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Review

Transition from Traditional Knowledge Retrieval into AI-Powered Knowledge Retrieval in Infrastructure Projects: A Literature Review

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Abstract: The transition from traditional knowledge retrieval to artificial intelligence-powered knowledge retrieval signifies a fundamental change in data processing, analysis, and use in infrastructure projects. This systematic review presents a thorough literature analysis, examining the transition of traditional knowledge retrieval strategies from manual-based and statistical models to modern AI methodologies. This study systematically retrieved data from 2015–2024 through Scopus, Google Scholar, Web of Science, and PubMed. This study underscores the constraints of traditional approaches, particularly their reliance on manually generated rules and domain-specific attributes, in comparison to the flexibility and scalability of AI-powered solutions. This review highlights limitations, including data bias, computing requirements, and interpretability in the AI-powered knowledge retrieval systems, while exploring possible mitigating measures. This paper integrates current research to clarify the advancements in knowledge retrieval and discusses prospective avenues for integrating AI technology to tackle developing data-driven concerns in knowledge retrieval for infrastructure projects.

Keywords: knowledge retrieval; AI; infrastructure projects; knowledge management; information extraction; traditional knowledge retrieval; artificial intelligence

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1. Introduction

Infrastructure project success in the modern era is largely attributable to knowledge management, which creates the groundwork for innovation, strategic planning, and well-informed decision-making. Transportation networks and urban development projects, which are examples of infrastructure projects, can be quite complex due to the many parties involved, various regulations, environmental factors, and technical difficulties. Infrastructure projects accounted for a sizable part of the global construction industry's valuation of over USD 7.3 trillion in 2021, which is expected to rise to USD 14 trillion by 2030 [1]. Due to the dispersed and compartmentalized nature of project information, standard knowledge retrieval methods are unable to handle as much as 95% of the data in infrastructure projects. For example, obtaining important insights from past projects and lessons learned can be a hassle because they are usually hidden in static reports or incompatible systems.

Knowledge retrieval, according to [2], is the act of finding and using pertinent data from large, often unrelated databases to solve particular problems and is fundamental to knowledge management. To keep projects on track in terms of time, money, and quality, the authors of [3,4] are of the view that knowledge retrieval must be effective. This will guarantee that teams have access to relevant historical data, best practices, and practical insights. In infrastructure projects, the importance of preventing project cost overruns, delays, quality defect, and other issues is acknowledged by other scholars [5–8].

An essential component of efficient knowledge retrieval in infrastructure projects is information extraction, which is the methodical procedure of discovering, organizing, and combining useful data from unstructured or semi-structured sources [9–11]. According to [12,13], design documents, contracts, progress reports, safety records, and contacts with stakeholders are just a few of the many sources contributing to the massive amounts of data generated by construction projects. At every stage of a project's lifetime, accurate and fast knowledge retrieval is essential for risk management, resource optimization, regulatory compliance, and decision support. For a long time, rule-based procedures and manual document reviews were the standard for knowledge retrieval in infrastructure projects [14–16].

According to [17,18], clients, architects, engineers, and contractors all bring unique experiences to the table when executing infrastructure projects. Due to this, it is difficult to retrieve knowledge cooperatively. Contrarily, several structural components made of various materials are typically found in infrastructure projects. As an infrastructure project progresses through its life cycle, the necessary knowledge is likely to evolve at various stages; therefore, there is a need for effective knowledge retrieval [19]. According to [20], traditional methods of knowledge retrieval do not take into account the interplay between previous knowledge retrieved, the accessibility of the knowledge retrieved, or the interdependencies between various projects.

Conversely, according to Baek, Namgoong [21], the goal of knowledge retrieval is to facilitate information interchange; nevertheless, it fails to foster mutual understanding among project participants if the right process is not utilized. Project documents, risk logs, site instruction logs, change orders, and post-project reviews are just a few examples of the many documents wherein knowledge is typically dispersed, making knowledge retrieval a challenge [6,7,21]. These approaches of traditional knowledge retrieval lay the groundwork but still have issues, especially since the structure, wording, and presentation of project documents might differ greatly, making it difficult to retrieve standardized information due to data format inconsistency [8].

A paradigm change in tackling these limitations has been presented with the emergence of artificial intelligence (AI). Artificial intelligence (AI), according to [22], is the emulation of human intellect in computers intended to carry out tasks like sensing, learning, reasoning, problem-solving, and decision-making that generally need human cognitive functions. Large volumes of data can be processed by AI systems, which can also identify patterns and make judgments with little help from humans [23]. According to [24], artificial intelligence (AI) can be broadly divided into two categories: narrow AI, which is made for particular tasks (like recommendation systems or virtual assistants), and general AI, which is made to be able to perform any intellectual work that a human can.

Researchers like [6,25,26] indicated that a centralized platform for AI could facilitate collaborative knowledge retrieval. Compared to traditional knowledge retrieval methods, research investigating AI-powered knowledge retrieval is still in its infancy, necessitating more work in contrast to the abundance of research examining the traditional approach of knowledge retrieval. Despite the numerous reviews covering various fields of study, no comprehensive systematic review has yet investigated AI-powered knowledge retrieval in infrastructure projects.

Therefore, improving knowledge retrieval efficiency in infrastructure projects while making full use of AI's unique capabilities is challenging. On the other hand, processing data remains AI's primary function in modern times [27,28]. For AI to have the most significant impact in infrastructure projects, it must progress from an information level to a knowledge level.

This study explores a thorough systematic literature review. The objective is to address the deficiencies present in the existing research. The objectives of this research are as follows: (i) to conduct a literature review on traditional knowledge retrieval (KR) and AI-powered KR; (ii) to identify the challenges encountered by traditional KR; (iii) to ascertain the capacity of AI to support KR; (iv) to explore methods by which AI can address these challenges; and (v) to propose future research avenues concerning AI that may facilitate effective KR.

In particular, this study aims to tackle important problems like data fragmentation and variability in data quality that are common in infrastructure projects. Conventional methods are not always up to the task of processing diverse and large amounts of infrastructure project data, and with the help of AI, knowledge retrieval can be automated to improve data accuracy, and gain real-time insights, all of which solve these long-standing problems. The significance of this research for theory and practice in infrastructure projects is further explained in the subsequent sections.

The subsequent section of this paper is as follows. The methodology of this research is elaborated in subsequent Section 2, by examining some traditional and AI-related knowledge retrieval publications. Also, traditional knowledge retrieval and AI-powered knowledge retrieval across diverse knowledge management activities will be examined. Finally, the research findings and their possible implications were discussed.

2. Methodology

2.1. Overview of Literature Review Methodologies

A systematic review is employed to fulfill the aims of this research. A literature review offers a contemporary comprehension of a topic, highlights critical concerns within the current body of knowledge, and establishes a foundation for subsequent research [5]. This systematic review provides a summary of prior research in a particular discipline and highlights knowledge gaps in the published literature [29]. This technique adheres to specified standards, including a systematically executed review of a clear methodology, and updatability, as well as the summation and synthesis of the primary subject of the research [30]. This research reviews the pertinent literature, encompassing previous studies on traditional knowledge retrieval and AI-powered knowledge retrieval. Ref. [31] asserts that a systematic review necessitates a transparent methodology, thorough search, screening protocol, logical analysis, and synthesis of evidence. This study comprises four primary phases illustrated in Figure 1. This research manually extracts information from selected publications, including journal/conference title, paper title, and publication year, as well as the emphasized project phase and targeted KR activities. To mitigate potential author bias, the databases and keywords were determined by a debate between the two authors. The primary author of this study independently chose the papers and extracted material, which was subsequently verified by the second author using the same criteria. The disputes were settled through dialogue to achieve consensus. All extracted data were organized, and descriptive statistical analysis was performed to present an overview of knowledge retrieval and AI-related publications.

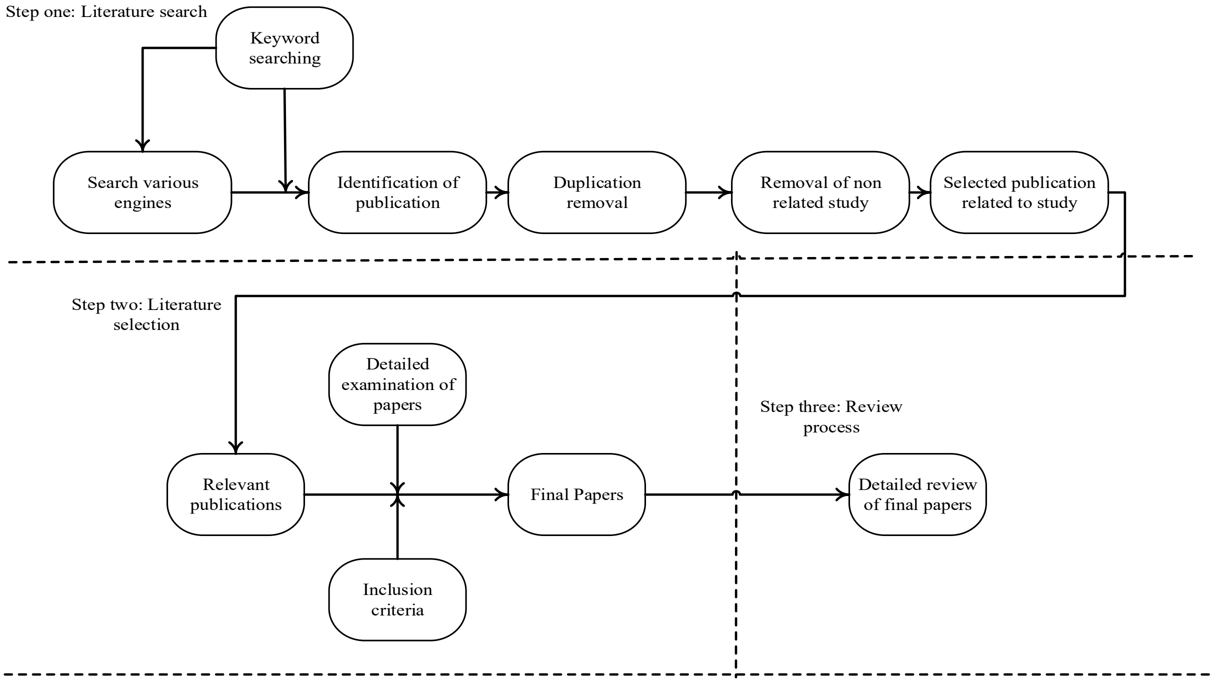

Figure 1. Research methods flowchart.

2.2. Literature Search

Since Scopus covers a wider range of scientific articles, it was chosen for the initial literature search [32]. Also, compared to competitors like Google Scholar, Web of Science, and PubMed, Scopus is known to have superior performance [33,34]. According to [33], compared to other databases, Scopus adds conference papers, indexes articles more quickly, and has more recent publications available. An extensive search was carried out using the two-part search phrase in Scopus's "article title/abstract/keyword" field. "Knowledge retrieval", "knowledge extraction", "AI", "Artificial intelligence", "AI technologies", and other similar terms made up the first section. Things like "construction", "infrastructure projects", "Roads and highways", and "Infrastructure engineering" made up the second section.

As this study's primary emphasis was on traditional knowledge retrieval and AI-powered knowledge retrieval in infrastructure projects, other processes, such as knowledge sharing and utilization, were omitted from the keyword set. Incorporating the findings of other research that has mostly reviewed the use of knowledge retrieval and AI in infrastructure projects [10,31] will amount to little more than reiteration. Publications from 2015–2024 were chosen for this review. The chosen time frame for this study is warranted due to the fast development and implementation of pertinent technology and processes across this duration. Beginning in 2015, it incorporated studies following the big AI innovation wave, when models like deep learning and machine learning became prevalent and significantly impacted how previous data on infrastructure projects were retrieved. Furthermore, this period encompasses significant advances, developments, and applications all the way up to 2024, giving a thorough picture of the status of research. By focusing on this time frame, it can be confidently assumed that the results are still applicable and steer clear of conclusions that are out of current and do not account for how knowledge retrieval and AI are changing in terms of both methods and technology. Since these formats highlight the most authoritative and trustworthy resources for information, "article" or "review" were also chosen as the document type [31,35].

The search query retrieved 45 publications, and due to the small number of publications retrieved by Scopus, a secondary search that included ScienceDirect and Web of

Science yielded 123 publications. The goal was to collect and analyze sufficient research papers about knowledge retrieval and AI in infrastructure projects. Publications that did not cover major infrastructure project-related topics were excluded during the initial screening. A total of 117 publications, including journal and conference articles, were obtained after duplicates were eliminated. After the exclusion criteria, the cumulative sum of papers was 117, sourced from 20 journals and conference proceedings.

A methodical and open strategy was utilized. Precise inclusion criteria established at the beginning of the review process formed the basis for the classification. The term "traditional knowledge retrieval" refers to papers that did not incorporate machine learning or AI but instead concentrated on tried-and-true methodologies such as manual retrieval processes and relational databases. On the contrary, articles that fall under the category of AI-powered knowledge retrieval made clear use of AI methods like neural networks, machine learning, or natural language processing to improve knowledge retrieval. A comprehensive evaluation of each publication's methodological and technological emphasis was used to establish the difference, as described in their abstracts, keywords, and major text. Table 1 displays the literature review search in the various databases and each number for traditional knowledge retrieval and AI-powered.

Table 1. Search results.

	WOS	Scopus	Science Direct	Total (Before Excluding Duplicate)	Total (After Excluding Duplicate)
Traditional KR	28	23	31	82	65
AI-powered	8	22	11	41	52

2.3. Literature Selection

Table 2 contains the selection criteria that were designed to filter out publications that do not pertain to infrastructure projects using either traditional or AI-powered knowledge retrieval. There are two parts to the selection process: (1) reading the paper's abstract, keywords, and title; and (2) reading the entire content.

Without reading the entire text, we eliminate any papers with a rating of 1 or 2 based on the abstract, keywords, and title. When deciding whether to include a paper in the literature review, it is necessary to read the entire text, not just the title, abstract, and keywords, for papers that have been graded 3 or 4. Contrarily, it is not required to go beyond scanning the title, abstract, and keywords to read the entire text of any paper ranked 5, as it is clearly appropriate for the literature review. Table 2 shows the number of papers chosen at each level of selection criteria after excluding irrelevant publications. After eliminating irrelevant publications, 65 were retained for traditional knowledge retrieval and 52 for AI-powered knowledge retrieval. Then, a snowball strategy was employed to lessen the likelihood of missing any pertinent publications. According to [36], the process of locating further publications by perusing a paper's reference or citation list is known as "snowballing". Although the snowball strategy is great, it can lead to bias if specific authors, journals, or viewpoints are overrepresented. Therefore, strategies such as exclusion and inclusion criteria, avoiding overreliance on the citation, and documentation of every criterion were used to minimize bias. This study uses snowballing based on the same criteria in Table 2. As a result, five more papers on traditional knowledge retrieval and four more on AI-powered knowledge retrieval were found and included. The literature review in this study concludes with 70 articles covering traditional KR and 56 articles covering AI-powered KR.

Table 2. Selection criteria and results.

Level	Traditional KR	Total Number of Selected Articles	AI-Powered KR	Total Number of Selected Articles
1	Articles on retrieval and extraction methods with no importance to traditional KR.	0	Articles on AI but with no importance to KR.	0
2	Articles related to retrieval and extraction methods with no importance to infrastructure projects.	0	Articles related to AI with no investigations into knowledge retrieval.	0
3	Despite the article's focus on KR, it fails to indicate in abstract, title, or keywords.	31	Though the article is about AI and contains KR in its abstract, title, or keywords, it was not easy to indicate whether or not the study is about AI-powered KR.	25
4	The abstract does not specifically address traditional KR, though keywords and titles had indications of such.	11	Although the article title, abstract, or keywords indicate AI and KR, the abstract does not highlight AI for KR.	15
5	Traditional methods of KR are strongly supported by the articles.	28	AI and KR are very consistent in the articles.	16

3. Content Analysis

This study analyzed the articles' content to discover the various traditional KR tools and their implications. It also examined the current state of KR and AI and how they could be used in infrastructure projects. The distribution of the various publications was also ascertained. The literature was categorized according to the stages of project design and construction. This research uses the descriptions for the design and construction phases found in the references.

3.1. Traditional Knowledge Retrieval Methods and Their Implications

In the stage of knowledge reuse, retrieval of knowledge is essential. Infrastructure project knowledge retrieval has been the subject of numerous related studies [1,37]. The traditional approaches to retrieving knowledge in infrastructure projects involve well-established methods for gathering, retaining, and disseminating knowledge and expertise among various project stakeholders [38]. These methodologies have played a fundamental role in effectively managing and leveraging knowledge throughout infrastructure project execution, facilitating the accumulation and seamless sharing of best practices, valuable insights, and knowledge over time [39]. This process heavily relies on human interaction, physical documentation, and the organizational memory infrastructure to ensure the efficient flow and preservation of crucial knowledge.

3.1.1. Experience-Based Knowledge Retrieval

Good knowledge retrieval is essential to guarantee an infrastructure project's success in the complicated and ever-changing world of construction. Experience-based knowledge retrieval, according to [40], is an effective strategy for incorporating lessons learned from completed initiatives into ongoing and future endeavors. Ref. [41] further stated that one of the primary means of retrieving experience-based knowledge is using knowledge repositories, which comprise collections of knowledge sourced from diverse outlets.

Numerous factors, including site, regulatory climate, and project scope, contribute to the inherent uniqueness of infrastructure projects. However, some commonalities help practitioners learn from one another's mistakes [42]. Improved decision-making, reduced risk, and optimized processes are all possible because of the ability of experienced-based knowledge retrieval to systematize the retrieval of insights from historical data.

Experience-based knowledge retrieval has many advantages in infrastructure projects. Teams can enhance project performance by anticipating and mitigating risks more efficiently, optimizing workflows, and capitalizing on past experiences [43]. Teams can build on prior achievements and test new ideas influenced by past results, encouraging innovation. Furthermore, it ensures that crucial insights are not lost by helping organizations retain important knowledge even when people leave or retire [44].

3.1.2. Document-Based Knowledge Retrieval

Infrastructure projects also rely heavily on document-based knowledge retrieval, which involves sifting through a wide variety of written and visual project documents [37], including but not limited to contracts [45], drawings [46], inspection reports, and communication logs in order to retrieve useful data [37]. Project goals, roles, responsibilities, schedules, risks, and other critical knowledge are typically found in these documents.

Notwithstanding the evident benefits, document-based information retrieval in infrastructure projects is not intricate. This encompasses overseeing the integration of various document formats and legacy systems, ensuring data security, and necessitating ongoing maintenance of the retrieval system [47]. However, document-based knowledge retrieval has serious shortcomings when handling the complicated and ever-changing requirements of modern projects, no matter how useful they are. The dependence on static information is a major drawback of document-based retrieval systems. These systems rely on materials stored in archives, which are great for learning about the past but do not always keep up with the dynamic nature of modern initiatives [45]. As an added limitation, document-based retrieval systems often suffer from information overload. It becomes more difficult to retrieve particular, actionable information as the number of project documentation increases [47]. People waste time and energy browsing through enormous archives since these systems frequently lack advanced filtering methods to prioritize the most important items. Because efficiency is critical in modern infrastructure projects, this restriction may have far-reaching consequences for output and the quality of decisions made.

Moreover, the caliber of the foundational data influences the efficacy of retrieval systems, which is why [48] advocated for maintaining accurate and well-organized documentation throughout the project's duration. Ref. [49] contends that forthcoming advancements in artificial intelligence (AI) are expected to enhance document-based knowledge retrieval further. They elaborated that these systems could predict knowledge needs, automate document categorization, and proactively counsel project teams.

3.1.3. Knowledge Repositories

Knowledge repositories, as part of the traditional knowledge retrieval method, act as centralized platforms that store, organize, and provide access to critical project knowledge. According to [50], they tackle the difficulties of overseeing enormous volumes of diverse data produced during infrastructure projects.

Ref. [50] posits that knowledge repositories have extensive data from prior projects, comprising technical specifications, project reports, and design documentation. These records provide valuable insights into the decisions and processes that impact a project's outcome. Ref. [51] asserts that the documentation of project procedures and methodologies functions as a decision-making guide for future projects and as a reference for best practices.

Ref. [52] maintains that these documents in a systematic archive enable project teams to leverage established strategies instead of commencing again. Ref. [53] asserts that accumulating insights from prior endeavors is a fundamental component of any knowledge repository. These insights often arise from evaluating the successes and failures encountered during the project's life cycle. Ref. [54] elucidated the importance of identifying patterns and trends that may not be immediately apparent by systematically recording successful and unsuccessful outcomes. This technique enables project teams to anticipate future challenges and mitigate risks [55]. Additionally, problem-solving methodologies that outline the resolution of specific issues are often incorporated into lessons-learned archives, providing a valuable reference for addressing similar challenges in future projects. Analytics powered by artificial intelligence, real-time dashboards, and collaboration platforms are becoming increasingly important in today's infrastructure project environments. The usefulness of these tools in project operations is limited since knowledge repositories do not always integrate seamlessly with them. The inability to immediately incorporate information from repositories into project models is one cause of segmented processes and decreased effectiveness of project teams in relation to knowledge repositories. Documents, templates, and reports are examples of the kinds of explicit knowledge that are commonly stored in knowledge repositories. Tacit knowledge, on the other hand, is more important in infrastructure projects; it consists of things like team members' perceptions, situations, and discoveries. There is a big limitation in meeting projects' complicated and nuanced needs since repositories do not always record or make it easy to share this tacit knowledge.

Notwithstanding its benefits, establishing and managing knowledge repositories in infrastructure projects can be arduous. Maintaining the accuracy and relevance of the data stored in the repository is a primary challenge [56]. Regularly updating the repository is crucial to include new information and insights as projects evolve and potential resistance to change poses an additional challenge. Ref. [57] posits that certain project personnel may resist embracing new methodologies and protocols, remaining used to conventional practices. To mitigate this resistance, effective change management strategies such as education, outreach, and demonstrating the tangible benefits of the knowledge base are essential [58]. Table 3 indicates the traditional knowledge retrieval methods and their implications.

Table 3. Traditional knowledge retrieval and its implications.

Category	Description	Implication	References
Experience-based knowledge retrieval	Utilizes previous infrastructure project experience and historical data to guide present project decision.	Improves problem-solving efficiency, minimizes error, encourages the use of validated solutions, and supports the ongoing enhancement.	[40,43,44]
Document-based knowledge retrieval	Concentrates on retrieving pertinent knowledge from contracts, reports, and various project documents.	Facilitates analysis, expedites knowledge retrieval, minimizes human error, guarantees conformity, and incorporates all documents.	[37,45,46,48,49]
Knowledge repository	Centralized system for the storage organization and dissemination of project knowledge.	Promotes accessibility and encourages multi-stakeholder participation in decision-making.	[55–58]

3.2. Integration of AI in Knowledge Retrieval

Infrastructure projects produce substantial quantities of information during their lifecycle. The retrieval of this knowledge is essential for effective decision-making and risk management. Artificial intelligence (AI) has emerged as a disruptive technology that enhances knowledge retrieval procedures in infrastructure projects, markedly enhancing efficiency, accuracy, and insight generation. According to [59], artificial intelligence technologies, including natural language processing (NLP), machine learning (ML), and computer vision, have exhibited significant potential for automating and enhancing knowledge retrieval processes. These technologies are very proficient in handling substantial quantities of unstructured data, including contracts, drawings, and reports [14,60]. NLP algorithms, according to the study by [61], can retrieve pertinent knowledge like deadlines, costs, and compliance requirements, minimizing the manual labor needed to analyze documents. Moreover, AI-driven solutions can consolidate and synchronize data from several sources, guaranteeing uniformity and availability [62]. Refs. [63,64] explained that, through the analysis of real-time data from IoT devices, drones, and sensors, AI may derive actionable insights concerning project advancement, resource allocation, and any impediments.

The incorporation of AI in knowledge retrieval offers multiple advantages. Firstly, it enhances precision by reducing human errors, guaranteeing that essential data are accurately gathered and processed [65,66]. Furthermore, the automation of repetitive operations improves efficiency, enabling teams to concentrate on critical initiatives and expedite project schedules [67,68]. Thirdly, AI enhances risk mitigation by recognizing patterns and abnormalities in data, allowing for early identification of possible threats and the execution of preventative measures [39]. Moreover, optimized data management diminishes overhead expenses linked to human data handling and error correction, resulting in substantial cost reductions [69,70].

The integration of knowledge retrieval in AI integrates various AI technologies, including natural language processing (NLP), machine learning, and deep learning, to create systems that can understand the complexities of human language, learn from data patterns, and adapt over time [71,72]. These systems can process vast quantities of unstructured data, identify patterns, and provide contextually pertinent and accurate information [73]. Ref. [74] asserts that AI-enabled knowledge retrieval encompasses multiple mechanisms that facilitate robots in comprehending and interpreting human language effectively for knowledge acquisition. Tokenization, which segments the text into manageable units; parsing, which analyses grammatical structures; and named entity recognition (NER), which identifies and classifies elements within the text, are all exemplars of AI methodologies [75]. Ref. [76] asserted that, by employing these tactics, AI systems might comprehend the intent of user inquiries and provide results that are more pertinent to the user's requirements. Refs. [77,78] asserts that the criticality of an AI-enabled system is essential for facilitating the learning and performance enhancement of AI systems over time. Ref. [79] also asserted that, in the realm of knowledge retrieval, AI systems can be trained on extensive datasets to identify patterns and predict the most pertinent information for a certain query.

3.3. Bibliometric Publication Indicators

The scientific impact on the global community is essential for evaluating the efficacy of a specific study. In qualitative research analysis, the primary emphasis should be on peer review, although bibliometric indicators are crucial for quantitative research evaluation [80]. Jin, Kang [81] asserted that bibliometric indicators must be precise, advanced, up-to-date, and integrated with expert knowledge and should be employed judiciously. The bibliometric study provides insights into a certain country's research focus and compares it to international research communities. This research employs the VOSviewer science mapping technique to examine the literature regarding traditional knowledge retrieval and AI knowledge retrieval applications in infrastructure projects. The VOSviewer® Version

1.6.20 program was selected for its capacity to generate, visualize, and utilize bibliometric networks [82]. This study's bibliometric analysis concentrated on active countries, institutional collaboration networks, and diverse authors in the research application of knowledge retrieval and AI in infrastructure projects.

3.4. Countries in Knowledge Retrieval and AI Application in Infrastructure Research

The analysis aimed at identifying countries highly engaged in knowledge retrieval and the use of AI for knowledge retrieval applications within infrastructure projects. This study utilized a "co-authorship" approach, with "countries" as the unit of analysis and "fractional counting" as the counting method. Fractional counting was chosen to guarantee that "highly cited publications exert a diminished influence in the formation of the bibliographic coupling network" and to mitigate the effect of publications with several authors. The "minimum number of publications from a country" and the "minimum number of citations from a country" were established at 1 to guarantee an optimal network. All selected countries met the criterion and were incorporated. Figure 2 illustrates that China, the United States, the United Kingdom, Australia, and Hong Kong are the five principal countries that are instrumental to knowledge retrieval and AI research in infrastructure projects and in the quantity of publications and citations. Due to the developing state of knowledge retrieval and artificial intelligence, along with the gradual adoption of new technologies in infrastructure projects, most of the publications emerged within the last three years. It can be noted that there is insufficient collaboration among countries in the research area; therefore, it is a necessity for enhanced cooperation among nations to facilitate global knowledge exchange and transfer.

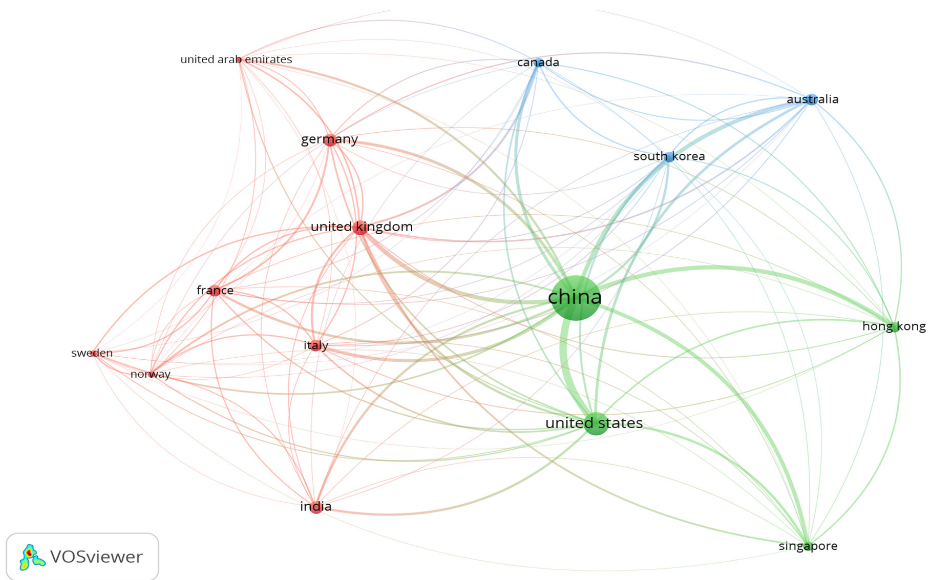

Figure 2. Countries with significant research in knowledge retrieval and AI in infrastructure projects.

3.5. Journal Publication of Articles on Knowledge Retrieval and AI Application in Infrastructure Projects

This section Figure 3 indicate the various journals with high publications on knowledge retrieval and AI in infrastructure projects. This analysis indicates that automation in construction journals has the highest number with 22 publications and 29 citations, followed by experts' systems with applications with 14 publications and 7 citations. Knowledge-based systems also had 11 published articles on knowledge retrieval and AI in infrastructure projects within the indicated years. Advanced engineering informatics also had 12 publications with 17 citations. These also indicate the readiness and importance of research in knowledge retrieval and the significance of the transition from traditional knowledge retrieval to AI-powered knowledge retrieval.

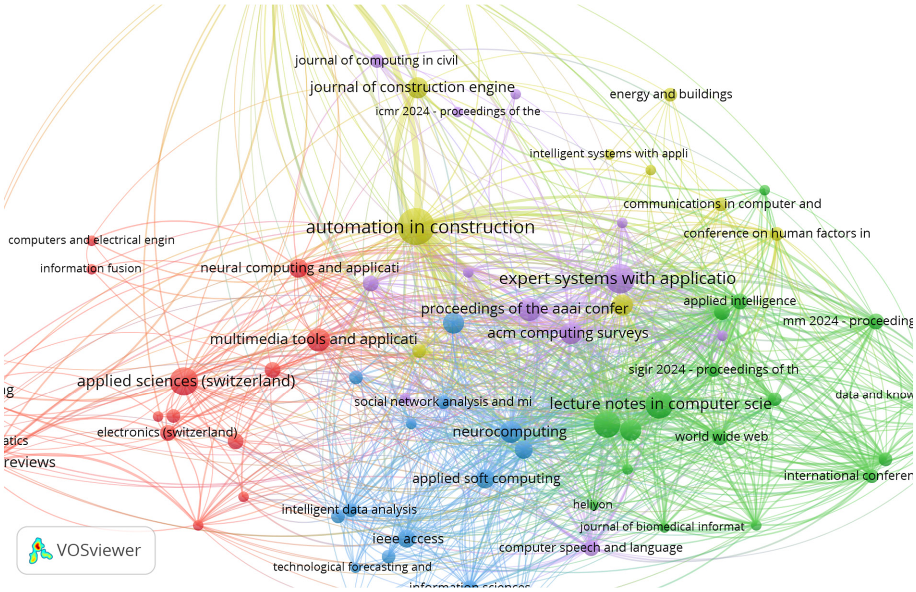

Figure 3. Journal publication with significant research in knowledge retrieval and AI in infrastructure projects.

3.6. Contributing Authors to Knowledge Retrieval and AI Application in Infrastructure Projects

This section presents the following reasons: (i) authors with potential for collaboration engaged in analogous studies within this research domain; (ii) it identifies researchers who are making substantial contributions to the application of AI in knowledge retrieval for infrastructure projects. (iii) Additionally, it aids in recognizing authors through comprehensive research investigations, formulating and suggesting pragmatic solutions to improve knowledge retrieval, and the introduction of AI to improve infrastructure projects. As can be seen from Figure 4, Liu y had nine publications with 20 citations, followed by Wang Y who had eight publications with 13 citations, and Wang J who had seven publications with 40 citations. All authors were either first authors or co-authors. Figure 4 also indicates the pictorial description of the most contributing authors in knowledge retrieval and AI in infrastructure project research.

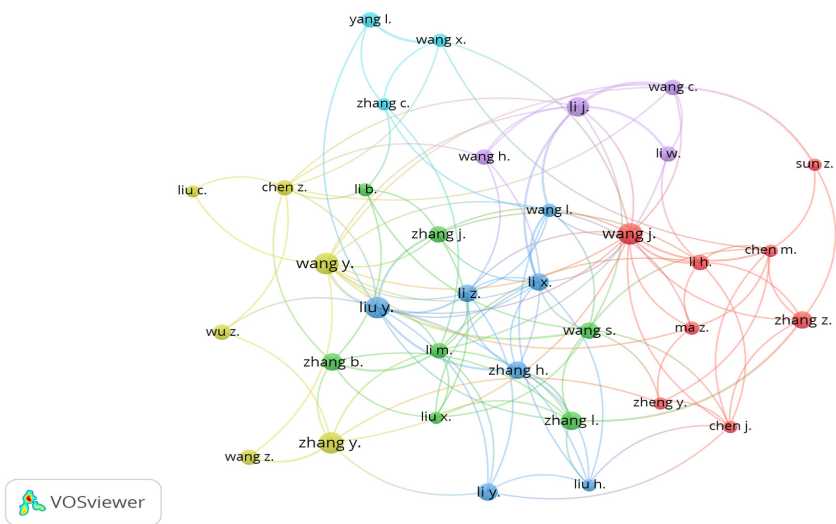

Figure 4. Most contributing authors in knowledge retrieval and AI in infrastructure projects research.

4. Application of AI-Powered Knowledge Retrieval in Lifecycle Phases of Infrastructure Projects

Infrastructure projects' substantial magnitude, complexity, and prolonged timescales necessitate diligent management throughout many lifecycle phases, including initiation, planning, execution, monitoring, and closing. AI-powered knowledge retrieval solutions significantly enhance these initiatives by facilitating the retrieval and interpretation of extensive data volumes with unmatched efficiency. This document examines the application of AI knowledge retrieval technologies in each phase of the infrastructure project lifecycle, emphasizing their substantial contributions to project success.

4.1. Application of AI-Powered Knowledge Retrieval in the Initial Phase

The initial phase emphasizes delineating the project's scope, objectives, and feasibility. This phase is fundamental, establishing the groundwork for all ensuing actions. AI knowledge retrieval techniques are essential at this juncture since they enhance efficiency and profundity in stakeholder analysis [83]. Through the retrieval of documents, emails, and meeting transcripts, AI may discern the principal individuals engaged in the project, along with their distinct responsibilities, interests, and degrees of influence [84,85]. This automated analysis guarantees that stakeholder mapping is thorough and unbiased, offering a lucid comprehension of the intricate human dynamics that may influence the project's course [34].

The initial phase also frequently entails the analysis of comprehensive and varied information, encompassing market reports, environmental evaluations, and legal papers [86]. AI-driven tools effectively retrieve pertinent knowledge from these sources, allowing project teams to assess the feasibility of the proposed initiative with accuracy. Moreover, AI systems with sentiment analysis functionalities offer significant insights into public and community sentiment [87]. Infrastructure projects frequently employ AI-powered techniques such as predictive modeling and geospatial analytic systems to assess environmental concerns, resource availability, and topographical conditions. In the UK's Crossrail project, for instance, machine learning algorithms were important in optimizing tunneling courses and reducing risk during the initial phase by analyzing historical data and running simulations. Artificial intelligence (AI) could help project teams make better decisions more quickly and precisely, saving money and preventing problems.

Risk identification, a fundamental aspect of the initial phase, is greatly enhanced by AI-powered knowledge retrieval [88]. Historical data from infrastructure projects are retrieved and examined to identify patterns and trends that may signify prospective issues, such as cost overruns, delays, or regulatory obstacles [89]. AI algorithms can identify location-specific dangers by analyzing data pertaining to environmental variables, political stability, and economic aspects [90]. This proactive strategy enables project teams to mitigate possible hazards prior to escalation, establishing a foundation for more effective risk management tactics at later stages.

4.2. Application of AI-Powered Knowledge Retrieval in the Planning and Design Phase

During the planning and design phase of projects, AI knowledge retrieval proves to be especially beneficial for analyzing technical documentation. The technology can evaluate intricate technical drawings, specifications, and building information models (BIMs) to retrieve essential design characteristics and detect potential conflicts prior to their occurrence on-site [57,65,86,91]. This functionality encompasses cost estimation, wherein machine learning algorithms analyze previous project data, vendor quotations, and contemporary market information to produce more precise cost estimates and budgets [83]. The system's capacity to retrieve and analyze risk-related information from prior projects and industry databases enhances the risk assessment process, equipping project teams with data-driven insights for risk mitigation measures.

The planning phase utilizes insights obtained during initiation and establishes the groundwork for project implementation. AI-driven knowledge retrieval streamlines the collection of requirements by analyzing voluminous paperwork to pinpoint technical, legal, and budgetary needs [86]. This guarantees that no essential detail is neglected. Cost estimate and budgeting are enhanced by AI's capacity to analyze historical project data, discern patterns, and forecast costs with exceptional precision. Artificial intelligence (AI) simplifies risk analysis, cost estimation, and complicated project scheduling throughout the planning phase. The Sydney Metro project in Australia, for instance, used predictive analytics driven by artificial intelligence to evaluate project deadlines and spot possible obstacles based on previous project data. Improved allocation of resources and overall project effectiveness were two outcomes of the system's analysis of past data from comparable projects. AI systems excel in contract analysis by identifying and summarizing essential terms, dates, and obligations, hence minimizing the potential for problems. AI enhances project timelines by examining plans to detect potential conflicts or dependencies, optimizing resource allocation. Moreover, AI technologies are essential for compliance monitoring since they analyze local, national, and worldwide rules to guarantee that all planning papers conform to applicable requirements.

4.3. Application of AI-Powered Knowledge Retrieval in the Construction Phase

AI-powered knowledge retrieval is particularly effective during the construction phase. Computer vision and natural language processing technologies collaborate to retrieve progress knowledge from various sources, including site images, daily reports, worker timesheets, and equipment logs [92]. This thorough knowledge retrieval facilitates real-time progress tracking and the early identification of any delays or problems. Quality control is greatly enhanced by AI's capacity to retrieve and analyze inspection reports and test results, autonomously extracting quality-related data and identifying potential compliance concerns [93].

The construction phase of infrastructure projects includes the implementation of plans formulated in prior stages and converting concepts and timelines into concrete results. This phase is characterized by considerable complexity, encompassing multiple parties, extensive data, and evolving real-time difficulties [94]. AI-powered knowledge retrieval technologies are essential for enhancing this phase by facilitating fast data processing, real-time monitoring, and informed decision-making. A primary application of AI during the construction phase is real-time progress monitoring [90,95]. Infrastructure projects produce substantial volumes of data via IoT devices, drones, and site inspections. AI systems harvest and analyze data to deliver precise updates on project progress, highlighting disparities between anticipated and actual performance. AI-powered computer vision systems can evaluate drone footage to assess task completion relative to project timelines [92,96]. These insights empower project managers to rectify delays or inefficiencies while maintaining project alignment immediately. In the construction phase, artificial intelligence-powered knowledge retrieval is changing the game for on-site operations, especially when it comes to tracking productivity, managing safety, and controlling quality. Drones equipped with artificial intelligence and computer vision technologies were used to track the progress of the Hong Kong–Zhuhai–Macau Bridge's construction and detect structural problems as they happened. This was implemented based on a previous failure from a past project. By implementing automated assessments in potentially dangerous places, these solutions increased project efficiency and drastically decreased safety concerns.

Resource optimization is a considerable difficulty in construction due to the extensive demands of labor, materials, and equipment [1,35,58,97]. AI tools retrieve and evaluate data from project management datasets to enhance resource allocation, guaranteeing efficient utilization without excess or waste. Predictive analytics can anticipate equipment requirements by analyzing past trends and current project data, thereby averting expensive downtime or shortages [88,98]. Likewise, AI can monitor workforce allocation, guaranteeing that labor is efficiently dispersed among jobs. Safety monitoring is a critical priority during the building phase, and AI-driven information extraction significantly contributes to improving site safety [99]. By examining safety records, event logs, and real-time site monitoring systems, AI detects possible hazards and forecasts locations susceptible to accidents. Computer vision systems can identify risky activities or conditions in real time, including workers not wearing protective equipment or operating in hazardous areas [100]. These notifications provide preemptive measures, mitigating the likelihood of accidents and ensuring adherence to safety requirements [101].

4.4. Application of AI-Powered Knowledge Retrieval in the Monitoring Phase

The monitoring phase of infrastructure projects is essential for verifying that current activities conform to established objectives, budgets, and schedules [102,103]. This phase necessitates ongoing supervision and adaptive decision-making to successfully tackle growing difficulties. AI-powered knowledge retrieval solutions transform this stage by facilitating real-time data analysis, improved risk management, and thorough performance assessment. A notable contribution of AI knowledge retrieval in infrastructure projects during the monitoring phase is real-time performance assessment [90]. AI-driven systems analyze and process data to generate comprehensive dashboards that present key performance indicators (KPIs) like budget compliance, schedule advancement, and resource allocation. These technologies furnish project managers with a current and comprehensive perspective on project health, facilitating proactive measures to rectify aberrations before they develop into significant problems. The Sydney Opera House is a real-life example of an infrastructure project that uses an AI-powered system to retrieve past and present environmental data, including temperature, humidity, and vibration. The project's long-term stability is guaranteed by using these data to foresee probable structural problems and optimize maintenance schedules. These applications show how AI improves lifecycle management by giving useful insights from constantly retrieved and analyzed infrastructure project data.

AI-powered knowledge retrieval significantly enhances risk reassessment during the monitoring phase [65]. Risks recognized in earlier phases may develop or new risks may arise as the project advances. AI solutions consistently retrieve past knowledge and analyze data from diverse sources, including environmental conditions, financial indicators, and operational logs, to dynamically discover and evaluate potential threats [104]. This ongoing risk management guarantees the project's resilience to unforeseen obstacles. Moreover, AI-powered instruments are essential for environmental and safety surveillance throughout this stage. By retrieving data from environmental sensors, AI guarantees adherence to sustainability requirements and reduces ecological effects. Likewise, safety monitoring systems utilize AI-powered knowledge retrieval to analyze real-time data from site inspections, incident reports, and sensor inputs, detecting possible hazards and suggesting preventive actions. These skills markedly diminish the probability of accidents and foster a secure working environment.

5. Summary of Findings on AI-Powered Knowledge Retrieval in the Various Lifecycle Phases in Infrastructure Projects

This review illustrates the substantial influence that traditional knowledge retrieval and AI-powered knowledge retrieval exert on infrastructure projects throughout the various lifecycle phases of infrastructure projects. AI-powered knowledge retrieval has the potential to pre-emptively tackle difficulties prior to their emergence. During the design phase of infrastructure projects, the majority of the literature concerning AI-powered knowledge retrieval applications pertains to the utilization of AI technologies. Despite the frequent application of knowledge retrieval in infrastructure projects, their influence has been minimal. Employing AI-powered knowledge retrieval throughout the design phase facilitates determining which components and knowledge should be retrieved or eliminated in the redesign and re-engineering process.

This technology revolutionizes project data management, analysis, and use, markedly enhancing decision-making processes and project results. During this phase of projects, AI systems adeptly retrieve extensive historical data and paperwork, deriving essential insights for feasibility assessments and preliminary planning. During the design and execution phases, these systems also retrieve previous technical drawings, oversee construction progress via computer vision, and process real-time data from several sources to monitor project advancement. The system is especially beneficial for quality control and compliance monitoring, instantly identifying potential faults and ensuring compliance with standards.

During construction phases, AI-powered knowledge retrieval facilitates predictive maintenance and performance optimization through the analysis of equipment data, maintenance records, and operational parameters. The technology is essential for knowledge retrieval, documenting lessons learned, and establishing important databases for future initiatives. Advanced functionalities such as natural language processing and machine learning facilitate the analysis of unstructured data from diverse sources, including site images, reports, and conversations. The deployment of AI-powered knowledge retrieval also yields considerable advantages, such as enhanced efficiency, diminished risks, and notable cost reductions via optimized resource allocation and predictive maintenance. Successful implementation necessitates a meticulous focus on data quality, system integration, and security issues.

In conclusion, AI-powered knowledge retrieval systems clearly outperform their traditional knowledge retrieval when compared across various criteria: processing speed, flexibility, accuracy, efficiency, contextual understanding, and scalability. Although traditional approaches were initially sufficient for knowledge retrieval, they are already falling short in today's data-driven world. Artificial intelligence (AI) technologies are crucial in today's complicated and ever-changing world because they overcome these constraints and provide new opportunities for better, more accurate, and more intelligent knowledge retrieval. Table 4 indicates a comparison of traditional knowledge retrieval and AI-powered knowledge retrieval with critical parameters.

Table 4. Parameter comparative for traditional knowledge retrieval and AI-powered knowledge retrieval.

Parameters	Traditional Knowledge Retrieval	AI-Powered Knowledge Retrieval
Speed	Manual labor and inflexible methods make it slower.	Quicker as a result of computers and sophisticated algorithms.
Efficiency	Using manual methods and keyword searches is time-consuming.	Quick and accurate; finds the data you need instantly.

Table 4. *Cont.*

Parameters	Traditional Knowledge Retrieval	AI-Powered Knowledge Retrieval
Accuracy	Dependence on exact keyword matches can lead to irrelevant results.	Utilizing natural language processing and semantic analysis provides findings that are contextually appropriate.
Adaptability	To include new information or modifications, manual updates are necessary.	Quicker as a result of computers and sophisticated algorithms.
Scalability	Has trouble handling big or unstructured datasets; lacks scalability.	Narrowly manages large, heterogeneous, and unstructured collections.
Contextual adversity	Skips over context in favor of matching keywords word-for-word.	Obtains context and user intent to provide nuanced and meaningful outcomes.

6. Current Research Status and Gaps

Numerous applications of traditional knowledge retrieval and AI-powered knowledge retrieval are delineated. Based on the review in the previous section, research gaps, particularly in traditional knowledge retrieval, are identified.

In contrast to traditional knowledge retrieval, AI possesses unique attributes that enhance knowledge retrieval capabilities. For instance, knowledge and insights can be readily retrieved through tailored algorithms developed by AI technologies like natural language processing. The connection between knowledge and its associated activities can be continuously and automatically accessed and preserved according to the limitations set by AI settings. Conversely, knowledge retrieval in infrastructure projects is enhanced by the predictive algorithms of artificial intelligence. AI-powered knowledge retrieval can retrieve both textual knowledge and visual (graphics) knowledge. Unlike textual knowledge retrieval, AI's visual/graphic retrieval can enhance mutual comprehension of knowledge across project stakeholders. As a centralized and integrated platform, AI facilitates collaborative efforts among various project stakeholders on a singular infrastructure project.

Improving AI systems' interpretability is a top priority. Deep learning and other sophisticated AI models frequently function as "black boxes", producing insights or predictions without divulging the reasoning behind their decisions. Due to the huge risk involved in infrastructure projects, this lack of openness makes it difficult to gain trust and implement the solution. To defend decisions to the infrastructure project team and guarantee alignment with project objectives, decision-makers like risk analysts and project managers need to comprehend the reasons behind AI outputs. This necessitates investigation into ways to improve the explainability of AI models while keeping their accuracy and scalability intact. Methods that need more investigation include visual analytics, model-agnostic explainability tools, and interpretable algorithms that are tailored to a given domain. In addition, there is a lack of frameworks that account for interpretability in certain contexts. Infrastructure, energy, and transportation are just a few of the many industries that infrastructure projects frequently touch, and each has its own unique set of processes, jargon, and risk zones. Due to their tendency to be overly generic, current interpretability techniques do not take these specifics into consideration. For instance, because operational priorities, regulatory requirements, and stakeholder expectations differ between various infrastructure projects, a risk factor in one may have different implications in the other and may be difficult to retrieve. To make AI tools more practical and applicable, it is crucial to develop tailored interpretability solutions that meet the complex needs of these areas.

The collaborative system provides a significant opportunity for project stakeholders to share their knowledge and expertise. These advantages illustrate the potential to transition from traditional knowledge retrieval to AI-powered knowledge retrieval. There is still a huge gap in integrating AI with current knowledge retrieval systems. Infrastructure projects depend significantly on tried-and-true technologies that have existed for a while. Decades of industry-specific insights are captured by these systems, which act as reservoirs of domain knowledge. However, the interoperability necessary to integrate with these legacy systems is sometimes missing from AI solutions built independently. Due to this fragmented strategy, AI cannot make use of domain knowledge, contextual information, and historical data—all of which are essential for proper risk assessment and management. Artificial intelligence (AI) systems should not be designed to replace current knowledge systems but rather to complement and augment them. It is essential that AI technologies in infrastructure projects work in tandem with human specialists, not as a substitute for them. Professionals, such as engineers and managers, bring a wealth of experience and expertise to the table when making decisions, even though AI can offer helpful insights. That is why it is crucial to incorporate AI technologies in a way that complements human skills, not replaces them.

The ongoing research on artificial intelligence for knowledge retrieval is continually evolving. Several critical challenges have not been thoroughly addressed in the existing research on AI-powered knowledge retrieval. The deficiencies in AI-related research on knowledge retrieval necessitate additional research.

6.1. Implication for Practice and Further Studies

AI-powered knowledge retrieval facilitates the integration of textual and graphic knowledge, significantly aiding in the resolution of infrastructure project difficulties. This is particularly apparent in knowledge-intensive projects such as infrastructure projects. This study offers a thorough examination of prior research on the utilization of AI-powered knowledge retrieval as an advantage over traditional knowledge retrieval in infrastructure projects. This study provides practitioners with a comprehensive reference that encapsulates the latest research on implementing AI-powered knowledge retrieval in infrastructure projects, detailing the associated concepts and technology. This provides practitioners the opportunity to evaluate their maturity in using AI knowledge retrieval. Evidence indicates that infrastructure project practitioners are sluggish in embracing innovation, particularly in adopting AI knowledge retrieval. Consequently, further studies should evaluate the infrastructure project's preparedness for the comprehensive integration of AI technology in its knowledge retrieval operations.

Despite the assistance of AI applications in overcoming numerous issues within the knowledge industry, their implementation in infrastructure projects has been minimal. Future research should investigate the essential success elements and obstacles to the effective application of AI-powered knowledge retrieval in infrastructure projects. This will enhance the inclination to utilize AI technology in addressing the issues faced within the execution of infrastructure projects.

There has been a lack of practical implications for practitioners about AI's ability to improve AI-powered knowledge retrieval in infrastructure projects despite the study providing a solid theoretical basis for this idea. To fill this need, it is important for practitioners to first examine current systems for inefficiencies, out-of-date data, and gaps in the retrieval process, all of which are examples of places where traditional methods for knowledge retrieval approaches fail. Practitioners can avoid using AI just for the sake of technological novelty by evaluating these to make sure that AI adoption properly addresses the most pressing demands. To determine where AI could have the greatest impact, involving important stakeholders in workshops, interviews, and surveys is helpful. When the requirements have been defined, a small-scale pilot project must also be launched. Organizations can conduct proof-of-concept experiments to gauge the potential effects of AI on knowledge retrieval before committing to a full-scale implementation.

Infrastructure project managers must prioritize building strong data for each infrastructure project to enable AI to retrieve accurate and dependable past data. Data accessibility, security, and the enforcement of well-defined policies are all responsibilities of practitioners. In order to complete this task, it may be necessary to integrate previously separate data sources and update current data management systems. If, for instance, data from procurement and safety were to be integrated, it would paint a more complete picture of risk and enable AI-powered knowledge retrieval systems to make more accurate retrievals. Data quality and conformity with industry standards can be better maintained by establishing data governance rules.

This study also analyzed the implementation of AI-powered knowledge retrieval in the various lifecycle phases of an infrastructure project. This can assist practitioners in comprehending and adopting this concept. Nevertheless, additional research is required to investigate the potential uses of AI knowledge retrieval.

The regulatory and ethical considerations that might arise from the use of AI in knowledge management and retrieval in infrastructure projects are also recommended for future research.

6.2. Limitations

This study possesses limitations, notwithstanding its merits. The search exclusively utilized the databases Scopus, Web of Science, and ScienceDirect. Consequently, more pertinent publications about the advantages and application of AI-powered knowledge retrieval in infrastructure projects may be absent. Consequently, the research findings may not comprehensively represent the entirety of the existing literature on AI knowledge retrieval within infrastructure projects. Despite the meticulous selection of pertinent papers, not all keywords may have been included in the literature search. Subjective judgments may have influenced the literature review in selecting pertinent publications and identifying applications across distinct lifecycle phases. The aforementioned limitations create opportunities for additional research and must be taken into consideration when interpreting this study's conclusions. This study advocates for the utilization of diverse datasets and a broader spectrum of literature.

Examining the practical limitations of using AI for knowledge retrieval is an important part of this research. Theoretical constraints have been considered, but practical limitations that impede the smooth application of AI tools must also be considered. Data availability, organizational preparedness, and financial ramifications are crucial to these considerations. The preparedness of the organization is another significant obstacle. Lastly, it is important to consider the financial aspects of implementing AI-powered knowledge retrieval in future studies.

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