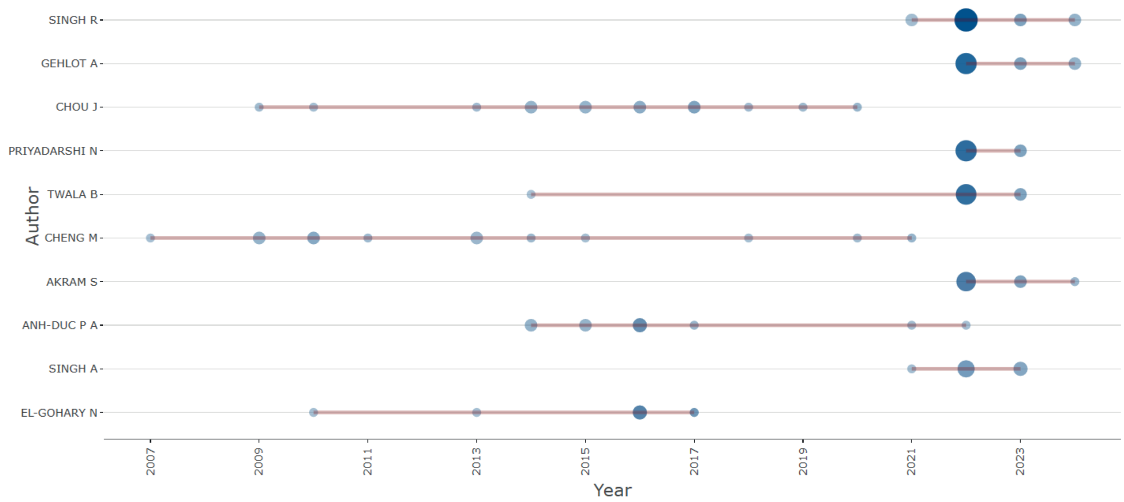

Figure 2. Top Authors' Production over Time from Biblioshiny. Lines represent the authors' timeline, color intensity is proportional to the TC per year, and bubble size is proportional to the number of documents. Publications cited in this study include Singh R. [27], Gehlot A. [28], Chou J. [29], Priyadarshi N. [30], Cheng M. [31], Akram S. [32], Anh-Duc P. A. [33], Singh A. [34], and El-Gohary N. [8].

Among the most prolific contributors, Singh R stands out as the most productive author, consistently publishing impactful research from 2021 to 2024. He is credited with at least 20 publications, many of which appear in high-visibility journals such as Sustainability, Electronics, and Applied Sciences (Basel). Notable contributions include "Technologies Empowered ESG: An Industry 4.0 Landscape" published in Sustainability [27] and "Energy System 4.0: Digitalization of the Energy Sector with Inclination Towards Sustainability" published in sensors [28], the latter recording one of the highest citations per year (10). His co-authorship network is particularly strong, frequently collaborating with Gehlot A, Twala B, and Priyadarshi N, as seen in high-impact papers on digitalization, sustainability, and industry 4.0 technologies.

Gehlot A mirrors this trajectory closely, contributing to at least 17 publications from 2022 onwards, most of which are co-authored with Singh R. Their shared works address topics such as digital supply chains, smart cities, and ESG frameworks. This concentration reflects both the productivity of specific research groups and the field's dependence on their work. While their contributions are valuable, it raises concerns about a limited diversity of perspectives, which upcoming studies should address. For instance, their co-authored paper on "Digitalization of Supply Chain Management" published in Processes [32] exemplifies both thematic alignment and scholarly impact.

Twala B and Priyadarshi N appear less frequently in the overall production count but maintain a visible presence through high-impact co-authored papers in 2022 and 2023. Notably, the four authors (Singh R, Gehlot A, Twala B, and Priyadarshi N) co-authored several documents together, such as "Digital Technology Implementation in Battery-Management Systems for Sustainable Energy Storage" published in Electronics [35] and "MOOC 5.0: A Roadmap to the Future of Learning Sustainability" [30], both of which show moderate to high citation performance.

Additionally, authors such as Cheng M and Chou J demonstrate long-term engagement, with productive periods dating back to 2007 and 2009, respectively. Though their recent output appears less concentrated than the newer cohort, their earlier works remain influential, with papers such as "Shear Strength Prediction in Reinforced Concrete Deep Beams" published in the Journal of Computing in Civil Engineering [29] and "Conceptual Cost Estimates Using Evolutionary Fuzzy Hybrid Neural Network for Projects in the Construction Industry" published in Expert Systems with Applications [31], achieving high citation counts and maintaining visibility over time.

Akram S also shows a noteworthy trajectory, with active publications from 2022 to 2024. His profile includes at least 12 publications, often co-authored with Singh R and Gehlot A, covering sustainability, AI applications in energy and construction, and digital finance. His participation in papers with Singh R, like "Energy System 4.0" mentioned before [28] and "Hospitality Feedback System 4.0" [36], aligns him with the core research cluster on industry 4.0 enablers in different sectors.

The convergence of authors such as Singh R, Gehlot A, Akram S, and others around themes like ESG, smart infrastructure, and digital innovation underlines the collaborative and interdisciplinary nature of this field.

Singh A appears as a recent and emerging contributor, publishing primarily between 2021 and 2023. His work focuses on AI applications in forecasting, sustainable agriculture, and IoT. Key publications include "Hybridizing AI Algorithms for Forecasting of Sediment Load" published in Water [34] and "Imperative Role of Integrating Digitalization in the Firm's Finance" published in Electronics [37]. He also shares authorship with Singh R, reinforcing the collaborative ties within this thematic group.

Anh-Duc P A presents a distinct contribution profile, with highly cited works spanning from 2014 to 2022. His research concentrates on hybrid AI models for energy forecasting, slope stability, and construction management. Noteworthy contributions include "Hybrid Artificial Intelligence Approach Based on Metaheuristic and ML for Slope Stability Assessment" published in Expert Systems with Applications [33] and "Developing a Hybrid Time-Series Artificial Intelligence Model to Forecast Energy Use in Buildings" published in Scientific Reports [38]. His earlier papers exhibit sustained influence through citations, demonstrating foundational work in integrating AI with civil engineering and environmental science.

Finally, El-Gohary N is characterized by impactful yet selective contributions between 2010 and 2017, with a focus on semantic NLP and automated compliance in construction. His top-cited publications—such as "Semantic NLP-Based Information Extraction from Construction Regulatory Documents for Automated Compliance Checking" published in the Journal of Computing in Civil Engineering [8] and "Integrating Semantic NLP and Logic Reasoning into a Unified System for Fully-Automated Code Checking" in Automation in Construction [39]—have achieved annual citation rates exceeding 18 and 20, respectively. These papers indicate a specialized but highly influential research agenda in AI-driven regulatory automation in the construction sector.

3.2. Most Local Cited References

Figure 3 displays the most locally cited references within the analyzed sample. Local citations refer to instances in which these sources are cited within the specific dataset under review, rather than in the broader academic literature. The most locally cited references highlight key studies that serve as the foundation for current research in the dataset, with 16 references cited 11 times each. This means that 11 of the 885 papers in my dataset on the research topic "AI and Project Management" mentioned each of these references. This concentration suggests a shared intellectual foundation among the documents analyzed, particularly around sources from the Financial Credit Act, AD ALTA—Journal of Interdisciplinary Research, and the International Journal of Computing Science and Networking. The uniform citation count among most top references reflects a coherent scholarly dialogue within the dataset, potentially pointing to a tightly connected research community or recurring reliance on a specific body of foundational literature. This pattern underscores the significance of these works in shaping the thematic and methodological orientation of the studies included in the systematic review.

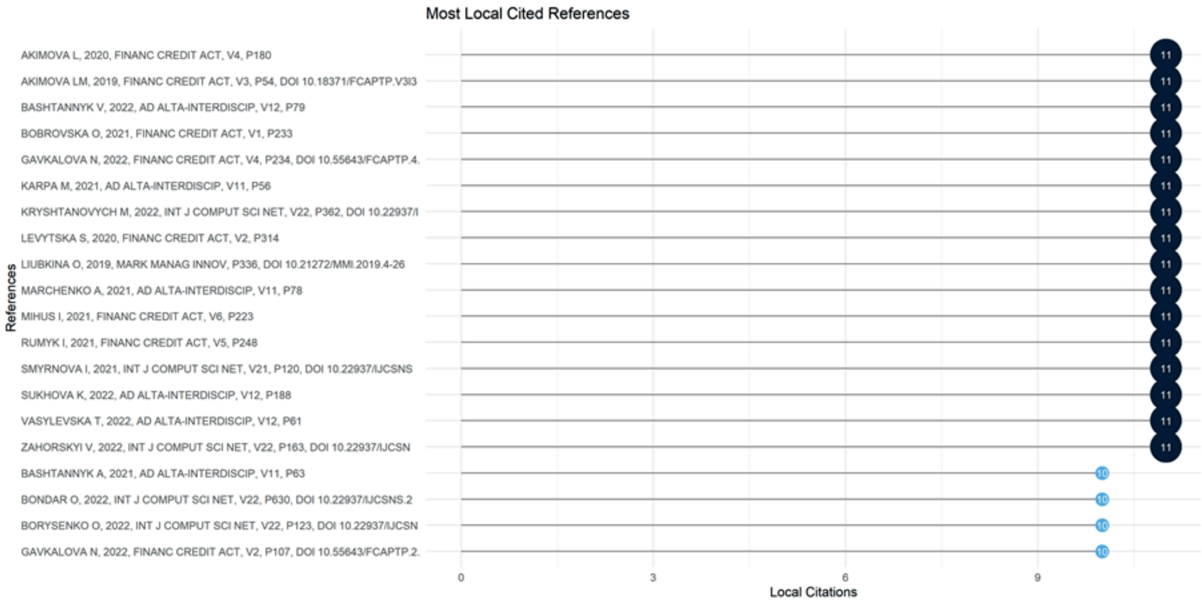

Figure 3. Most local cited references from Biblioshiny. The chart shows how often each reference was cited within the dataset. Numbers like 11 and 10 represent the count of local citations.

El-Gohary et al. [8] used semantic NLP to automate compliance checks in construction projects and proposed a rule-based approach to streamline regulatory analysis. Cheng et al. [31] investigated robust visual tracking algorithms for real-time monitoring in project environments, whereas Malik et al. [12] examined machine-learning applications in wireless sensor networks to improve communication efficiency, a development with significant implications for IoT project management. Singh et al. [40] developed fuzzy clustering techniques for image segmentation, which aid AI-driven decision-making in healthcare and imaging. Similarly, Gohary and Chua [41] created CBR for hazard identification in construction, demonstrating a knowledge-intensive AI solution. Yezioro et al. [42] used ANNs to predict energy usage in buildings, providing tools for sustainable project management. Arditi and Pulket [43] demonstrated AI's predictive abilities in construction litigation outcomes, whereas Lu et al. [15] advanced DTs concepts by incorporating AI into construction project monitoring. Wen et al. [44] demonstrated machine learning's potential in software project estimation, while Priyadarshi et al. [45] contributed to AI applications in solar energy prediction.

Collectively, these studies highlight AI's interdisciplinary impact, offering novel solutions for managing complex projects in construction, healthcare, energy, and software development. They emphasize AI's transformative role in improving accuracy, efficiency, and predictive capabilities in project management across a variety of industries.

3.3. Co-Occurrence Network

Figure 4 presents a keyword co-occurrence network visualizing the conceptual structure of research at the intersection of AI and project management. The most prominent terms—artificial intelligence and project management—demonstrate the highest betweenness centrality (367.15 and 252.78, respectively), indicating their role as crucial bridges connecting otherwise distinct thematic areas. Betweenness reflects how often a keyword appears on the shortest path between other terms, highlighting its function in integrating diverse topics. These same terms also exhibit the highest PageRank scores (0.145 and 0.149), a measure that captures a node's overall influence. These findings demonstrate how AI research trends significantly impact project planning, monitoring, and control processes in project management contexts.

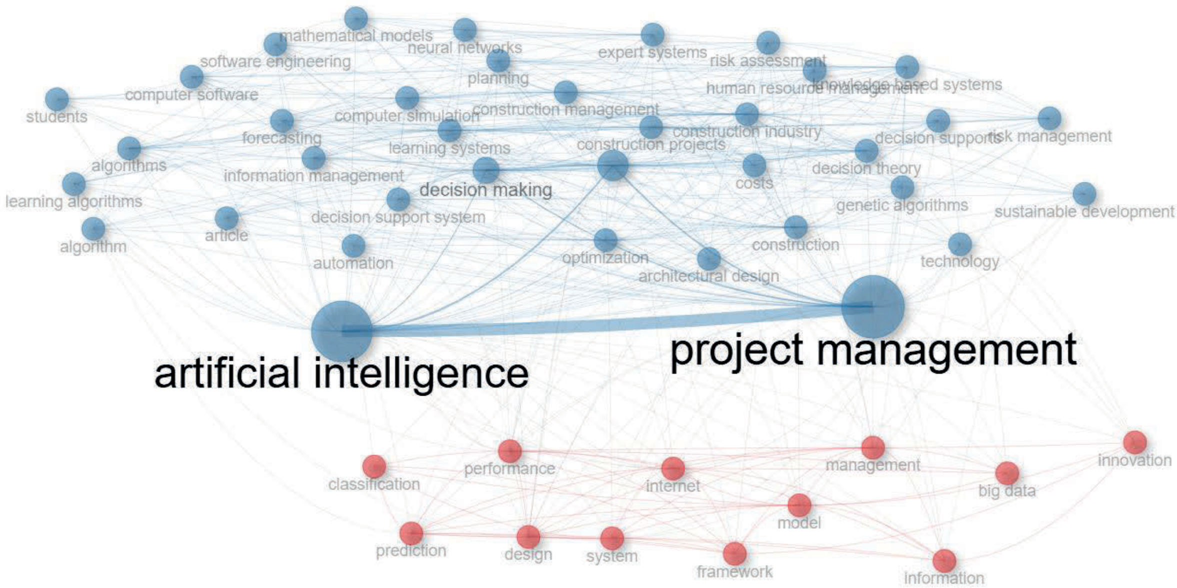

Figure 4. Co-occurrence network from Biblioshiny.

The network highlights two dominant thematic clusters, represented by the large nodes for artificial intelligence and project management, which form the intellectual core of the field. Surrounding these core terms are closely related keywords such as decision support systems, decision-making, construction management, algorithms, and learning systems, which exhibit high levels of interconnectivity, particularly within the blue cluster. These terms suggest a methodological focus on intelligent computational tools to support planning, optimization, and management activities within project contexts. The red cluster, while somewhat peripheral, comprises terms such as big data, internet, prediction, performance, and framework, indicating a complementary stream of research concerned with data-driven models, digital infrastructure, and innovation processes. The size of each node reflects the frequency of keyword occurrences, while the proximity and thickness of connecting lines indicate stronger co-usage relationships. This structure underscores a convergence between technological advancement and project execution strategies, emphasizing the central role of AI in enhancing decision-making and management functions across diverse application domains.

Within Cluster blue, keywords such as decision support systems, decision-making, and construction industry serve as key intermediaries, with decision support systems showing notable betweenness (17.07) and PageRank (0.063), indicating its conceptual relevance in linking AI tools to project-based applications. Meanwhile, Cluster red includes terms like model, management, performance, and design, which—although less connected to AI-centric terms—form a cohesive sub-network representing operational and evaluative dimensions of project environments.

Overall, the network reveals a dual-core structure: one methodological (AI and computation) and one managerial (performance and systems), with select keywords bridging the two—underscoring the growing convergence of intelligent technologies and strategic project practices in contemporary research.

3.4. Thematic Map and Trend Topics

The thematic map shown in Figure 5 is structured along two axes: centrality (horizontal) and density (vertical), producing four quadrants—Motor Themes, Basic Themes, Niche Themes, and Emerging or Declining Themes. Centrality reflects the thematic importance within the overall field, while density indicates the degree of internal development of each theme. Complementing this visual representation, the associated thematic table provides detailed indicators, including occurrences, betweenness centrality, and PageRank centrality, which enable a more in-depth interpretation of the conceptual structure. These results highlight how AI research trends directly contribute to project planning, monitoring, and control processes in project management contexts, For practitioners, the highlighted Motor Themes, particularly 'project management' and 'decision support systems', represent mature, high-impact domains where AI integration can deliver immediate operational benefits.

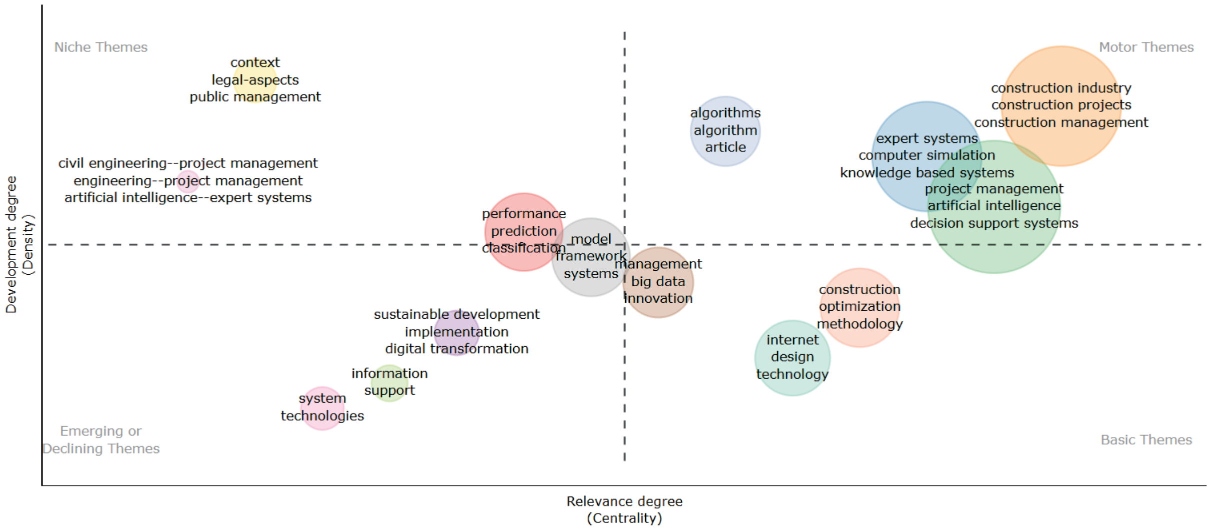

Figure 5. Thematic map from Biblioshiny.

The map is divided into four quadrants—Motor Themes, Basic Themes, Niche Themes, and Emerging or Declining Themes—based on two axes: centrality (horizontal) and density (vertical). Centrality represents a theme's importance to the field, while density reflects its internal development. Complementing the visual representation, the corresponding thematic table provides detailed indicators, including occurrences, betweenness centrality, and PageRank centrality.

Motor Themes (High Centrality, High Density) in the upper-right quadrant include three main colored thematic bubbles—orange, green, and blue—signaling well-developed and central topics. The orange bubble comprises "construction industry," "construction projects," and "construction management," each exhibiting substantial structural relevance. For example, "construction industry" shows high occurrences (86), substantial betweenness (480.257), and PageRank (0.019). These scores highlight its pivotal role across domains. The green bubble groups "project management," "artificial intelligence," "decision support systems," and "decision making." "Project management" (439 occurrences) and "artificial intelligence" (433) are particularly dominant, with respective PageRanks of 0.084 and 0.079, and strong betweenness centralities (20.672 and 10.157). "Decision support systems" (138 occurrences, betweenness 378.112, PageRank 0.031) and "decision making" (112 occurrences, PageRank 0.024) strengthen the core conceptual link between intelligent systems and managerial decision-making. The blue bubble contains "expert systems," "computer simulation," and "knowledge-based systems." These are equally central. "Expert systems" (33 occurrences, betweenness 353.022) and "computer simulation" (31 occurrences, betweenness 209.511) confirm this cluster's maturity. "Knowledge-based systems" also display high PageRank (0.007), underscoring its integrative potential.

Situated in the upper-left quadrant, Niche Themes are characterized by strong internal development yet limited influence across the broader conceptual landscape. This quadrant contains three distinct thematic bubbles: one yellow, one light pink, and one red, each representing specialized yet relatively insular areas of scholarly focus. The yellow bubble encompasses the terms "context," "legal aspects," and "public management." These topics exhibit low centrality—for example, "context" registers 11 occurrences, with betweenness centrality of 0.414 and PageRank of 0.003—but their coherent internal linkage positions them as deeply specialized domains. Despite their peripheral location, their high density suggests intellectual maturity, likely tied to normative or policy-oriented frameworks within public administration and regulatory contexts. The light pink bubble comprises "civil engineering--project management," "engineering--project management," and "artificial intelligence--expert systems." These compound concepts represent methodologically bounded subdomains. "Civil engineering--project management" has seven occurrences, betweenness centrality of 9.915, and a PageRank of 0.001, indicating limited cross-thematic bridging but strong internal cohesion. This cluster captures AI-focused applications within engineering practices, yet it remains marginal in terms of interdisciplinary connectivity. The red bubble, positioned at the intersection of Niche and Emerging Themes, consists of "performance," "prediction," and "classification." These terms form a technically oriented cluster, each with relatively high occurrences—"performance" (40), "prediction" (28), and "classification" (22)—and meaningful betweenness values (e.g., "performance" = 289.639). Despite these structural metrics, the cluster's proximity to the Emerging quadrant signals transitional status: it is well-formed internally but still peripheral in broader scholarly debates, possibly due to methodological specificity or limited generalization. In sum, the Niche Themes quadrant encapsulates domains with focused intellectual depth but lower crosscutting impact, implying mature internal conversations, offering a valuable foundation for future integration into broader thematic frameworks.

Basic Themes (High Centrality, Low Density) are positioned in the lower-right quadrant and are characterized by high relevance to the research field but limited internal development. This quadrant contains three distinct bubbles: one light pink, one light green, and one light brown. The light pink bubble encompasses the terms "construction," "optimization," and "methodology." Among these, "optimization" emerges as a structurally significant theme, with the highest betweenness centrality in the entire dataset (868.735), along with 48 occurrences and a moderate PageRank centrality (0.010). Despite its central bridging role across domains, the relatively low density suggests a fragmented or evolving theoretical structure. The light green bubble comprises "internet," "design," and "technology." These terms demonstrate strong centrality scores: "internet" registers 34 occurrences and a betweenness centrality of 605.329, while "technology" shows 24 occurrences and an even greater betweenness of 663.966. Nevertheless, the lower density values indicate a need for tighter thematic cohesion within this emerging cluster of digitally driven concepts. The light brown bubble features "management," "big data," and "innovation." While these terms are recurrent in multidisciplinary discussions, their low betweenness centralities (e.g., "management" = 676.766; "big data" = 275.541) and modest PageRank scores (0.007 and 0.004, respectively) suggest they function more as supporting constructs than as fully integrated core themes.

Located in the lower-left quadrant, Emerging or Declining Themes represent concepts that are either in the early stages of development or losing traction within the research landscape. This quadrant displays three distinct thematic bubbles: a pink bubble, a green bubble, and a purple bubble, all positioned far from the conceptual core, denoting limited relevance (centrality) and sparse internal cohesion (density). The pink bubble encompasses "systems" and "technology." While "systems" has a relatively high frequency (31 occurrences) and a PageRank centrality of 0.004, its betweenness centrality (179.419) indicates some structural importance within isolated segments of the field. In contrast, "technology" shows 24 occurrences, but despite a comparatively high betweenness centrality (663.966)—suggesting a bridging potential—its PageRank of only 0.004 reflects weak recursive influence. The green bubble includes "information" (21 occurrences) and "support" (11 occurrences), both of which possess low betweenness (24.763 and 27.501, respectively) and modest PageRank values (0.004 and 0.003). Both bubbles suggest that while these terms may support foundational infrastructure, they remain peripheral and disconnected from major thematic developments, possibly due to their generality or redundancy within more dominant clusters. The most structurally promising is the purple bubble, which integrates "sustainable development" (25 occurrences), "implementation" (14 occurrences), and "digital transformation" (6 occurrences). These terms are conceptually aligned with current socio-technological imperatives. Notably, "digital transformation" exhibits a very high betweenness centrality of 465.274, indicating substantial potential as a thematic bridge, although its PageRank remains low (0.002)—suggesting it is not yet embedded in the conceptual center. Similarly, "sustainable development" (betweenness 273.671) and "implementation" (122.763) show promise, but their centrality scores confirm their status as emergent rather than established focal points. Themes like "digital transformation" and "sustainable development" are categorized as emerging rather than declining. Their low density demonstrates the novelty of these themes rather than obsolescence, suggesting possibilities for future research rather than decreasing relevance.

The temporal evolution of thematic trends is presented in Figure 6. Each horizontal line traces the lifespan of a term based on its first (Q1), median, and last (Q3) year of prominence, while bubble size reflects term frequency—thereby offering a dual lens of temporal breadth and thematic emphasis.

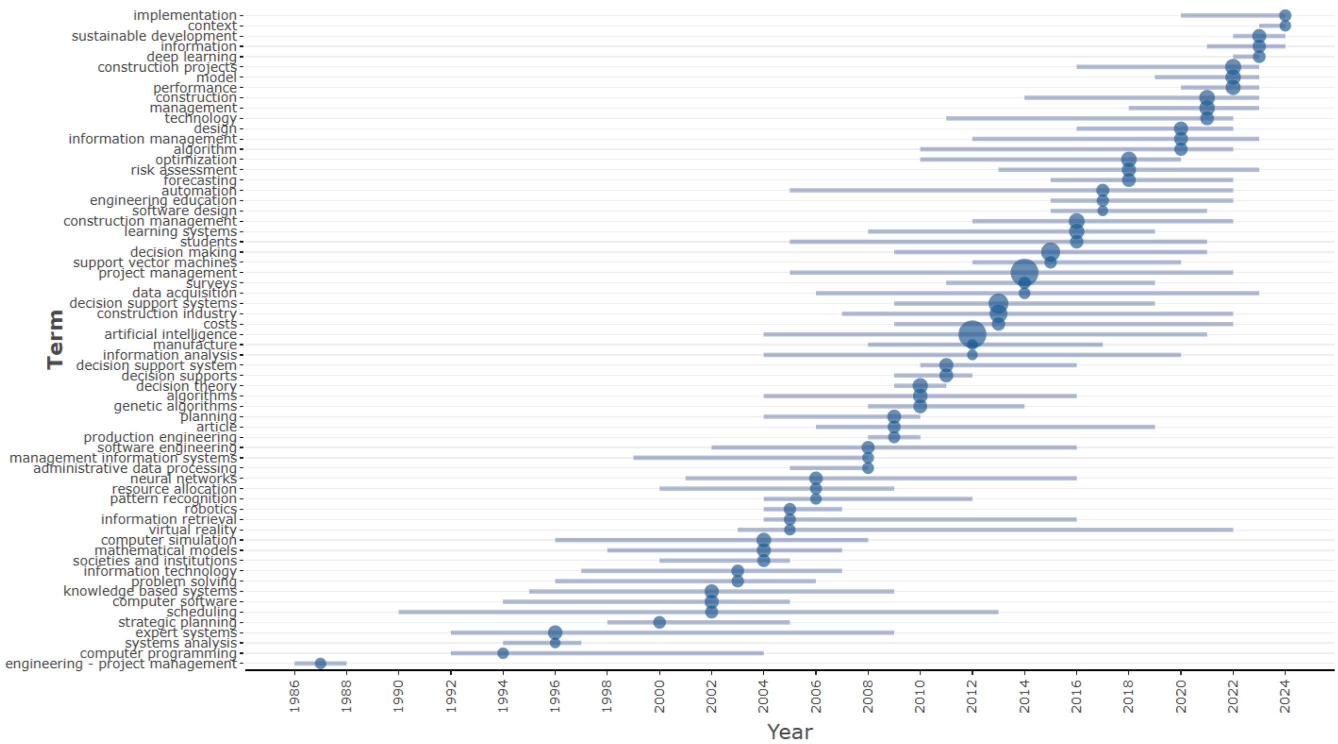

Figure 6. Temporal evolution of thematic trends.

In the earliest phase, between 1986–2000, themes such as engineering–project management (median: 1987), computer programming (1994), and expert systems (1996) dominate. These topics reflect the foundational alignment of computing and engineering concerns, establishing a methodological and technical groundwork. Notably, systems analysis (1996) and strategic planning (2000) suggest an early preoccupation with systemic approaches to organizational and infrastructural challenges. These topics, though limited in current frequency, serve as pillars that supported subsequent thematic complexity.

The transition period, during the first decade of the 21st century (2001–2010), witnessed a methodological diversification. Terms like computer simulation (median: 2004, frequency: 34), knowledge-based systems (2002, 31 occurrences), and mathematical models (2004, 28 occurrences) rose to prominence, indicating a shift towards computational modeling and simulation-driven strategies. Simultaneously, neural networks (2006), virtual reality (2005), and software engineering (2008) emerged as indicators of deepening digitalization. Furthermore, this period marked the initial surfacing of decision-centric themes such as decision theory (2010, 44 occurrences), decision support system (2011), and decision making (2015). These terms reflect the growing role of computational intelligence in assisting human decision processes. It is also notable that artificial intelligence (2012, 452 occurrences) and algorithms (2010) became increasingly central, laying the groundwork for modern AI applications.

From 2011 onwards marks a consolidation period when the literature reflects an intensifying integration of AI and domain-specific practices. Central themes such as project management (median: 2014, 448 occurrences), construction industry (2013), and decision support systems (2013) reflect a concerted focus on digital transformation in real-world managerial and infrastructural contexts. Likewise, topics like support vector machines (2015), optimization (2018), and risk assessment (2018) indicate the embedding of AI-powered predictive and prescriptive analytics. Additional attention to learning systems (2016), data acquisition (2014), and automation (2017) highlights the era's transition towards smart, self-adaptive systems. The breadth of terms during this decade underscores the consolidation of earlier methodologies into a more mature and application-driven research corpus.

The most recent years (2021–2024) show an accelerated shift towards themes aligned with sustainability and digital reform. Sustainable development (2023, 28 occurrences), implementation (2024), and digital transformation—though previously less central—have gained salience, suggesting a conceptual realignment towards environmentally and socially responsible innovation. Likewise, the appearance of deep learning (2023) and context (2024) indicates a surge in complex modeling and context-aware systems, pushing the boundaries of AI's relevance to both technical and humanistic domains.

Newer entries such as performance (2022, 40 occurrences), model (2022, 45 occurrences), and management (2021, 47 occurrences) reinforce a holistic turn towards operational efficacy and strategic foresight.

3.5. Three Field Plot

The Three-Field Plot for "AI and Project Management" illustrates clear connections between key journals, authors, and research themes. Figure 7 presents a three-field plot generated via Biblioshiny. The journals are grouped into four thematic blocks. At the top, journals focused on sustainability and interdisciplinary research are prominent, including Sustainability and Ad Alta: Journal of Interdisciplinary Research. In the project management domain, the only specialized outlet represented is the International Journal of Project Management. The central section comprises journals with a focus on electronics and computing, such as Electronics, Applied Sciences—Basel, Journal of Computing in Civil

Engineering, Automation in Construction, Expert Systems with Applications, and Applied Artificial Intelligence. At the bottom, the group includes construction-related journals such as the Journal of Construction Engineering and Management, Buildings, Civil Engineering and Management, and the Journal of Information Technology in Construction.

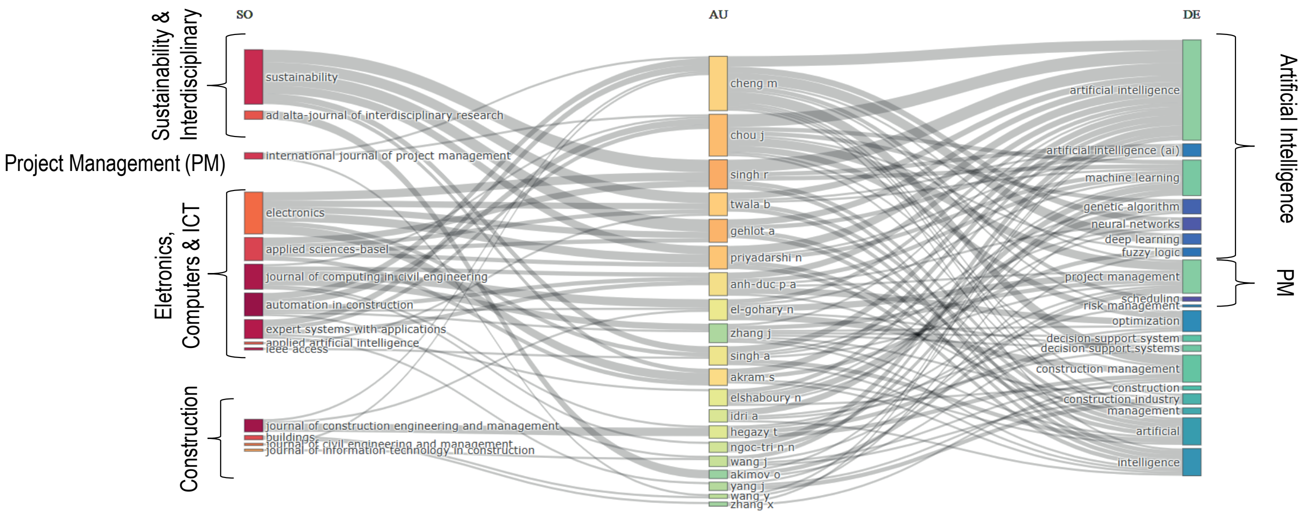

Figure 7. Three field plot: sources (SO)-authors(AU)-keyword plus (DE) from Biblioshiny.

The central column displays a set of core authors. Within the sustainability and interdisciplinary cluster, key contributors include Cheng M., Chou J., Singh R., and Twala B. The electronics and computing cluster is represented by authors such as Gehlot A., Priyadarshi N., Pham-Duc P., El-Gohary N., Zhang J., and Akram S. The construction-oriented group features Elshaboury N., Idr A., Hegazy T., Ngoc-Tri N.N., Akimov O., Yang Y., Wang Y., and Zhang X. For example, Cheng M. frequently publishes in the Journal of Construction Engineering and Management, focusing on keywords such as “predictive analytics” and “AI-based project scheduling,” demonstrating significant influence both within that journal and across the broader research community. Similarly, Wang L. is associated with Automation in Construction, contributing to research on “AI-driven cost management,” thereby advancing this specialized area of the industry.

On the right-hand side, the dominant keywords reveal thematic concentrations. In the upper region, terms related to AI and specific tools such as ML, genetic algorithms, neural networks, deep learning, and fuzzy logic indicate strong ties with emerging technologies. Centrally located keywords relate to project management, scheduling, and risk management. Towards the bottom, domain-specific terms such as decision support systems, construction management, construction industry, optimization, and management underscore the practical applications of AI in the built environment. This structured distribution highlights a layered research landscape that integrates sustainability, digital technologies, and construction management. Moreover, the links between journals such as Automation in Construction and keywords like “machine learning” and “optimization algorithms” underscore the centrality of these themes not only within individual publications but across authors and sources throughout the field. This interconnectedness reveals how prominent research topics are aligned with the contributions of leading scholars and journals, offering valuable insights into the evolving landscape of AI and project management research. The lack of project management-specific journals (aside from IJPM) among top-impact outlets shows disciplinary diffusion, with AI-PM research appearing more frequently in engineering, computing, and sustainability journals than traditional PM outlets. This suggests a probable siloing of AI research from mainstream PM discussions.

The application of Bradford's Law to the dataset revealed a core set of highly influential journals that form Zone 1—those contributing the highest volume of relevant publications in the field of AI and project management. This nucleus comprises 29 journals, cumulatively responsible for 294 publications, indicating a strong concentration of knowledge production. Automation in Construction leads the list with 33 articles, followed closely by the Journal of Construction Engineering and Management (30), the Journal of Computing in Civil Engineering (21), and Expert Systems with Applications (19). Other prominent sources include IEEE Access, Sustainability, Applied Sciences—Basel, and the International Journal of Project Management, each contributing between 13 and 15 articles. The composition of Zone 1 reflects a multidisciplinary intersection of construction engineering, computer science, sustainability, and project management. This concentration of publications in a relatively small number of journals supports the bibliometric premise of Bradford's Law, highlighting the pivotal role of these sources in shaping the core intellectual structure of research at the intersection of AI and project management.

3.6. Content Analysis

This section uses content analysis to investigate the role of AI in project management, drawing on insights from articles in the dataset. Both approaches enable themes, relationships, and patterns to emerge directly from the data (Figure 8).

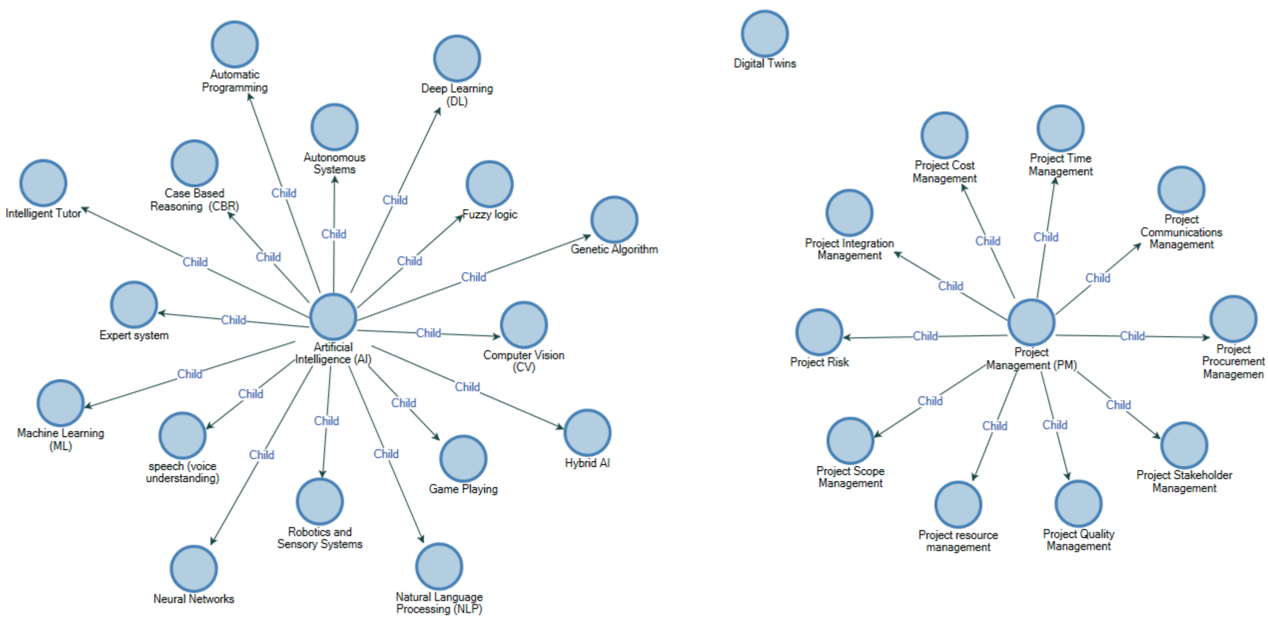

Figure 8. Coding map from NVivo.

The analysis identified the following main themes:

Predictive Capabilities in Project Management: ML algorithms such as Support Vector Machines (SVM), ANN, and CBR have been shown to accurately predict project timelines and costs. These models address uncertainties in the early stages of a project by using historical data to provide more accurate estimates.

Risk and Knowledge Management: AI methods, particularly CBR, have proven useful in risk identification and management. CBR mimics human reasoning, providing tailored solutions to construction problems by referencing previous cases. This technique promotes transparency and adaptability, making it a valuable tool for knowledge-based project management.

Integration of Digital Twins: DTs use AI and big data to simulate construction processes, track project performance, and reduce risks such as budget overruns and safety concerns. These tools represent a shift in construction management to more proactive approaches.

Automation for Compliance Checking: NLP, a branch of AI, has been used for automated compliance checking (ACC). Rule-based and machine learning-based NLP approaches extract regulatory information from construction projects, lowering manual errors and increasing efficiency.

Effort Estimation Techniques: Advanced ML algorithms have outperformed traditional estimation methods, addressing biases such as over-optimism in cost and duration projections. The use of ANN and hybrid AI models only strengthens this trend.

This study has used NVivo's advanced analytical tools to validate existing hypotheses and identify relationships between AI applications and key project management outcomes like cost efficiency, schedule adherence, and quality control. This structured analysis will ensure that the findings are rigorous and consistent with the broader academic discourse. We discovered the relationship between AI and project management, as shown in the table below. Machine Learning (ML) has the strongest associations with Project Risk Management and Project Time Management, each with a frequency of 27. ML also shows a strong relationship with Project Cost Management, with a frequency of 23. Natural Language Processing (NLP) follows with a frequency of 19 in Project Communications Management, while Case-Based Reasoning (CBR) shares the same frequency (19) in Project Risk Management. Finally, Expert Systems, Fuzzy Logic, Neural Networks, and others show frequencies of 3, 2, and 1, indicating moderate and emerging relevance across project management areas.

The content analysis reveals relationships between major branches of AI, including Expert Systems (ES), NLP, Speech Understanding, Robotics and Sensory Systems, Computer Vision and Scene Recognition, Intelligent Computer-Aided Instruction, Neural Computing, Language Translation, Fuzzy Logic, Genetic Algorithms, Intelligent Agents, ML, and Deep Learning, and project management aspects such as cost, time, scope, integration, risk, resources, communication, stakeholders, and procurement. Unfortunately, we can see a strong relationship among ML, NLP, CBR, cost, time, risk, and communication, but other branches of AI and project management domains need further study and have been identified as research gaps for further studies. This underrepresentation may be due to implementation problems (such as cost, scalability, and technical maturity), rather than irrelevance. It also indicates a gap in research in the application of robots and CV to project management frameworks. (Table 1).

Table 1. The relationship of AI and project management by NVivo content analysis.

AI Major Branches/ Project Management Knowledge Areas	Project Communications Management	Project Cost Management	Project Integration Management	Project Quality Management	Project Resource Management	Project Risk Management	Project Time Management	Project Procurement Management	Project Scope Management	Project Stakeholder Management	Illustrative Quotations	References
Case Based Reasoning (CBR)	0	0	0	1	0	19	0	0	0	0	CBR systems utilize past knowledge and experiences to solve new problems, making them particularly effective in risk management and dispute resolution.	Okudan et al. [11]

Table 1. *Cont.*

AI Major Branches/ Project Management Knowledge Areas	Project Communications Management	Project Cost Management	Project Integration Management	Project Quality Management	Project Resource Management	Project Risk Management	Project Time Management	Project Procurement Management	Project Scope Management	Project Stakeholder Management	Illustrative Quotations	References
Genetic Algorithm	0	0	0	0	0	2	0	0	0	0	Genetic algorithms solve optimization problems by mimicking natural selection processes.	Chen and Hsu [14]
Machine Learning (ML)	2	23	0	2	2	27	27	0	0	0	Reviewed machine learning applications in wireless sensor networks, enhancing communication efficiency, which has implications for project management in IoT.	Malik et al. [12]
Natural Language Processing (NLP)	19	0	0	0	0	1	0	0	0	0	Semantic rule-based NLP models deliver high precision and recall, significantly reducing the time and cost of manual compliance efforts.	Zhang and El-Gohary [8]
Generative AI	1	1	0	0	0	0	1	0	0	0	Generative AI has been increasingly used to generate project reports and planning documents, enhancing automation and foresight.	Vergara et al. [46]
AI + IoT + Blockchain+ Robotics	1	0	1	0	0	0	0	0	0	0	Integrating AI with IoT and blockchain enables enhanced traceability, transparency, and cross-platform optimization.	Kozhakmetova et al. [16]
LLMs and Hybrid AI	0	3	0	0	0	1	2	0	0	0	LLMs and hybrid models offer wide applicability across PM knowledge areas by combining symbolic reasoning with data-driven models.	Reznikov [3]
Automatic Programming	0	0	0	0	0	0	0	0	0	0	Automatic programming techniques minimize manual coding by generating code based on definitions of problems and domain models.	Rich & Knight [47]
Autonomous Systems	0	0	0	0	0	0	0	0	0	0	Autonomous systems use AI techniques to perceive, reason, and act without intervention from humans, enabling applications ranging from self-driving cars to drones.	Russell & Norvig [48]
Computer Vision (CV)	0	0	0	0	0	0	0	0	0	0	Computer vision enables systems to interpret visual data for purposes such as defect detection, image classification, and remote sensing in construction projects.	Yezioro et al. [42]
Deep Learning (DL)	0	0	0	0	0	0	0	0	0	0	Deep learning models, with their layered neural network structures, enable high-performance recognition of patterns and forecasting in complex project scenarios.	Singh et al. [45]

Table 1. *Cont.*

AI Major Branches/ Project Management Knowledge Areas	Project Communications Management	Project Cost Management	Project Integration Management	Project Quality Management	Project Resource Management	Project Risk Management	Project Time Management	Project Procurement Management	Project Scope Management	Project Stakeholder Management	Illustrative Quotations	References
Expert system	0	3	0	0	0	1	2	0	0	0	Expert systems simulate human decision-making through the application of rule-based logic to structured knowledge bases, which makes them ideal for cost estimation and diagnosis.	Cheng et al. [31]
Fuzzy logic	0	3	0	1	1	2	2	0	0	0	The use of fuzzy logic enables reasoning under uncertainty by simulating human judgment, making it useful for quality control and allocation of resources in complex projects.	Saatchi [29]
Game Playing	0	0	0	0	0	0	0	0	0	0	Game-playing algorithms simulate decision-making processes, serving as testbeds for strategic planning and multi-agent interacting in project environments.	Russell & Norvig [48]
Intelligent Tutor	0	0	0	0	0	0	0	0	0	0	Intelligent tutoring systems use AI to tailor instructional strategies, improving project training and stakeholder education through customized learning paths.	Vergara et al. [46]
Neural Networks	0	3	0	0	0	1	1	0	0	0	Neural networks learn patterns from data using interconnected layers, providing predictive insights for planning resources and risk prediction.	Aria & Cuccurullo [23]
Speech (voice understand-ing)	1	0	0	0	0	0	0	0	0	0	Speech understanding systems use artificial intelligence to transcribe and interpret spoken language, thereby streamlining stakeholder communication and documents.	Vergara et al. [46]
Digital Twins	0	0	0	0	0	0	0	0	0	0	Digital twins use real-time data and AI models to virtually mirror physical systems, which helps with predictive analytics and project performance simulations.	Lu et al. [15]

4. Discussion

AI has emerged as a foundational technology across multiple sectors, including project management, where its implementation continues to alter established practices. AI draws from diverse disciplines to simulate cognitive capabilities such as learning, reasoning, and decision-making. Rich and Knight [47] define AI as "behavior by a machine that, if performed by a human being, would be called intelligent." Similarly, Russell and Norvig [48] describe it as "the study of agents that receive percepts from the environment and perform actions," emphasizing adaptability and context-sensitive action. Within project management, AI supports data analysis, automation of decisions, and optimization of constrained resources under uncertainty.

To address the evolving state of the art, this study included recent contributions (2023–2024), such as emerging research on AI integration in sustainability-driven project design and industry surveys highlighting AI adoption barriers in project contexts. By placing these within established theories such as Contingency Theory and Dynamic Capabilities, we provide a more comprehensive theoretical foundation and demonstrate how AI supports adaptive responses in the context of uncertainty. Our dataset's most locally cited references originate mainly from adjacent disciplines such as finance, computer science, and engineering, rather than core project management literature. This pattern reflects the interdisciplinary nature of AI-PM research and highlights how scholars outside the traditional PM domain are currently leading conceptual and methodological developments. Their prominence suggests that project management is still in the early stages of integrating AI, with a heavy reliance on external frameworks. This emphasizes the importance of PM researchers actively contributing domain-specific insights to shape AI applications that are contextually grounded and tailored to project environments.

Overall, the findings suggest that AI applications in project management are mostly focused on cost prediction, scheduling, risk management, and resource optimization, with a growing interest in generative AI and blockchain-integrated systems. The analysis of results demonstrates how AI functions as a system for managing project complexity. The combination of ML with DTs and NLP enables both task-specific efficiency and comprehensive decision support through their ability to handle intricate project relationships.

AI has been applied to a range of project management tasks, including risk forecasting, compliance assessment, effort estimation, and resource optimization. ML techniques such as SVM and ANN provide predictive insights based on historical project data, improving forecasts of cost, duration, and likely bottlenecks [14]. Vergara et al. [46] noted a growing interest in generative AI applications that can automatically generate project reports and planning documents, further enhancing predictive and operational capabilities.

NLP plays a growing role in extracting actionable information from unstructured project data such as reports and regulations. Rule-based NLP models, particularly those employing semantic logic, improve precision and recall in tasks such as compliance checking and knowledge extraction [8]. NLP has also gained traction through its integration with generative models, enabling not only interpretation but also automatic synthesis of planning artifacts [46].

DT technology builds dynamic digital representations of physical assets or systems. When integrated with AI and IoT infrastructures, DTs provide real-time monitoring and simulation that support proactive project decisions. Their use has expanded in domains such as construction and infrastructure planning, where they simulate execution scenarios and visualize cascading risks [15,49]. Kozhakmetova et al. [16] argue that the synergy between AI, IoT, and blockchain represents a critical avenue for increasing data traceability and transparency across project systems.

ES, which formalize domain knowledge into decision rules, provide structured support for tasks such as compliance verification and dispute resolution. These systems operate through inference engines that mimic expert judgment and reduce dependency on human input [8,48]. Neural computing, particularly through ANN architectures, supports advanced forecasting by detecting non-linear patterns in project histories [2].

Fuzzy logic and genetic algorithms have also gained ground in addressing the ambiguity and optimization challenges inherent to resource allocation and scheduling. These approaches facilitate approximate reasoning and adaptive exploration of project constraints. CBR, which draws on past experiences to resolve new problems, has proven particularly valuable in risk modeling and conflict mitigation in project contexts [11].

AI-powered robotics extends the use of automation into the physical domain. In construction projects, for instance, robots equipped with vision and haptic sensors undertake repetitive or hazardous tasks and relay environmental data in real time. When combined with AI and neural models, such systems enhance feedback loops and support dynamic adaptation to operational disruptions [13,49]. These insights assist project managers in selecting AI tools appropriate for their lifecycle stage, while also informing policymakers about the governance frameworks required for responsible AI integration.

Despite the extensive potential of AI, its deployment in project environments continues to face several limitations. Most notably, the performance of AI systems is closely tied to the availability of high-quality, structured data. In many cases, data inconsistencies and incompleteness hinder accurate modeling [2]. However, the diversity of study designs, AI techniques, and project contexts limits the direct comparability and generalizability of the provided results. Integrating AI into existing project frameworks often demands cross-disciplinary collaboration and system reengineering, which can lead to operational resistance. Zia et al. [19] highlight ethical and institutional challenges, including transparency in automated decisions, bias in algorithms, and the need to retrain project personnel for AI-supported roles. In addition, bridging the communication and collaboration gaps between AI developers and project management (PM) professionals is critical to the success of AI initiatives. A lack of understanding can result in scope creep, unrealistic timelines, and, eventually, project failure. Nonetheless, recent developments demonstrate a growing shift towards hybrid AI architectures that combine symbolic and data-driven approaches. These models improve interpretability while maintaining adaptability to complex project dynamics [50]. In practice, hybrid AI architectures can assist enterprises in balancing the interpretability requirements of governance frameworks with the adaptability required for changing project conditions. Although hybrid AI models offer interpretability and adaptability, empirical validation in project contexts is still scarce. Future studies should clearly compare hybrid approaches to pure ML in order to assess performance and applicability.

Emerging applications in NLP, DTs, and generative models suggest a future in which AI systems extend beyond automation to become integral actors in strategic planning and adaptive execution [3].

Future research should concentrate on longitudinal evaluations of AI systems in real-world project environments, cross-industry benchmarking of AI performance, and the ethical implications of using generative AI in high-stakes project decision-making.

5. Conclusions

This study expands on previous SLRs (e.g., Reznikov [3]; Adamantiadou & Tsironis, [4]) by providing more up-to-date coverage and integrating theoretical frameworks with empirical findings. These additions improve the generalizability and academic rigor of our conclusions. The current study has undertaken an extensive bibliometric and thematic analysis to map the intellectual structure and evolution of research at the intersection of AI and project management, with construction-related domains considered as illustrative case contexts. Through co-occurrence networks, thematic mapping, citation analyses, and longitudinal trends, the findings provide a robust synthesis of the field's conceptual terrain, key actors, and thematic trajectories.

From a theoretical standpoint, the findings reveal a field that is both consolidating and diversifying. Core themes such as project management, AI, and decision support systems emerge as "motor themes," characterized by high centrality and density. These serve as conceptual anchors, linking diverse strands of inquiry including optimization, automation, and simulation. The strong presence of sustainable development and digital transformation in more recent years—though still classified as emerging themes—suggests a paradigmatic shift toward more socially responsive and systemically integrated models. This trend aligns with global frameworks such as the United Nations' Sustainable Development Goals (SDGs), which promote responsible innovation, resource efficiency, and sustainability in project contexts. The thematic clusters demonstrate that theoretical advancements are not occurring in isolation but are rather cross-pollinating across clusters such as ES, knowledge management, and construction management. This interdisciplinary entanglement calls for an updated theoretical framework that captures the convergence of digital technologies, decision-making logic, and sustainability-oriented design. One interesting direction is to integrate AI capabilities into PMBOK® knowledge domains (for example, embedding predictive analytics into cost/time management or NLP into communications management). This provides a concrete way to update theoretical frameworks.

These findings underscore the growing integration of AI tools—such as ML, SVM, and optimization algorithms—into project-based environments, particularly in areas like risk assessment, resource planning, and performance forecasting. The prominence of themes like automation, information management, and construction reflects a broader shift towards data-driven and adaptive practices. For practitioners in engineering and project management, this signals the importance of digital fluency and the strategic deployment of AI tools within organizational workflows. In parallel, the rising emphasis on sustainability and context-awareness calls for a balanced approach that addresses not only operational efficiency but also ethical and environmental responsibilities. These findings provide evidence to support the design of governance frameworks that encourage responsible AI use in project management. For practitioners, they underline the need for digital upskilling and strategic AI deployment. Concrete initiatives include specific AI certifications for project managers, cross-disciplinary training modules that combine data science and project management, and the incorporation of AI toolkits into professional development programs.

While AI promises enhanced accuracy, efficiency, and strategic alignment, its successful adoption requires addressing key challenges, including data quality, system customization, and ethical considerations. There is room to advance the dual question of whether AI helps navigate complexity in project management and to what extent it introduces new complexities and ambiguities into project environments. This is a topic that warrants careful attention in future research agendas.

While the bibliometric techniques employed offer a comprehensive and replicable view of the field, several limitations must be acknowledged. First, the analysis is constrained by the coverage and indexing practices of the underlying bibliographic database. Second, the co-occurrence-based clustering is inherently sensitive to terminology choices and may conflate semantically distinct but lexically similar concepts. Moreover, although the use of centrality metrics (e.g., betweenness and PageRank) enhances interpretative granularity, these measures do not capture the depth or quality of conceptual interlinkages. Furthermore, the citation threshold applied may have excluded some relevant but under-cited works; however, sensitivity analysis revealed that essential thematic patterns remained constant. These limitations may have caused selection bias and thematic underrepresentation, reducing the generalizability of the conclusions. The exclusion of non-English publications, combined with the use of citation thresholds, may reduce generalizability across global PM contexts, possibly underrepresenting regional or emerging contributions.

We included literature systematically only until November 2024 to proceed with the stages of grooming, screening, and analysis. We discussed some 2025 studies narratively to indicate ongoing developments but we did not include them in the systematically screened dataset or the results. This decision limits this review because the field evolves quickly and future work may extend or revise the insights reported here. Researchers should adopt a living systematic review (LSR) approach to ensure continuous integration of the most recent evidence [51].

Future studies may enhance this analysis by employing full-text semantic methods or NLP to increase thematic precision and reveal causal relationships between concepts. Longitudinal case studies could further explore how key themes—such as digital transformation, sustainable development, and decision-making frameworks—are operationalized in organizational settings over time. Future research should include longitudinal, cross-industry case studies, comparative evaluations of AI techniques, and the integration of ethical impact assessments into AI-PM frameworks. Additionally, future research should address the ethical, legal, and human-centered aspects of AI adoption, which remain underexplored relative to technical and managerial perspectives. Advancing this field will require the development of standardized frameworks for AI integration, interdisciplinary collaboration, and exploration of advanced hybrid models and core AI branches in relation to project management. Bridging these gaps will be essential to fostering adaptive, ethical, and resilient strategies in increasingly complex project environments.

In sum, this study provides a comprehensive synthesis of AI's existing and emerging roles in project management, laying the groundwork for both scholarly research and informed practice in the digital era.

Supplementary Materials: The PRISMA-ScR Checklist can be downloaded at: https://www.mdpi.com/article/10.3390/systems13100913/s1 [21,52].

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