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Review

Decoding a decade: The evolution of artificial intelligence in security, communication, and maintenance within the construction industry

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ABSTRACT

This paper analyzes the evolution of Artificial Intelligence (AI) in the construction industry from 2014 to 2023, focusing on enhancing security, communication, and maintenance. It combines in-depth analysis of 121 papers with visualizations of 507 articles from major databases such as SCOPUS, IEEE, ACM, Science Direct, and Google Scholar to map AI advancements in construction. The study found that security is established as a mature research domain, whereas communication and maintenance are at comparatively earlier stages of development. Specifically, the analysis reveals a shift from Radio Frequency Identification (RFID) to more sophisticated technologies such as Internet of Things (IoT), Virtual Reality (VR), blockchain, Building Information Modeling (BIM), and digital twins, which significantly improve security. Communication and maintenance have also evolved towards greater digital integration and predictive analytics. The integration of AI innovations with human expertise is emphasized as a strategic direction to enhance decision-making and operational efficiency in construction.

1. Introduction

The construction industry has encountered numerous challenges, leading to significantly lower productivity levels compared to other industries [1]. It is known not only as the most hazardous industries, with the highest fatality rates, but also as the least digitized globally [2]. The lack of digital skills and slow adoption of technology within the construction sector are associated with increased costs, project delays, substandard quality, uninformed decision-making, and poor outcomes in productivity, health, and safety [3]. Consequently, there is a clear imperative for the construction industry to swiftly adopt digital technology and enhance its technological capabilities to address labor shortages and the necessity of building sustainable infrastructure [4,5]. To directly address these pressing issues, our study specifically focuses on the areas of security, communication, and maintenance. These sectors represent critical vulnerabilities in the construction industry, where AI can potentially offer the most transformative impacts [6,7].

The adoption of AI in construction security, including advanced surveillance systems and hazard identification algorithms, has fundamentally altered the approach to site safety. This focus is justified by the acute need to reduce the high incidence of accidents and fatalities, which are considerably more prevalent in construction than in other sectors [8]. Nevertheless, the dependency on AI for safety management prompts concerns regarding the sufficiency of these systems in managing unpredictable real-world scenarios and their propensity to miss nuanced safety issues that demand human judgment. Researchers emphasize the critical importance of combining technological solutions with human expertise, especially in complex project environments where safety is paramount [8,9].

Similarly, in construction communication, AI-driven tools have streamlined the flow of information. Effective communication is essential for the timely and on-budget completion of projects, and AI offers tools that can mitigate the traditional barriers and inefficiencies encountered in project management. However, the dynamic and often unforeseeable nature of construction projects introduces significant challenges. There are evolving risks and inconsistencies in intelligent services, highlighting the necessity for transparent communication regarding these limitations within the construction context. This underlines the importance of integrating AI communication tools with a thorough understanding of the complexities of construction projects and stakeholder requirements [6].

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Moving to construction maintenance, the transition to AI-enabled predictive maintenance has transformed the management of equipment and assets. By focusing on maintenance, our study highlights how predictive technologies can significantly reduce downtime and extend the operational life of critical machinery. This study reviews the application of deep learning in the construction industry, addressing challenges such as site planning, health and safety, and construction cost prediction. It also explores limitations related to the opaque nature of deep learning, ethical concerns, compliance with the General Data Protection Regulation (GDPR), cybersecurity risks, and the costs associated with implementing these technologies [10].

There is a fact that numerous articles highlight the crucial roles of AI in the construction industry at large, as well as specific aspects such as security, communication, and maintenance. The selection of these specific areas over others is strategic, focusing on where immediate improvements are possible and where the consequences of inefficiencies are most detrimental. However, there exists a noticeable gap in research that methodically traces the evolution of AI technologies through a chronological analysis, utilizing visualization and in-depth examination of related studies. Such an approach would show up clearly AI's contributions to addressing the aforementioned challenges within the construction sector. Moreover, there is a need for research to assess the maturity of these technologies and explore how they have been inherited, refined, and advanced over the last decade—a period characterized by the most rapid evolution in AI applications.

In order to address the current gaps, it is important to answer the following research questions. (1) how has AI's role in construction, specifically in security, communication, and maintenance, inherited, adapted, and evolved over the past decade; (2) what evolutionary trends and challenges have AI applications faced in these sectors, and how have subsequent studies imitated or diverged from previous findings; (3) given AI's historical trajectory in construction, what future research paths should focus on innovation, adaptation, and preservation in security, communication, and maintenance.

The specific objectives of this study are to (1) Analyze AI's evolution: Investigate AI's development in construction's security, communication, and maintenance over the past decade, focusing on the movements of innovations and inherited aspects per each year (2) Examine trends and challenges: Assess the trends and challenges faced by AI in these sectors and how newer studies align or diverge from past research (3) Outline future research: Based on AI's past trajectory in construction, define research priorities that target innovation, adaptation, and sustainable application in three considered key sectors.

This study is unique in its examination of AI in the construction industry for three main reasons. First, it is the first study to track how AI techniques have evolved and helped in three key areas of construction. Second, it considers at a wide range of topics, from the well-known and mature issue of safety to newer areas like communication and maintenance, showing AI's broad impact. Finally, it utilizes visual tools such as network and density visualizations, alongside in-depth analyses of related research, to offer a comprehensive overview of AI's progression in the construction sector, focusing on three distinct areas. It details not just the annual advancements but also the cumulative progress over the past decade, which helps provide a deeper insight into the trends and developments in this field.

The rest of the paper is organized as follows: Section 2 outlines the research methods employed in this study. Section 3 delves into the findings and discussions of the research, spotlighting the roles of AI in construction in 3.1, areas within the construction sector where AI has been applied in 3.2, an analysis of publications related to the study in 3.3, and the evolution of AI applications across three dimensions over a decade in 3.4. Section 4 highlights limitations and potential future research directions in these areas before concluding the paper in Section 5.

2. Methods

An extensive review of the literature was conducted to identify the existing application of artificial intelligence in the construction industry, especially focusing on three aspects: security, communication, and maintenance, for the dates ranging from 2014 to 2023. Both topic-based bibliometrics and chronological approaches were used during the study. While topic-based bibliometrics is a data-driven approach that aims to analyze and understand research trends, chronology is used to organize and analyze datasets and articles based on their chronological sequence to catch up on the trends of studies over time.

A variety of databases were used to conduct the study. All search queries were run on the SCOPUS database and validated by data in other databases, such as Institute of Electrical and Electronics Engineers (IEEE), Association for Computing Machinery (ACM), and Science Direct, for the last 10 years, from 2014–2023. SCOPUS was selected as the main data source because it is the largest citation database of research literature and quality web sources and holds information about publications in IEEE, ACM, and Science Direct [11]. Based on the search results from SCOPUS, full-text access to articles was obtained from ScienceDirect, IEEE Xplore, or ACM Digital Library. Furthermore, to ensure a comprehensive understanding of the existing body of knowledge, an extensive search on Google Scholar was also conducted. This approach allowed us to explore a broad range of previous studies, covering as much related work as possible [12].

In terms of define the queries search, they were based on five key terms of the study, which were derived from the keywords of the title, including "Artificial Intelligence", "Security", "Communication", "Maintenance" and "Construction Industry". All these terms were generated into a list of synonym words to include as many related articles as possible. In which, for searching articles related to the "Artificial Intelligence" term, we inherited twenty-night (29) free-text keywords of the subfields that have been proposed in the study [6]. For four other key words: "Security", "Communication", "Maintenance" and "Construction Industry", we used methods suggested in the study [13] to obtain good boolean queries to search for related studies. The list of boolean queries searched according to key terms is shown in Table 1.

In Table 1, each key term was considered a criteria in the boolean query search. We defined criteria A to search for "Artificial Intelligence" related papers. Criteria B, C, D, and E were defied for "Security", "Communication", "Maintenance" and "construction industry", respectively. We used the AND operator to narrow down the search results for each aspect.

In the search for the review, in order to take a deep search and mining articles database, we did a variety of advanced searches on both titles, article abstracts, and keywords to achieve the focus study in each aspect of the study. The table below shows six advanced search queries according to the six aspects that we considered.

As shown in Table 2, the study defined six advanced search queries designed for the specific facets of this study, facilitating a targeted and exhaustive review. Initially, the first three boolean queries are employed: the first locates papers relating to artificial intelligence, the second identifies studies within the construction industry, and the third isolates research that investigates AI applications in the construction sector. The information obtained from these queries provides an overarching view of the interplay between AI research, construction studies, and their intersection. Subsequently, the remaining three queries aim to collect papers that address the key areas this study focuses on, which are marked innovations in artificial intelligence within the construction industry's domains of security, communication, and maintenance. The goal is to include a significant number of literature for detailed analysis. The six-step process used to filter and analyze these studies is summarized in Table 3. The study sorting datasets by aspect and chronologically to monitor developments from 2014 to 2023.

As shown in Table 3, based on the last three queries, specifically queries 4, 5, and 6 in Table 2, it yielded 827, 341, and 239 publications

Table 1
Search queries for related studies.

Key terms/Criteria	Search terms
Artificial Intelligence (A)	"Robotics" OR "Computer vision" OR "Machine learning" OR "Expert System" OR "Knowledge-based Systems" OR "Optimisation" OR "Natural Language Processing" OR "Artificial Intelligence" OR "K-Means Clustering" OR "Hierarchical Clustering" OR "Fuzzy Clustering" OR "Model-based Clustering" OR "Linear Discriminant Analysis" OR "Monte Carlo" OR "Deep Belief" OR "Deep Boltzmann" OR "Deep Learning" OR "Convolutional Neural Network" OR "Stacked Autoencoders" OR "Recurrent Neural Network" OR "Deep Neural Network" OR "Speech processing" OR "Evolutionary computing" OR "Evolutionary Algorithms" OR "Swarm Intelligence" OR "Discrete Optimisation" OR "Convex Optimization" OR "Automated Planning" OR "Automated Scheduling" [6].
Security (B)	"Security" OR "Cybersecurity" OR "Safety" OR "Surveillance" OR "Data Protection" OR "Intrusion Detection" OR "Threat Management".
Communication (C)	"Communication" OR "Data Communication" OR "Wireless Communication" OR "Digital Communication" OR "Communication Technology" OR "IoT" OR "Internet of Things"
Maintenance (D)	"Maintenance" OR "Equipment Maintenance" OR "Facility Maintenance" OR "Building Maintenance" OR "Predictive Maintenance" OR "Preventive Maintenance" OR "Maintenance Strategy" OR "Asset Management".
Construction Industry (E)	"Construction Industry" OR "Building Industry" OR "Construction Sector" OR "Building Sector" OR "Architectural Industry"

in the areas of security, communication, and maintenance, respectively. After refining the search to include only English-language articles and exclude conference papers, these numbers were significantly reduced to 383, 116, and 78. Further meticulous screening refined the selection to 381, 102, and 76 articles, respectively, based on a detailed evaluation of titles, abstracts, and, when necessary, introductions if the titles and abstracts alone were insufficient for decision-making. In the next step, removing duplicates, there were 507 articles remaining for further analysis, and the distribution of these articles over the last decade is shown in Table 4.

The final two critical steps involved analyzing visualization observations with VOSviewer and conducting a deep dive content analysis of papers with NVivo:

For the visualization observation step, the study found that visualization plays a crucial role in enhancing our ability to retrieve and remember information. This is grounded in the fact that our brains primarily process images rather than words [14]. Therefore, the study utilized visualization tools as one of the techniques to support the analysis during the exploration of the evolution of AI techniques in construction studies. The VOSviewer tool was used to extract key term occurrences and create network maps based on co-occurrences in the titles and abstracts of the remaining 507 papers identified in Table 4. Additionally, visualizing and interpreting data with VOSviewer allowed us to adjust the layout, node size, colors, and labels to make our maps more informative and visually appealing. By exploring clusters and citation patterns, we gained insights into major themes, key papers, and emerging trends in our research area [15].

Meanwhile, in the final stage of our research, we imported 507 papers into NVivo, which had been previously collected and meticulously organized by year and specific research areas to establish a structured foundation for our analysis. This organizational structure was maintained in NVivo, with papers sorted both annually and by distinct research areas. Utilizing the explore tool within NVivo, we conducted a systematic search of this organized dataset, focusing on key criteria such as research gaps, datasets used, AI techniques employed, advantages, limitations, and potential research avenues. To ensure extensive coverage of relevant terms, we expanded our queries using synonyms and the OR Boolean operator. The results from these searches were then precisely categorized and saved as codes. Throughout our analysis, we continuously refined these codes by delving deeply into the content of each related part, ensuring we retained only the results and content that aligned with our research objectives. This iterative process of coding and recalibration culminated in a detailed synthesis of the 121 most pertinent papers, which significantly contributed to our deep dive content analysis. Through this methodical approach, we thoroughly explored and documented the key findings and themes that emerged, providing a robust and systematic review of the literature.

The combination of VOSviewer analysis and NVivo content examination delineates the progression of innovation on an annual basis, from a macroscopic to a microscopic perspective. Overall, this dual approach significantly enhances the study's capacity to map out major themes, trends, and both mature and nascent research areas.

3. Results and discussions

3.1. The roles of AI in the construction industry

3.1.1. Enhanced decision making and project management

Artificial Intelligence (AI) is significantly transforming the Architecture, Engineering, and Construction (AEC) industry's approach to project management and decision-making. Darko et al. (2020) emphasize AI's role in enhancing predictive analytics, where genetic algorithms and neural networks effectively forecast project outcomes and identify risks, enabling proactive mitigation and informed planning [16]. Similarly, Pan and Zhang (2021) identify AI's profound impact on resource scheduling and project planning, noting substantial efficiency gains in construction management. These advancements in AI technology are streamlining construction processes, reducing time and costs, and pointing towards a revolution in construction project management [17].

However, the implementation of AI in the AEC sector is not without challenges. Regona et al. (2022) discuss the hurdles in AI adoption, including the fragmented nature of the industry and the need for enhanced data management strategies to fully utilize AI's potential for accurate forecasting [18]. Complementing this, Smith and Wong (2022) explore the use of AI-based decision support systems in promoting sustainable construction practices, indicating a growing trend in integrating sustainability goals into early-stage project predictions through hybrid AI models [19]. While AI offers promising tools for risk assessment, resource allocation, and sustainability, its full benefits in the AEC industry hinge on overcoming data fragmentation and aligning AI adoption with industry-specific needs.

3.1.2. Improvements in planning and design phases

The integration of Artificial Intelligence (AI) in AEC industry significantly impacts planning and design, but faces distinct challenges. Regona et al. (2022) emphasize AI's role in enhancing planning accuracy while identifying the fragmented construction industry and data management issues as major barriers to its effective implementation [18]. Darko et al. (2020) and Pan and Zhang (2021) explore the evolving use of advanced computational methods like genetic algorithms, neural networks, and a growing interest in robotic automation and convolutional neural networks, indicating diverse yet crucial areas of AI application in the AEC sector [16,17].

Conversely, An et al. (2021) underscore the need for a deeper understanding of AI's capabilities in managing construction project complexities [20]. Liu et al. (2018) highlight a critical gap between academic AI research and its practical application in construction, stressing the importance of bridging theoretical potential with tangible,

Table 2
Six Boolean queries defined searching on SCOPUS.

No.	Terms searching for related studies	Boolean queries search
1	Artificial Intelligence studies	(A)
2	Construction industry studies	(E)
3	Artificial Intelligence in the construction industry studies	(A) AND (E)
4	Artificial Intelligence in security within the construction industry	(A) AND (E) AND (B)
5	Artificial Intelligence in communication within the construction industry	(A) AND (E) AND (C)
6	Artificial Intelligence in maintenance within the construction industry	(A) AND (E) AND (D)

Table 3
Six-step process of preprocessing and analysis.

Step No.	Actions	# Articles related to AI-driven studies (2014–2023)		
		Security	Communication	Maintenance
1	Boolean queries search No. 4, 5, and 6 in Table 2	827	341	239
2	Include English articles, exclude conferences	383	116	78
3	Screened filter	381	102	76
4	Removed duplicates		507	
5	Analyzing visualization observations with VOSviewer		507	
6	Deep-Dive content analysis of papers with NVivo		121	

Table 4
Number of articles was used in the visualization analysis (2014–2023).

Years	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Total
#Articles	7	10	15	16	25	46	59	70	100	159	**507**

real-world benefits [21]. This suggests that while AI holds significant promise for the AEC industry, its full potential hinges on addressing the industry's fragmentation, enhancing data management strategies, and narrowing the gap between research and practical application.

3.1.3. Automation and robotics in construction

The integration of Artificial Intelligence (AI) and robotics in the construction sector represents a transformative shift, enhancing productivity and revolutionizing safety protocols. Pan and Zhang (2021) critically analyze this shift, noting the emergence of smart robotics and digital twins as harbingers of digital transformation in construction engineering and management [17]. Gharbia et al. (2020) further explore this evolution, focusing on the potential of robotics in areas like additive manufacturing and automated installation, poised to redefine efficiency in construction processes [22]. This technological advancement, however, also brings about a reconfiguration in labor demands and necessitates an increase in digital expertise, as discussed by García de Soto et al. (2019) in the context of Construction 4.0 [23].

Emphasizing the practical application of these advancements, Stenmark and Malec (2015) advocate for a knowledge-based approach to simplify robot programming and operation in the dynamic environments typical of construction sites [24]. This progression in AI and robotics is not just a technological leap but a fundamental overhaul of traditional construction practices. It promises to tackle long-standing industry challenges such as safety risks and efficiency bottlenecks, heralding a future of a more sustainable, efficient, and adaptable construction industry.

3.1.4. Advancements in quality control and sustainable construction practices

Artificial Intelligence (AI) and Machine Learning (ML) technologies are revolutionizing quality control in construction, markedly advancing automated inspections and defect detection. A significant innovation in this field is the Artificial Intelligence Quality Inspection Model (AI-QIM) developed by Kardovskyi and Moon (2021), which utilizes Mask Region-based Convolutional Neural Network (Mask R-CNN) and stereo vision technology. This breakthrough enables precise, efficient inspection of steel bars in concrete structures, showcasing AI's potential to significantly enhance quality assurance while reducing time and labor costs. With its proven accuracy and efficiency, AI-QIM is a testament to the transformative power of AI in ensuring construction quality and adherence to strict industry standards [25].

Simultaneously, AI's integration into sustainable construction practices is fostering a significant shift towards environmental stewardship and resource optimization. Vaio et al. (2020) and Manzoor et al. (2021) emphasize AI's role in developing sustainable business models and its impact on civil engineering for sustainable development. Moreover, Mehmood et al. (2019) highlight AI and Big Data's effectiveness in creating energy-efficient buildings, thus contributing significantly to the Sustainable Development Goals. These developments mark a paradigm shift in the construction industry, with AI-driven technologies leading the way in promoting sustainable practices and resource-efficient, environmentally conscious construction [26–28].

3.1.5. AI in communication and maintenance

In AEC industry, AI is revolutionizing communication and maintenance practices. Pillai and Matus (2019) emphasize AI's role in enhancing stakeholder communication, advocating for regulatory frameworks to standardize AI integration for improved collaboration and operational efficiency [29]. Similarly, AI's incorporation in predictive maintenance represents a significant shift towards more sustainable practices, as Cinar et al. (2020) highlight its application in monitoring equipment health, which is pivotal for smart manufacturing and cost reduction [30].

However, the broader application of AI in the AEC sector, especially in planning and design, faces challenges due to the industry's fragmented nature, as noted by Regona et al. (2022) [18]. While AI promises to enhance project outcomes and streamline processes, overcoming hurdles like data fragmentation and establishing effective regulatory frameworks are critical for its successful implementation. This necessitates a collaborative industry approach for a unified adoption of AI-driven models, balancing AI's transformative potential with the practicalities of its integration, to ensure a more efficient and sustainable future in construction and maintenance practices.

3.2. AI-driven study areas in the construction sector

Employing a comprehensive bibliometric analysis, this section elaborates on the dominant themes within AI-driven research in the construction sector, drawn from an extensive dataset of 2599 SCOPUS-indexed articles from 2014 to 2023. Using VOSviewer, a tool for visualizing bibliometric networks, we analyzed the recurrence of key terms in titles and abstracts. This refined approach, focusing on terms that appeared at least ten times, narrowed down the dataset to 1785

Table 5
Ten most frequent terms in AI-driven studies in construction (2014–2023).

Term	Occurrences
Concrete	654
Energy	586
Construction project	553
Energy consumption	508
Compressive strength	441
Building sector	432
Risk	426
Prediction	426
BIM	421
Machine	381

significant terms. Further refinement highlighted the 60% most impactful terms, totaling 1071, which were then visually mapped to delineate prevailing research trajectories.

The most ten frequent terms extracted from the analysis is shown in Table 5, the density visualization is presented in Fig. 1, and the network visualization is depicted in Fig. 2.

The Table 5 provides a snapshot of the most frequently occurring terms, serving as indicators of key research foci. These terms have been identified and categorized into thematic areas based on their prevalence and context within the analyzed literature. For example, in material science, terms like "Concrete" and "Compressive Strength" appear frequently. Their categorization under material science reflects their common association with research focused on the optimization of material properties and the advancement of construction materials using AI techniques. Similarly, "Energy" and "Energy Consumption" are categorized under energy management, highlighting their central role in research aimed at enhancing energy efficiency and sustainability in building projects through AI-driven solutions. For project management, terms such as "Construction Project" and "BIM" (Building Information Modeling) are frequently discussed. These terms are particularly associated with studies that leverage AI to streamline project management processes, improve planning accuracy, and integrate digital technologies like BIM for enhanced project execution.

Fig. 1 shows the density visualization analysis, which helped to visually cluster research themes, showing "Energy" as a particularly dense node of activity. The focus on energy underscores a significant academic and industry drive towards sustainable building practices, illustrating a critical intersection of AI with green construction initiatives. Furthermore, the network visualization analysis in Fig. 2 presents a visual representation of how different AI-related terms are interconnected, forming clusters that depict areas of intensive study. These clusters, including project management & safety, environmental impact & energy efficiency, and materials science & engineering, demonstrate the dynamic interplay between AI technologies and construction practices. Each cluster is a nexus of innovation, reflecting the integration of AI in addressing complex challenges within the construction sector.

However, these visualizations do not clearly highlight how AI is applied in the areas of security, communication, and maintenance. This indicates a need for further research or more detailed visualizations that could clearly show these specific uses of AI in construction. This is why our study aims to conduct further analysis to explore more about the evolution of these specific areas.

3.3. Analysis of publications

The data extraction based on boolean search queries defined in Table 1 results almost starting point of period where found studies related to AI studies in security, communication and maintenance the construction studies at around 1980s, compared to the first AI studies in construction sector was the end of 1960s.

3.3.1. The history of AI participation in construction studies

This section of the study aims to highlight the historical progression of publications from the time AI was first introduced into the construction industry, since 1970s, for each period of ten years. It concentrated on publications related to AI in construction, specifically those that applied AI to security, communication, and maintenance within the sector. The term "Other" was defined to categorize publications that did not fit into the aforementioned three categories. However, the details publication analysis from 2014–2023 will be presented in Section 3.3 to get insight into the considered period of the study.

Firstly, taking into account the starting points, which marked the first research on each considering aspect. While Artificial Intelligence (AI) term was first coined by John McCarthy in 1956 [31], the integration of AI in construction was a gradual process with contributions from various research and development efforts, and the construction industry has been considered as the least digitalized compared to other industries [32], the study provides insight into how AI began to influence the construction industry, particularly through expert systems, which were among the first AI technologies to be applied in this field was conducted by [33] in 1970s. In this trends, the studies of AI in construction industry focusing on security, communication and maintenance has been found. For example, the very first paper related to it was found based on queries search defined which was conducted in 1988 by [34]. Besides, studies focused on communication was found in 1988, which was conducted by [35] and it simply offered a detailed description of optical recognition systems used in key industries like process engineering and automobile manufacturing. It outlines the system's components, including a television camera as the sensor, a microprocessor-equipped analyzer, a user interface, and a display monitor. Lastly, in the maintenance aspect, the very first research focused on this issue was conducted by [36], which highlighted the potential revolution in the United States construction industry through new technologies, addressing the need for extensive infrastructure repair. It points to a significant market opportunity, with projected costs up to $3 trillion, but lacks a detailed analysis of the challenges in implementing these technologies.

Secondly, in terms of the publication trends, Fig. 3 presents for each period of publications, focusing on five categories are the number of publications related to AI-driven studies construction in general, and in security, communication, maintenance and "Other" in particular. In which, the "Other" category capturing the remaining publications not classified under the security, communication and maintenance categories. The figure displays a striking progression in the number of publications within the field of AI-driven construction studies across more than six decades. Starting from the 1968–1983 period, in six teen years, there were virtually no publications in the categories of Security, Communication, and Maintenance, indicating nascent or non-existent research in these specific applications of AI within the construction industry at that time. Over the years, each category has seen growth, albeit at different rates. By the 1984–1993 period, publications began to emerge: Security (7), Communication (9), and Maintenance (10), with a modest presence compared to the "AI in construction" category (194). This trend of growth continues, with 'AI in construction' showing a steep climb from 225 publications in the 1994–2003 period to a staggering 2595 by 2014–2023, suggesting a compound annual growth rate that far outstrips the other categories.

In addition, looking at the most recent decade 2014–2023 and one more decade before 1994–2003, the data illustrates an exponential increase, particularly for AI in construction, which jumps from 636 publications in 2004–2013 to 2595 in the period of 2014–2023. "Security" shows a more gradual increase from 56 to 331 publications, while "Communication" and "Maintenance" exhibit modest growth with "Communication" going from 26 to 102 and "Maintenance" from 21 to 76 publications in the same periods. The "Other" category shows a dramatically increase from 533 to 2086 papers compared between 2004–2013 and 2014–2023, potentially indicating a shift towards more

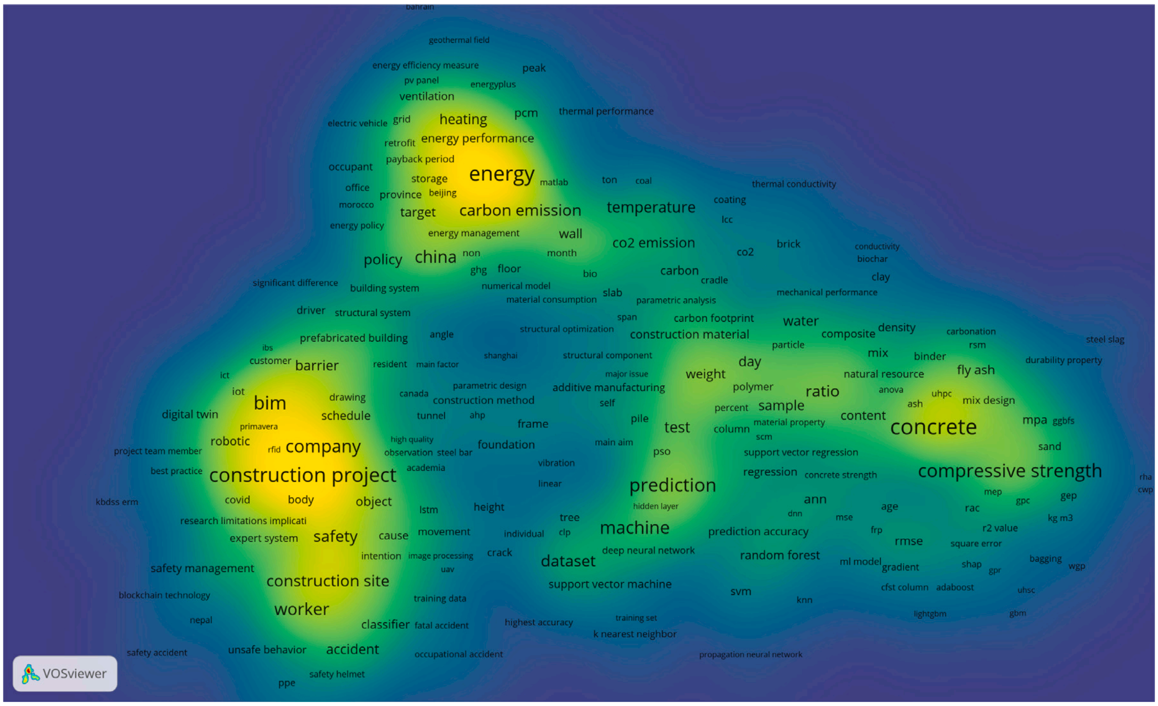


Fig. 1. Density visualization terms based on title and abstract of AI-driven studies in the construction sector (2014–2023).

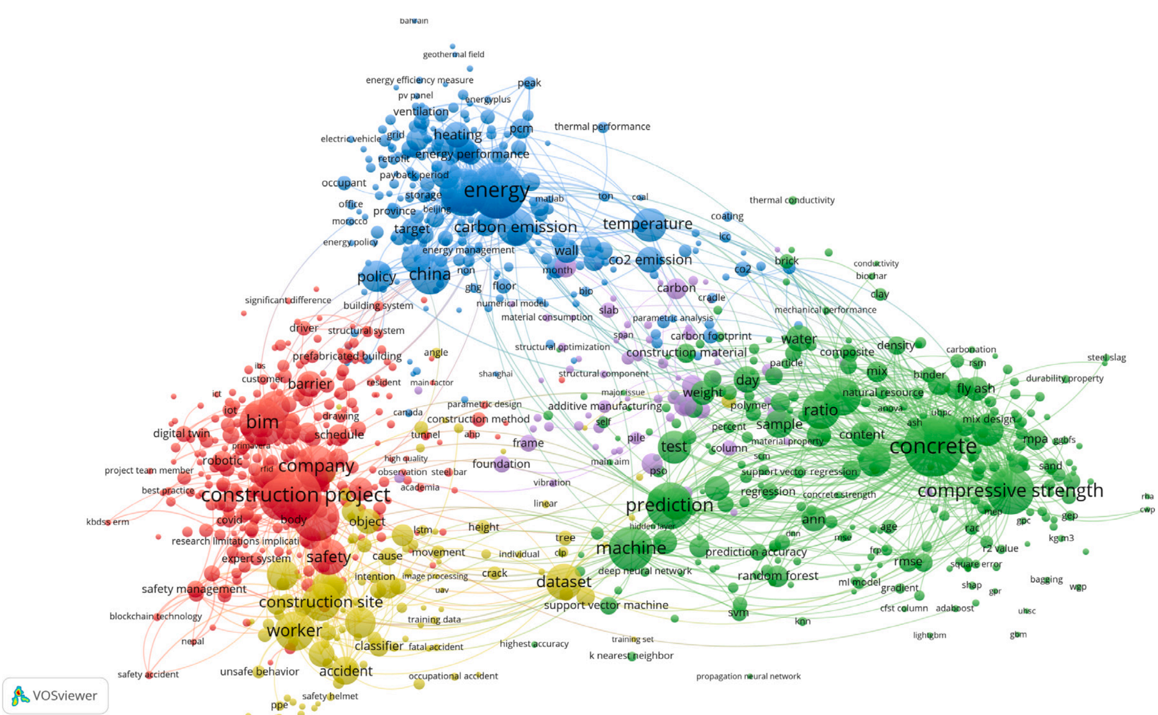


Fig. 2. Network visualization terms based on title and abstract of AI-driven studies in the construction sector (2014–2023).

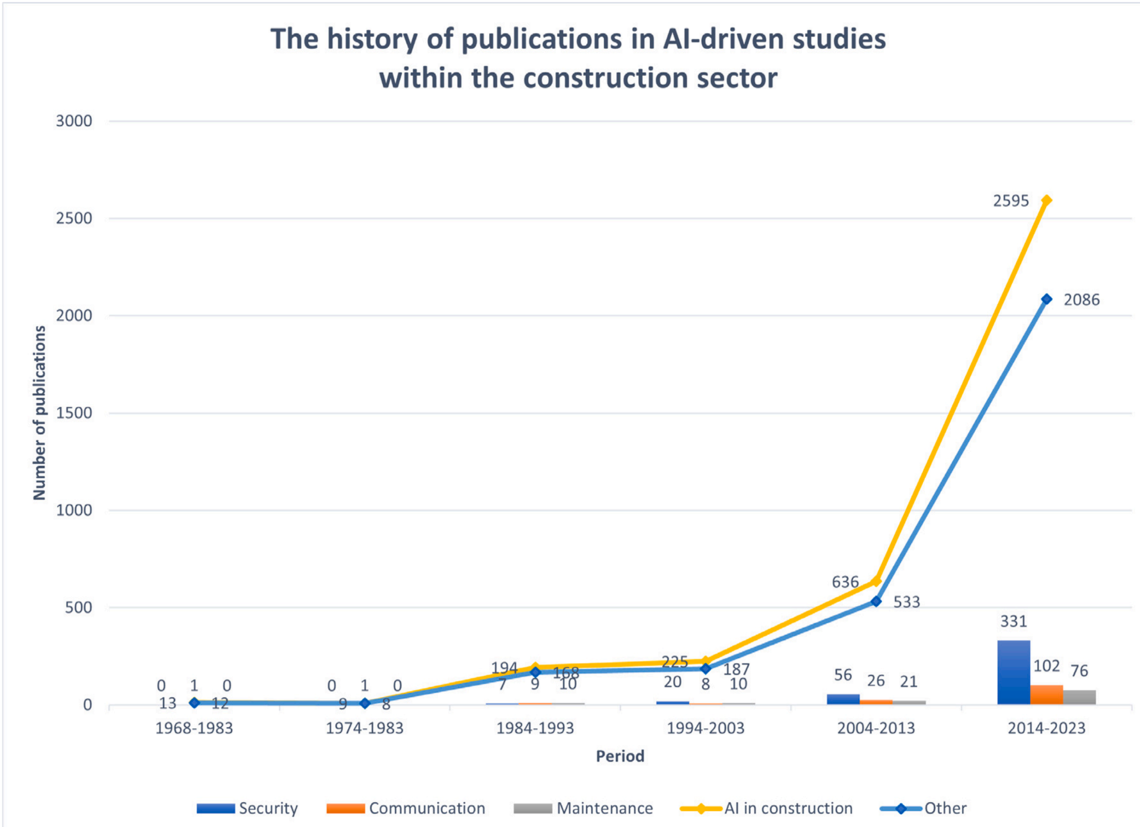


Fig. 3. History of publications in AI-driven construction studies (1968–2023).

defined research areas within AI in construction. The graph reveals a clear prioritization of investment in AI within the construction industry, with a particularly notable acceleration in the last decade, suggesting a burgeoning interest and potential advancements in AI applications specific to this field.

3.3.2. Publication comparisons between studies related to AI, construction, and AI in construction

Based on data from the first three boolean queries outlined in Table 2, this section compares the publication counts across three distinct categories: AI-related publications, construction-related publications, and publications at the intersection of AI and construction.

Fig. 4 displays the trend lines based on the number of studies published over the last decade, representing AI, Construction, and AI in Construction. These trend lines are presented as Eqs. (1), (2), and (3), respectively. The equation for the trend line of AI publications is presented as follows:

$$y = 269.69x^2 - 1462.9x + 3431.1 \quad (R^2 = 0.9939) \tag{1}$$

The equation for the trend line of Construction publications is given by:

$$y = 324.29x^2 + 546.45x + 25187 \quad (R^2 = 0.9863) \tag{2}$$

The equation for the trend line of AI in Construction publications is given by:

$$y = 1.1603x^3 - 7.9965x^2 + 29.313x + 55.567 \quad (R^2 = 0.9989) \tag{3}$$

In details, Fig. 4 presents over the last decade, the research landscape has demonstrated a remarkable growth in rate of escalation and volume over the years across Artificial Intelligence (AI), Construction, and AI within Construction domains, as revealed by polynomial regression models.

In terms of comparison between the rate of escalation, the AI research, modeled by Eq. (1), indicates a steady acceleration, with the quadratic term suggesting a substantial year-over-year increase in publications, affirmed by an R-squared value of 0.9939. This quadratic term effectively captures the increasing momentum in AI research, indicating a continuous and robust upward trajectory in the volume of publications.

In contrast, Construction studies, characterized by a higher quadratic coefficient of 324.29 in the model represented by Eq. (2), depict a more pronounced acceleration rate. This higher coefficient underscores a faster rate of growth in construction research compared to AI, despite both fields having similarly high predictive power, as indicated by a comparable R-squared value of 0.9863.

Significantly, the cubic model for AI in Construction studies, with trend line of Eq. (3) introduces a third-degree polynomial, reflecting a more volatile growth pattern with potential inflection points. These points likely indicate periods of both intensified research interest and plateauing growth, as evidenced by the model's complexity and its high R-squared value of 0.9989. The cubic model is crucial for illustrating the dynamic and multifaceted growth of AI applications within the construction sector, capturing fluctuations that may correspond to technological shifts or market developments.

Furthermore, considering the overall publications between three these fields, Fig. 4 presents that the construction research has the highest publications throughout the period from 2014 to 2023. This indicates that construction research is a mature and well-established field with a large body of ongoing research and a substantial research community. The construction studies are followed by AI's publications, and AI in Construction studies keep the lowest in volume when compared to the other two. However, this is expected as it is a specialized area at the intersection of AI and construction with a relatively small number of publications, this field has seen a rapid increase in recent years. This exponential growth suggests an exploding interest, likely

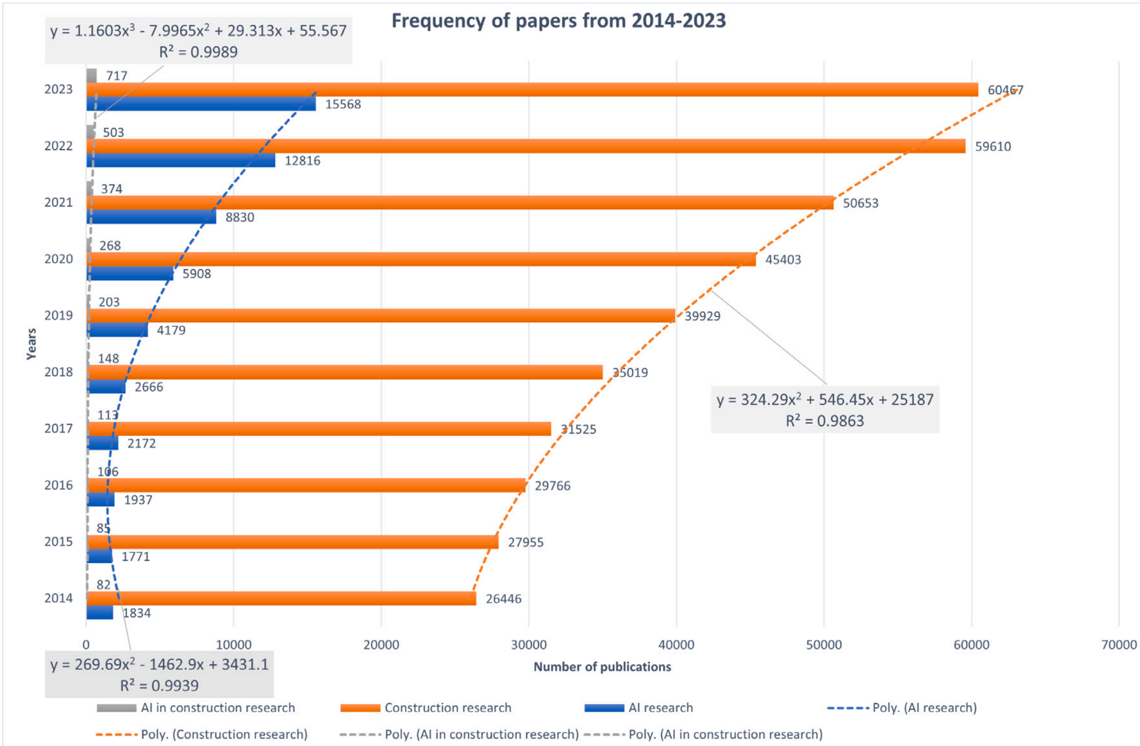


Fig. 4. AI, Construction, and AI in construction publications (2014–2023).

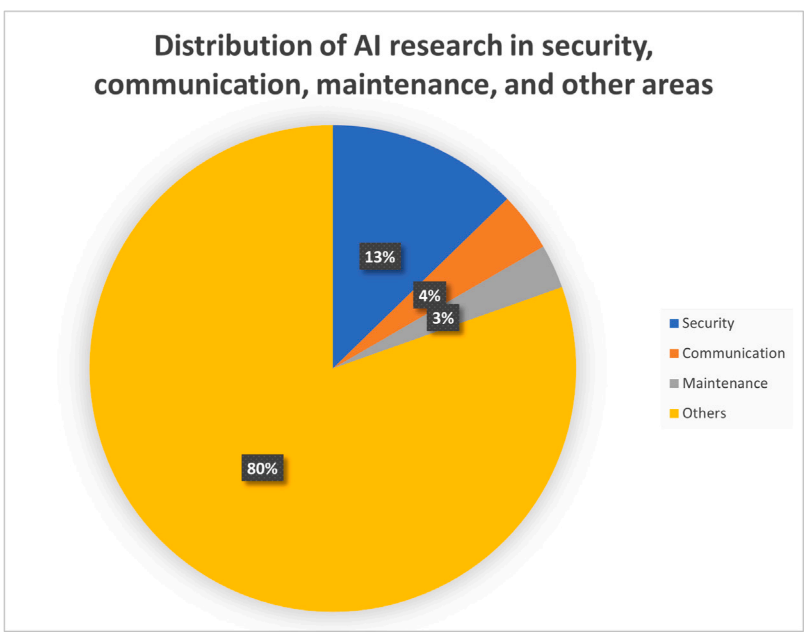
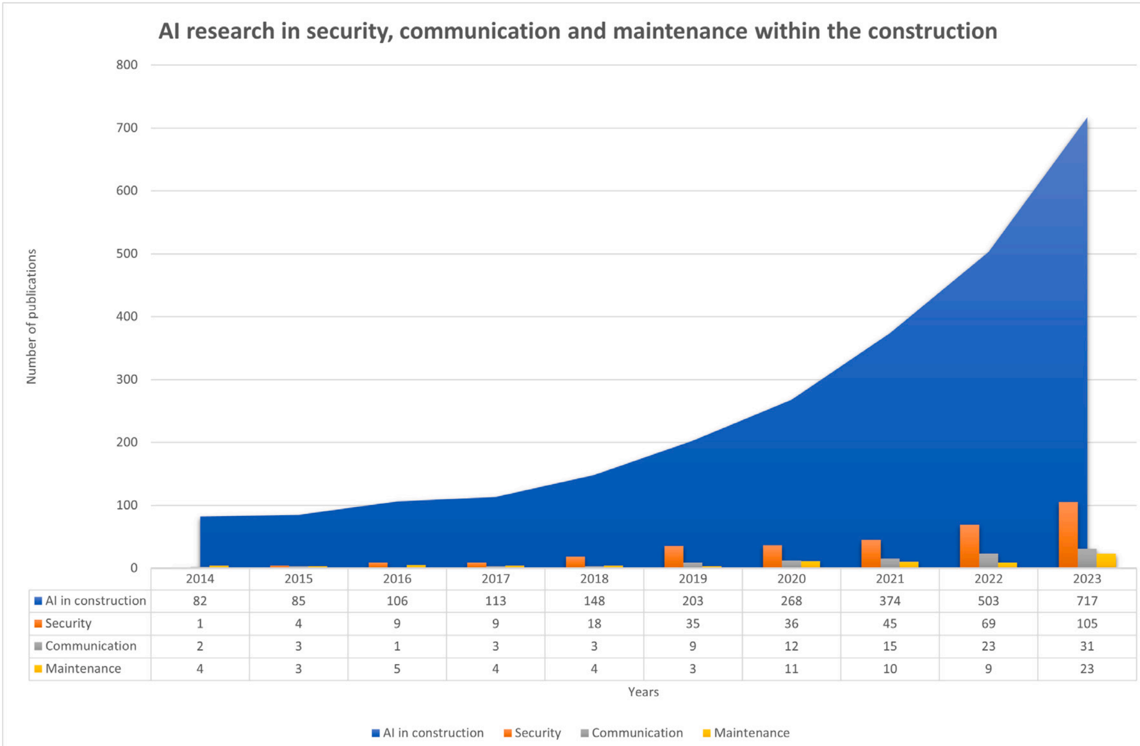


Fig. 5. Distribution of AI-driven studies in construction research.

due to technological advancements in AI that are now being applied to the construction sector. Overall, the data represents that while AI research consistently grows, Construction studies are increasing at higher speed and volume as well, and the integration of AI within Construction is subject to multifaceted growth dynamics.

3.3.3. Distribution of AI research in security, communication, maintenance, and other areas within construction

Fig. 5 provides a visual representation of how AI research efforts are distributed across different domains within the construction industry. The figure specifically highlights the proportion of studies focused on three critical areas—security, communication, and maintenance. It contrasts these with the broader category labeled "Others", which encompasses AI-driven studies in the construction industry that do not fall into the categories of security, communication, or maintenance. Firstly, regarding the aspect of security, research dedicated to this area comprises 13% of the overall study corpus, reflecting a pivotal, yet underrepresented focus within the field. This segment highlights a critical gap in addressing the pronounced risks associated with construction environments, which are often sites of significant hazards and frequent



	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
AI in construction	82	85	106	113	148	203	268	374	503	717
Security	1	4	9	9	18	35	36	45	69	105
Communication	2	3	1	3	3	9	12	15	23	31
Maintenance	4	3	5	4	4	3	11	10	9	23

Fig. 6. AI research trends in construction: security, communication, and maintenance (2014–2023).

accidents. The application of AI in this domain is primarily aimed at enhancing safety protocols and risk management strategies, with the potential to substantially mitigate the incidence of work-related accidents. Despite its modest proportion, this area offers considerable scope for impactful research and development.

Secondly, at 4%, AI-driven communication research in the construction sector is relatively limited but plays a crucial role in project management success. AI-enhanced communication systems are instrumental in facilitating real-time updates and automating coordination tasks, thereby augmenting project efficiency and reducing both time and cost overruns. The current research investment in this area suggests a substantial gap, highlighting the need for further exploration and development to fully exploit AI's potential in streamlining construction project communications.

Thirdly, representing a mere 3% of AI research, the focus on maintenance signals an emerging interest in leveraging technology to improve the longevity and operational efficiency of construction assets. Predominantly, AI in this area is geared towards predictive maintenance strategies that optimize resource utilization and enhance the durability of infrastructure. This sector, though small, is identified as another significant research gap, underscoring the opportunity for substantial advancements in AI applications that can lead to more sustainable construction practices.

Lastly, the "Others" category, which represents 80% of the research, includes a broad spectrum of AI applications within the construction industry, such as automation, robotics, design optimization, and sustainable practices. This substantial portion of our analysis underscores a diverse and exploratory research landscape, reflecting the wide range of interests and innovative approaches in the field. However, the dominance of this category also highlights a notable under representation of more specialized areas such as security, communication, and maintenance. These areas are crucial for addressing specific operational challenges in the construction industry, including safety, efficiency, and longevity of infrastructure. The limited focus on these essential aspects suggests a critical research gap, which could have significant implications for optimizing industry practices and enhancing operational efficiencies. This observation calls for a targeted increase in research efforts within these key areas to fully leverage AI's potential in meeting the demands of the construction industry.

In summary, the distribution of AI research as depicted in Fig. 5 illustrates a strategic, albeit uneven, focus across different domains. The foundational areas of security, communication, and maintenance, despite their critical importance, receive less attention than might be warranted given their potential to profoundly impact industry practices. This analysis underscores the necessity for a more targeted research agenda that aligns more closely with the unique challenges and operational demands of the construction industry, thereby maximizing the transformative capabilities of AI technologies.

3.3.4. AI studies in security, communication and maintenance within the construction from 2014–2023

Fig. 6 provides more details about the yearly developments of AI research within the construction sector from 2014 to 2023, with a distinct focus on security, communication, and maintenance. The overarching trend indicates a robust increase in AI in construction publications, escalating from 82 to 717 over the observed period.

In terms of security aspect, it has shown remarkable growth, escalating from 1 publication in 2014 to 126 publications in 2023, signaling a concentrated effort to enhance safety measures and data protection in construction through AI. This surge could reflect the industry's response to evolving security challenges and the advancement of AI technologies that are becoming increasingly adept at addressing such issues. Turning to the communication field, during 10-year period, there has been a steady climb from 2 to 31 publications in this area underscores the sector's ongoing commitment to improving interaction frameworks. Despite its modest growth compared to security, it indicates a persistent acknowledgment of AI's role in streamlining communication. In contrast, maintenance research follows a less predictable trajectory but ultimately demonstrates growth, from 4 to 23 publications. This pattern suggests a more measured integration of AI into maintenance, indicative of the sector's cautious approach to adopting AI in this domain.

It can be seen that the data reveals a clear contrast between the overarching expansion of AI in construction and the relatively measured growth in the focused areas. The disproportionate surge in security-related research points to a sector prioritizing the mitigation of risks through AI innovations. The less dramatic but steady increases in communication and maintenance research volumes suggest these areas are developing at a more gradual pace, possibly due to specific industry challenges or a lag in realizing AI's full potential in these domains.

Overall, the data indicates a significant embrace of AI within construction, with security standing out as a critical area of interest. This may denote a strategic response to priority challenges within the industry, while the tempered progress in communication and maintenance suggests a more complex integration landscape for AI in these specific areas.

3.4. The evolution of AI technologies in construction security, communication and maintenance studies (2014–2023)

This section presents in details AI applications in three considering aspects: security, communication and maintenance based on studies collected during the period of 2014–2023.

3.4.1. The evolution of AI applications in security issues

This section provides in two observations aimed at gaining insights into the study trends of AI applications in the construction security studies over the last decade, from 2014 to 2023. It incorporates both visual and detailed analyses of the relevant literature.

Initially, the focus is on visualizations, presenting as network visualizations of key terms extracted from AI construction security studies. This approach aims to illuminate general findings concerning innovations and challenges within the security aspect of construction, followed by an annual breakdown of key terms to trace the evolution of these innovations. By utilizing the *.RIS file exported from the SCOPUS database for studies related to AI applications in the security area from 2014 to 2023, we employed VOSviewer to create a map. A threshold was established to include only terms that appeared a minimum of 10 times. From a total of 381 papers, yielding 11,096 terms, with 299 terms meet this threshold. For these 299 terms, a relevance score was calculated, and the most pertinent terms were selected based on this score. By choosing the default option of selecting the top 60% of terms for their relevance, 179 terms were ultimately chosen for further analysis and visualizations. It results in the density visualization shown in Fig. 7 and the network visualization presented in Fig. 8.

The density visualization is illustrated in Fig. 7, employs color gradients to denote the concentration of key terms, where warmer colors signify a higher density. Notably, areas associated with "technology", "optimization", and "efficiency" are marked with vibrant colors, indicating these as the focal points of contemporary research. This clustering underscores the industry's priority to boost efficiency through technological innovations. Meanwhile, terms like "algorithm", "machine learning", and "neural network" are depicted with cooler colors, suggesting a lower concentration and indicating that, although important, the exploration of sophisticated AI techniques is less prevalent than direct technological applications. The transition from warmer to cooler colors, moving from "technology" towards "project management" and "risk management," may suggest a research focus hierarchy, with practical technology applications prioritized over theoretical AI explorations.

Besides, the network visualization is shown in Fig. 8, identifying distinct clusters through various colors. For instance, the blue cluster emphasizes terms such as "BIM", "sustainability", and "integration" pointing towards efforts to meld sustainable practices with BIM. The red cluster focuses on "worker", "safety harness", and "accident", highlighting the emphasis on worker safety and accident prevention. The prominence of this cluster indicates a considerable concern for worker safety within construction AI research. The green cluster, featuring terms like "project", "management", and "risk management", suggests a concentration on the administrative and strategic elements of construction projects. Intriguingly, connections between clusters, such as the link between the blue and red clusters via "technology" and "robot", hint at interdisciplinary research efforts aiming to leverage BIM technology to enhance worker safety. Similarly, the nexus between the green and blue clusters through "technology" reveals an increasing reliance on new technologies in management strategies.

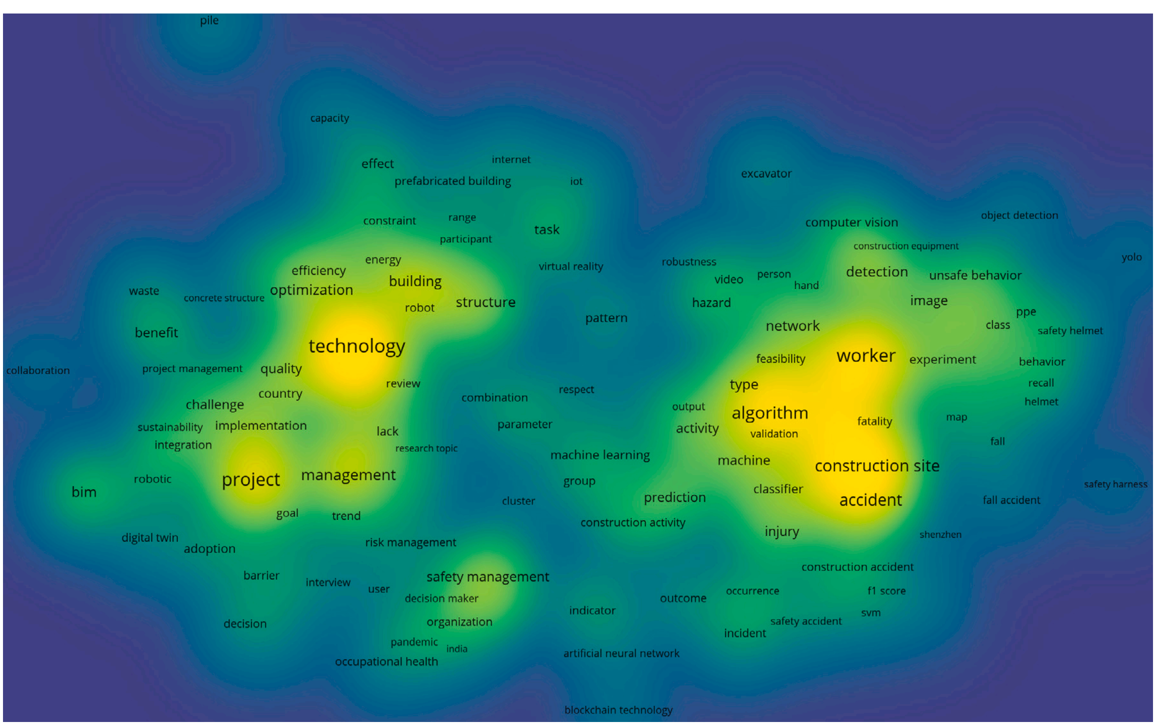


Fig. 7. Visualization of keyword density for AI construction security studies (2014–2023).

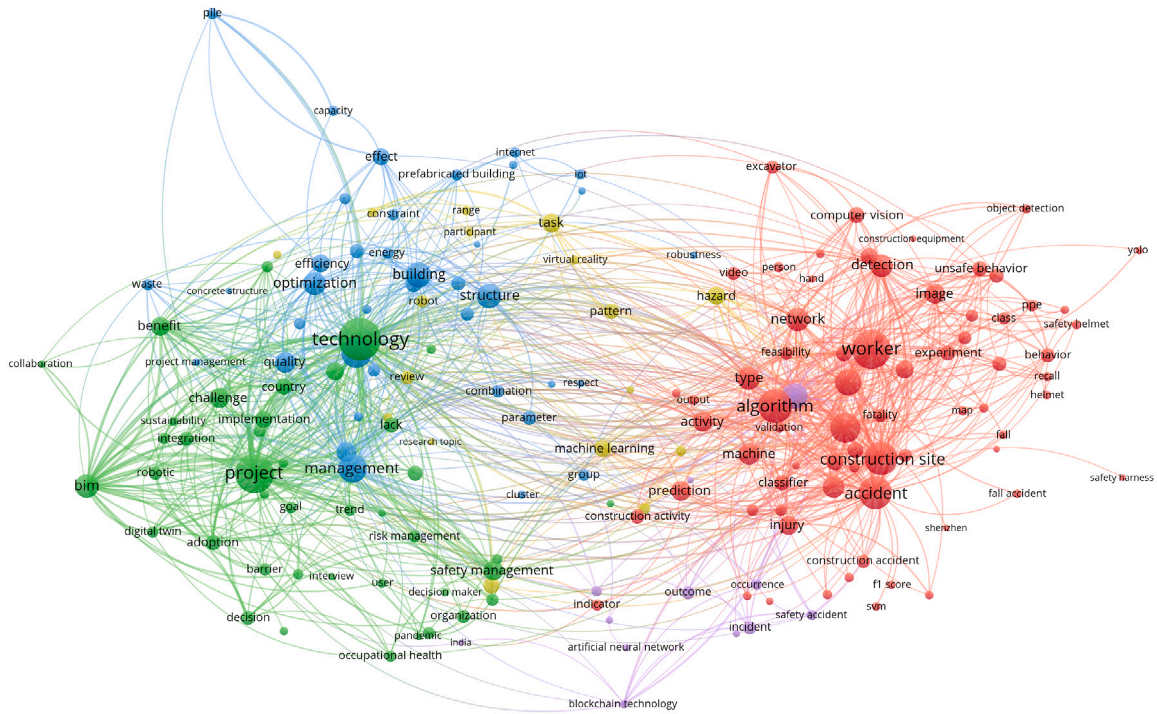
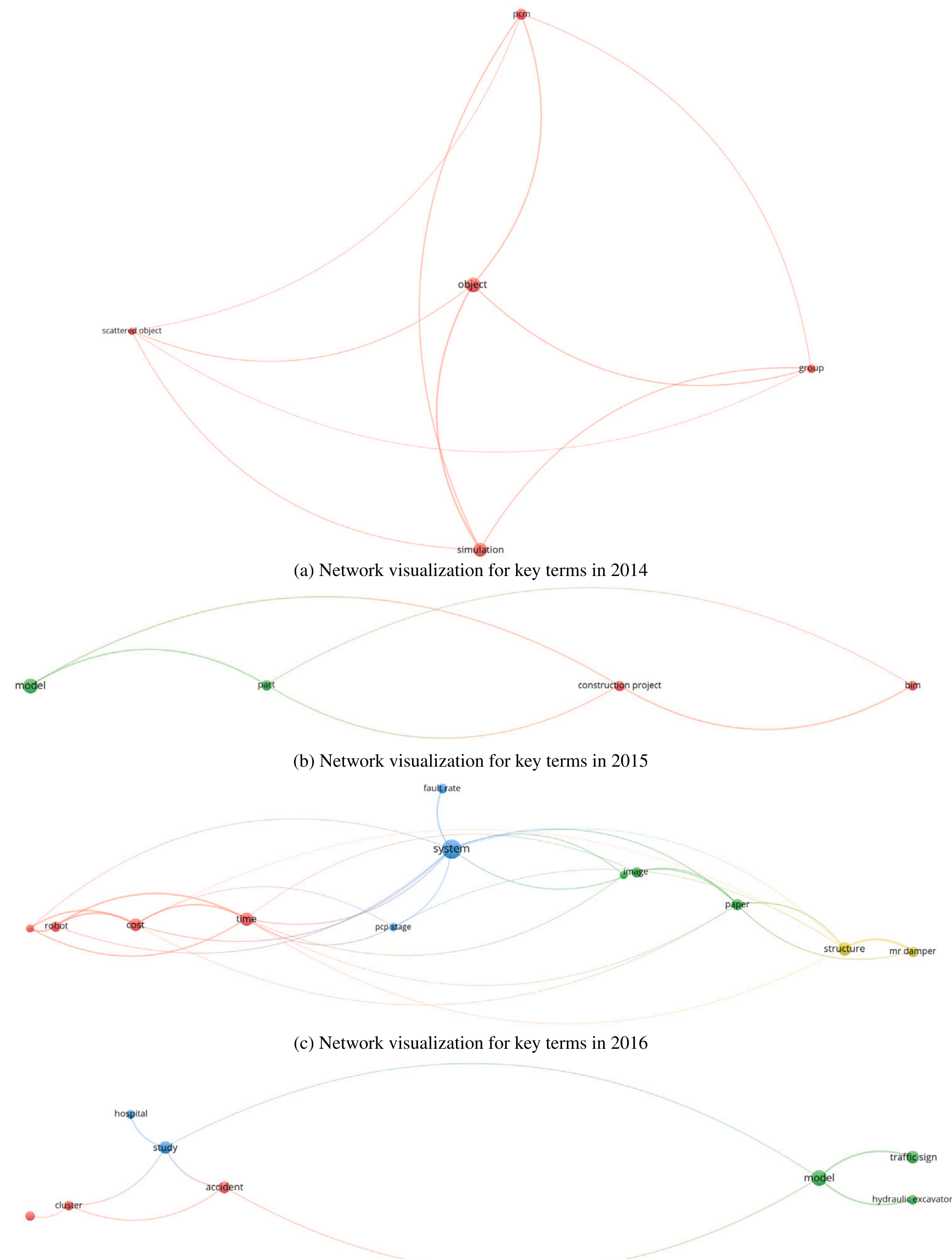


Fig. 8. Network visualization of keywords for AI in construction security studies (2014–2023).

In the next step, the study focuses on visually tracking the progress of AI advancements in construction security from 2014 to 2023 annually. By examining the most commonly used key terms, creating visual representations of the connections between these terms using VOSviewer [37], and thoroughly analyzing the content of related research for each year. This approach provides a clear and comprehensive overview of how the concept of "evolution" in construction security has developed over the ten-year period, offering insights into the changes and trends that have emerged. For this analysis, the *.RIS file was exported from SCOPUS, targeting AI-driven studies in construction security for each year over the last decade. Using the VOSviewer tool, terms from the titles and abstracts were extracted employing the full counting method. The threshold was set to identify terms based on their minimum occurrence frequency. Firstly, the extraction process focused on both titles and abstracts, omitting structured abstract labels and copyright statements. Following this, the full counting method tallied the total occurrences of each term before applying the threshold. Only terms that passed the threshold were then assessed to calculate their relevance score by VOSviewer. Finally, based on these scores, the most pertinent terms were chosen by opting to select the 60% most relevant terms as the default criterion.

Fig. 9 displays the network visualizations representing key concepts extracted from titles and abstracts of construction security studies over a decade. This mapping illustrates the evolution of the intellectual structure and thematic shifts within the field. Specifically, it can be observed that during the first three years, from 2014 to 2016, as presented in the ranges of Figs. 9(a), 9(b), and 9(c), the early networks show sparsity with a few isolated but foundational topics such as "risk", "safety", and "regulation", reflecting the nascent stage of research focused on establishing baseline knowledge and understanding core issues. However, from 2017 to 2018, there is a noticeable increase in the interlinking of nodes like "technology", "training", and "policy", suggesting an integration of practical applications with theoretical research, indicating a push towards operational improvements and regulatory development as shown in Figs. 9(d) and 9(e). Subsequently, Figs. 9(f) and 9(g) present a burgeoning complexity and cluster formation highlighting a surge in topics like "automation" and "digital monitoring", pointing to technological advancements being incorporated into the research agenda, alongside growing concerns for "worker safety" and "compliance" for the period from 2019 to 2020. Moreover, in the period from 2021 to 2022, Figs. 9(h) and 9(i) show dense and vibrant clusters encompassing terms like "AI", "remote sensing", and "cybersecurity", reflecting a sophisticated understanding and application of high-tech solutions to enhance construction site security, emphasizing predictive analytics and proactive risk management. Significantly, in the year 2023, the highly interconnected network with nodes such as "blockchain", "IoT", and "machine learning", alongside "safety protocols" and "workforce training", indicates a holistic approach to construction security, integrating cutting-edge technology with human-centered safety practices 9(j). To conclude, the network visualization from 2014 to 2023 in construction security research vividly illustrates the field's transition from foundational safety and risk management to a nuanced ecosystem incorporating advanced technologies and proactive strategies, marking a shift towards integrated, intelligent security solutions tailored to the dynamic nature of construction sites.

Turing to the second part of the section, the deep mining content of related studies are taken into account. It can be seen that Artificial Intelligence (AI) significantly enhances construction site security through the deployment of advanced surveillance and monitoring technologies. By employing AI-driven algorithms, these systems enable real-time detection of potential threats and ensure adherence to safety protocols, thus markedly reducing the risk of accidents and unauthorized entries. This is achieved by analyzing video footage to identify hazardous behaviors or conditions, promptly alerting supervisors to take preventive action against possible safety incidents, showcasing the critical role of AI in maintaining secure construction environments [17]. However, the application of AI for security purposes is accompanied by challenges, including concerns over privacy, data protection, and the necessity for algorithms that can accurately differentiate between normal and potentially hazardous situations. The development of highly accurate AI



(a) Network visualization for key terms in 2014

(b) Network visualization for key terms in 2015

(c) Network visualization for key terms in 2016

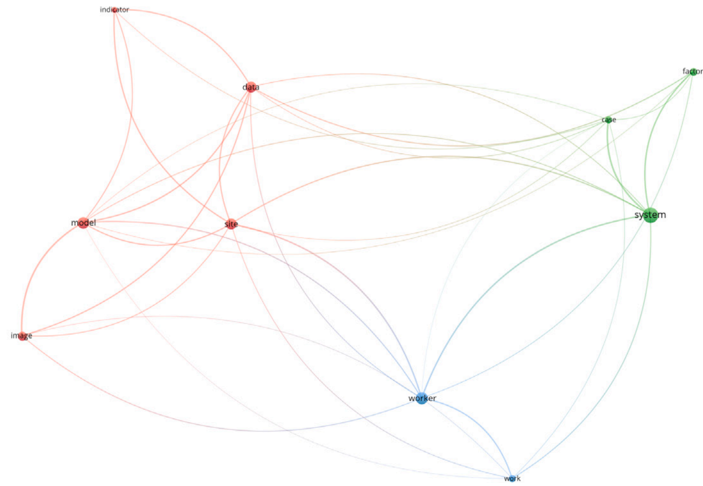
(d) Network visualization for key terms in 2017

Fig. 9. Network visualizations for key terms extraction from AI construction security studies (2014–2023) .

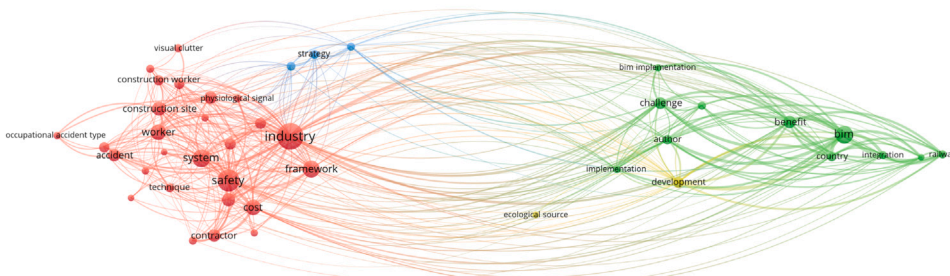
algorithms is essential to prevent the issuance of false positives, which could lead to unwarranted alerts and disrupt construction operations. Thus, while AI offers substantial benefits for enhancing safety and security on construction sites, it also necessitates a careful consideration of the ethical and operational issues involved in its deployment [30,38]. These references underscore the importance of balancing the technological advancements AI brings to construction site security with the need to address associated challenges effectively. In details, the analysis is presented according to each year as the following section.

It shows that in 2014, the new adoption of RFID technology for process management throughout the building's lifecycle was noteworthy, while simulation techniques for bridge safety continued to be refined. After one year, in 2015, the industry introduced participatory video as a novel tool for enhancing health and safety engagement among workers and BIM technology was increasingly used for visualizing construction safety management. The focus on improving safety through technology remained consistent, showcasing an ongoing commitment to advancing construction safety practices with innovative solutions [39–41].

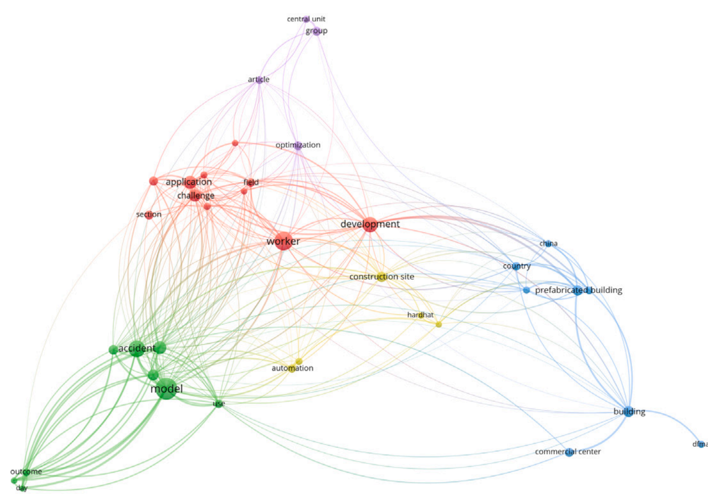
In 2016, the construction industry saw a significant application of AI for safety, employing techniques like image recognition for hazard detection and natural language processing to analyze accident reports, which marked an improvement over 2015's technology-driven approaches such as participatory video and BIM for safety management. While 2015 focused on participatory engagement and virtual modeling for safety, 2016 introduced more autonomous AI systems that could learn from data and provide real-time safety enhancements, indicating



(e) Network visualization for key terms in 2018



(f) Network visualization for key terms in 2019



(g) Network visualization for key terms in 2020

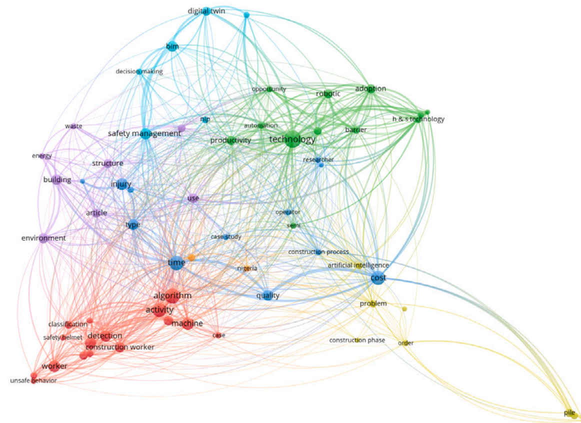
Fig. 9. (*continued*).

a shift towards more proactive and predictive safety measures. The evolution from 2015 to 2016 retained the core objective of improving safety but shifted towards more advanced, data-driven AI technologies for anticipating and mitigating risks [42,43].

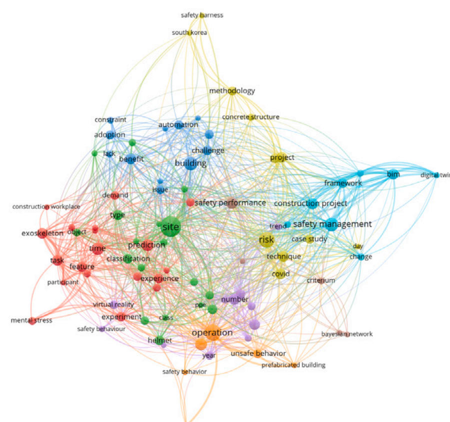
In 2017, the construction industry experienced a significant evolution in the security aspect with the integration of AI and wearable technologies, focusing on real-time health monitoring, risk management, and safety training enhancement. This shift towards leveraging electroencephalography (EEG) systems, Building Information Modeling (BIM) for risk analysis, and sophisticated data analysis techniques for accident prevention underscored a proactive approach to identifying hazards, assessing worker attention and fatigue, and ultimately, fostering a safer construction environment [44,45].

In 2018, the construction industry witnessed a remarkable shift towards enhancing site security and safety through AI applications, prominently featuring deep learning for worker certification verification, machine learning approaches for identifying safety leading indicators, and the innovative use of computer vision for real-time hazard detection and resource tracking significantly advancing proactive risk management and accident prevention strategies [46,47].

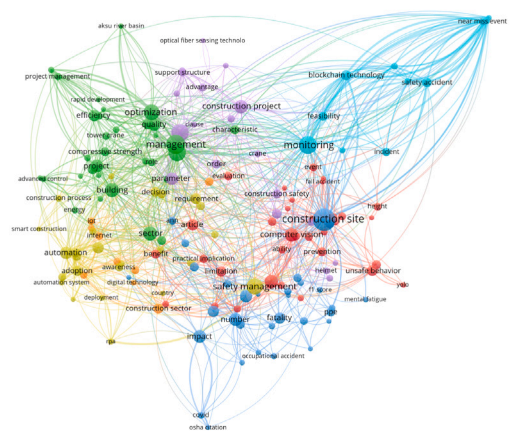
The advancements in 2019 have marked a significant leap in construction safety, where AI-driven systems have transitioned from reactive to proactive safety measures, utilizing real-time data analysis and predictive modeling to anticipate hazards, enhance decision-making, and automate safety compliance, leading to a paradigm shift in ensuring worker protection and reducing on-site accidents. It means that it



(h) Network visualization for key terms in 2021



(i) Network visualization for key terms in 2022



(j) Network visualization for key terms in 2023

Fig. 9. (*continued*).

emphasis the shift from traditional methods to AI-powered proactive strategies, emphasizing the role of AI in predictive safety and automation, which contributes to a safer construction environment [48,49].

In 2020, the application of AI in the construction industry's security aspect predominantly focused on leveraging various advanced techniques such as machine learning, natural language processing, deep learning, computer vision, and Ergonomic assessment using AI. These technologies were used for a range of purposes including risk prediction, safety management, ergonomic assessment, hazard detection, and accident prevention. The integration of these AI innovations was aimed at enhancing safety protocols, reducing the incidence of accidents, and ensuring the well-being of workers on construction sites [50,51].

In 2021, the application of Artificial Intelligence in construction notably advanced the domain of safety management through the development of an innovative settlement calculation model for Geosynthetic-Reinforced Pile-Supported Embankments (GRPSE). This model leverages AI to optimize the bearing capacity of soil between piles, fully exploiting the membrane effect, and thereby not only enhancing the safety and integrity of construction projects but also offering a cost-effective design solution [52].

The 2022, innovation in AI application within the construction industry, especially in safety and security, showcases advanced integrations of AI and machine learning for risk assessment, computer vision

Table 6
Timeline of AI evolution in construction industry security.

Year	New developments	Consistency	Evolution	Limitations	References
2014–2015	Introduction of RFID technology for process management and participatory video for worker engagement.	Continued refinement and use of simulation techniques and BIM.	Shift from traditional management to interactive and visual safety tools.	Challenges with specific bridge types and broader H&S assessments.	[40,57–59]
2016	Adoption of image recognition for hazard detection and NLP for accident report analysis.	Focus on advanced AI technologies for safety management.	Transition to autonomous AI systems for proactive safety.	High costs of robotics and big data infrastructure needs.	[42,60]
2017	Real-time health monitoring using AI and wearable technologies like EEG systems.	BIM continues as a valuable tool for risk analysis.	Integration of wearable technology for real-time monitoring.	Implementation complexity and high-quality data requirement.	[44,61]
2018	Deep learning for worker certification verification and computer vision for hazard detection.	Continued development of ML applications for safety indicators.	Proactive risk management and accident prevention through AI.	Data quality issues affecting model accuracy.	[62–64]
2019	Predictive modeling for hazard anticipation and automation in safety compliance.	Continued use of AI for enforcing safety measures.	Shift from reactive to proactive safety measures.	Challenges with unobtrusive data collection and AI biases.	[48,65,66]
2020	Ergonomic assessment using AI and comprehensive safety management with ML, NLP.	Diverse use of AI in safety management.	Wider application of AI technologies for integrated safety management.	Data quality and resource integration challenges.	[51,67–69]
2021	AI-optimized bearing capacity model for GRPSE.	Emphasis on construction safety and integrity.	AI application in geotechnical engineering.	High costs and data scarcity for wider tech adoption.	[52]
2022	Digital twinning, IoT, and VR integration for safety management.	Continued use of BIM and computer vision for hazard detection.	Comprehensive risk assessment and management using advanced technologies.	Fragmented data and system interoperability issues.	[70–72]
2023	Blockchain for construction automation and ML for PPE compliance.	Ongoing use of advanced analytics and detection technologies.	Integration of digital twins and blockchain with predictive safety measures.	Industry resistance and integration costs.	[55,56]

for hazard detection, and predictive modeling for accident severity. Incorporating technologies like BIM, Digital Twinning, IoT, and VR into safety management marks a significant advancement in construction site security [53,54].

In 2023, the construction industry has made innovative strides in leveraging AI for predictive safety and health management, utilizing machine learning and computer vision for real-time PPE compliance and hazard detection, and adopting digital twins and blockchain to push the boundaries of automation and sustainable construction, albeit with the ongoing challenge of aligning these advanced technologies with the industry's existing workforce and practices [55,56].

Overall, the timeline for the evolution of AI in addressing security aspect in construction studies is presented in Table 6. the overall trend and evolution have shifted from reactive to proactive, with a clear transition from reactive safety measures to proactive, predictive models. Additionally, there is an increase in complexity and specialization; proposed AI applications have become more specialized, addressing specific challenges within the construction industry. Moreover, there has been integration with emerging technologies such as IoT, VR, blockchain, and digital twins to address security issues. Last but not least, despite the evolving technologies, the core objective of enhancing safety and efficiency in construction remains consistent.

3.4.2. The evolution of AI applications in communication issues

Based on the RIS file exported from the SCOPUS when searching for related studies in AI applications in communication area from 2014 to 2023, we created a map using VOSviewer, a threshold was set such that only terms appearing a minimum of 5 times were included. Out of 116 papers, which yielded 4012 key terms, and 108 terms meet the threshold of minimum 5 occurrences. For each of the 108 terms, a relevance score will be calculated, then based on the score, the most relevant terms will be chosen. By using default choice is to select 60% of most relevant terms, it results 65 selected terms. The density visualization is presented in Fig. 10, and the network visualization is depicted in Fig. 11.

The density heatmap has been shown in Fig. 10 provides a vibrant snapshot of key concepts surrounding AI's role in construction communication, highlighting terms like "model", "BIM", "internet", "IoT", and "digital twin". Each term's prominence, indicated by the intensity of the color gradient, hints at their relative importance and usage frequency. "Model" and "BIM" at the core suggest a foundational role in the industry's AI discourse, while "IoT" reflects the trend towards interconnectivity in construction operations. "Digital twin" emerges as a bridge between the physical and digital, pointing to a future where real-time simulation and analysis are integral to construction projects. These terms, bathed in green and yellow hues, stand out, indicating a nexus of active discussion and innovation. In addition, the network map in Fig. 11 complements the heatmap by visualizing the intricate relationships between these concepts. It shows that the proximity of "internet" and "IoT" nodes to "building" and "energy efficiency" underscores a narrative where smart technology is poised to revolutionize traditional practices. Meanwhile, "digital twin" sits adjacent to "performance" and

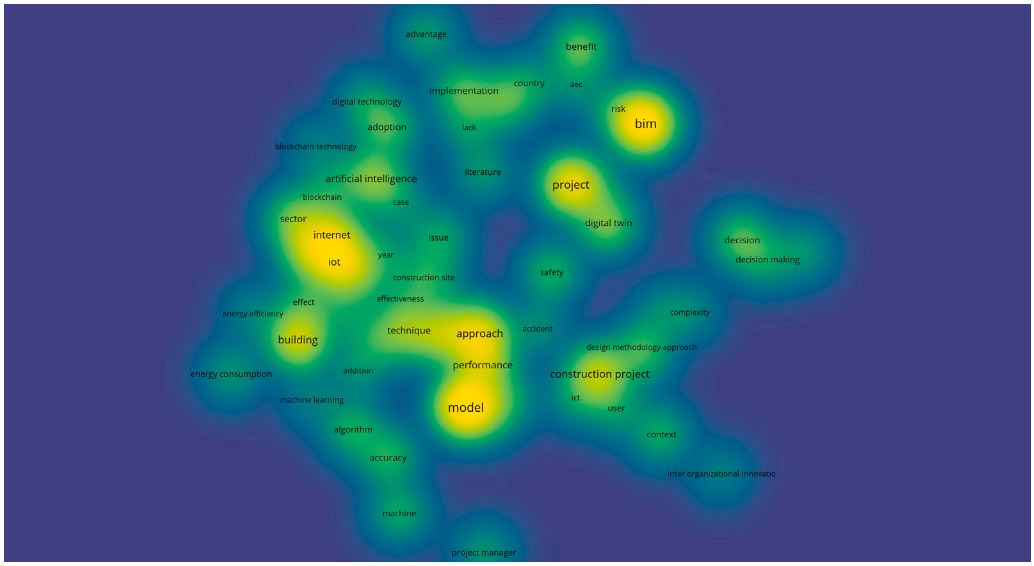


Fig. 10. Visualization of keyword density for AI construction communication studies (2014–2023).

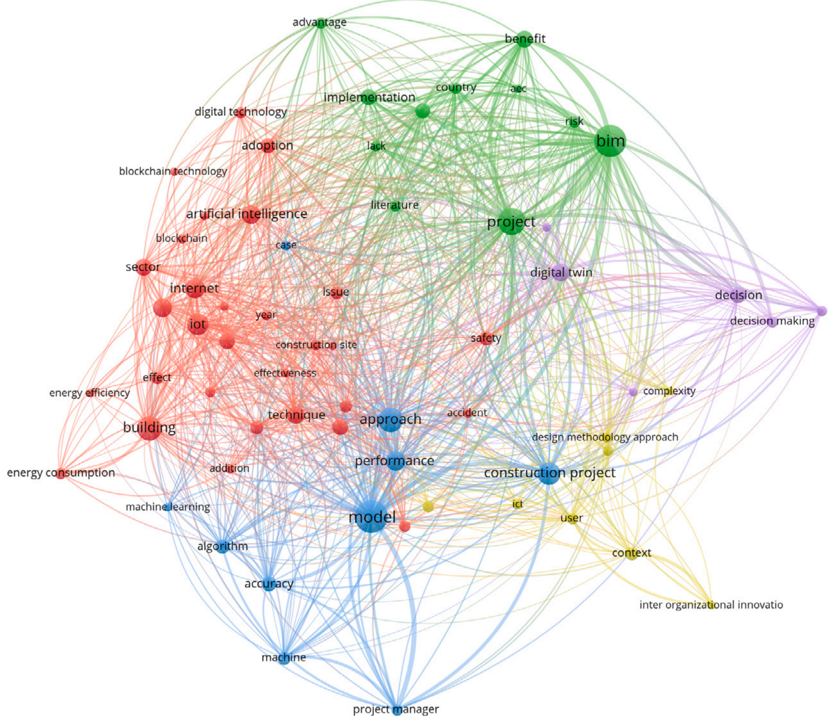


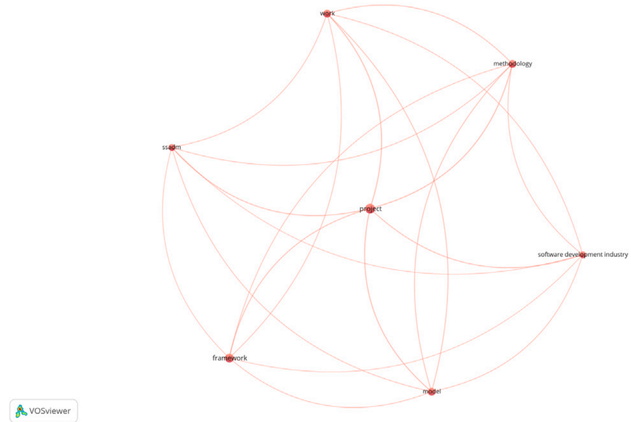
Fig. 11. Network visualization of keywords for AI in construction communication studies (2014–2023).

"construction project", suggesting an evolution in project management towards more dynamic and responsive models.

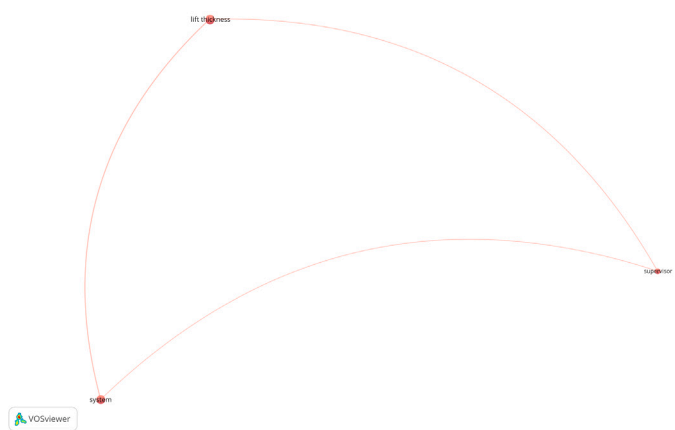
In the next step, the analysis detailing the evolution of AI-driven studies in the construction communication sector from 2014 to 2023 is conducted through network visualizations of key terms, before delving deeply into the content of related studies annually.

The network visualization is highlight in Fig. 12. This figure presents the revolution in the construction industry's communication over a decade, driven by AI, as evidenced by the evolving complexity in network visualizations from 2014 to 2023. In detail, it can be seen that the networks began with a sparse layout. The initial focus on "solution" and "simulation" in 2014 transitions to a slightly more complex web in 2015 with terms like "software development industry" surfacing, suggesting the earliest explorations of AI within the context of construction communication, as shown in Figs. 12(a) and 12(b). Then, according to Figs. 12(c) and 12(d), from 2016's continued simplicity with basic constructs like "work" and "project" to 2017's increased connectivity, there is an apparent shift from foundational concepts towards a more nuanced integration of AI in facilitating communication across construction projects. Additionally, the 2018 visualization depicts denser connections, indicative of AI's growing impact, as shown in Fig. 12(e), which, by 2019, has led to the emergence of clusters highlighting specialized applications in areas such as "digital technology", pointing towards a phase of substantial technological adoption, as presented in Fig. 12(f). Continuously, a significant leap is seen in 2020 with complex interconnectivity representing AI's deep integration into communication strategies, which evolves by 2021 into a well-established research domain with AI being central to various communication processes

(a) Network visualization for key terms in 2014



(b) Network visualization for key terms in 2015



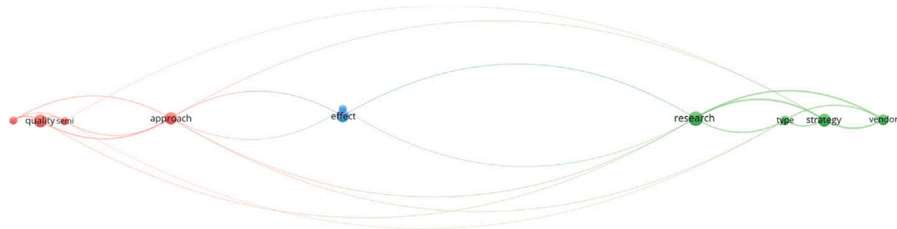
(c) Network visualization for key terms in 2016

(d) Network visualization for key terms in 2017

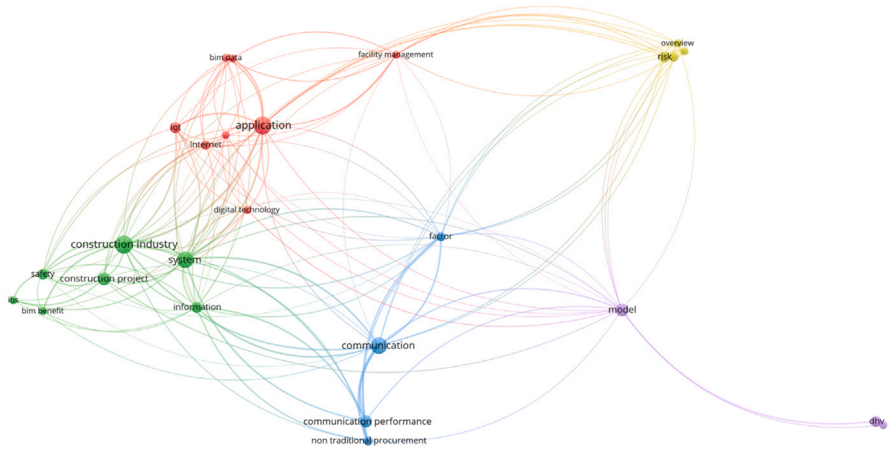
Fig. 12. Network visualizations for key terms extraction from AI construction communication studies (2014–2023).

within the construction industry, as shown in Figs. 12(g) and 12(h). Finally, in the last two years from 2022 to 2023, the intricate networks in 2022, featuring terms like "cyber–physical systems", progress to 2023's extensive web of nodes, showcasing AI's critical role and its synergistic integration with a variety of advanced technological and management practices in construction communication, as presented in Figs. 12(i) and 12(j). In conclusion, the network visualizations reflect an overarching trend of growth from AI being a supplementary tool for improving construction communication to becoming an essential, deeply integrated component that enhances collaboration, efficiency, and real-time decision-making in construction projects. The networks over these years depict a field increasingly influenced by sophisticated AI applications, marking a transition towards a future where AI is a cornerstone of construction communication practices.

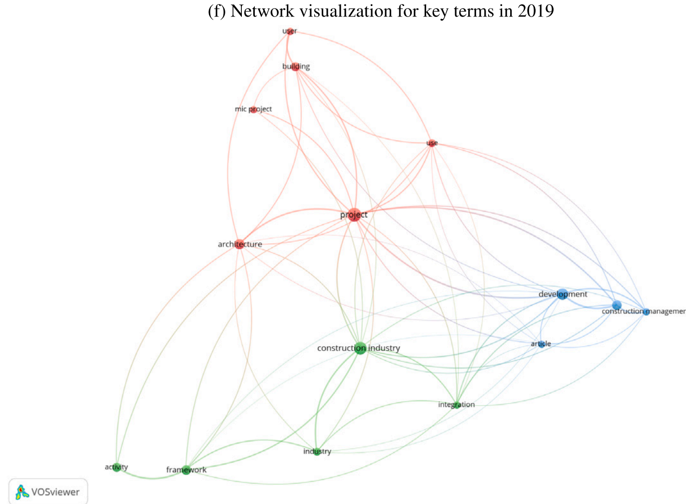
Turning to the deep diving content of the AI-driven studies in construction communication sector, the study finds that in 2014, the Simulation of Environmental Impact of Construction (SimulEICon) was introduced by [73], enhancing sustainable decision-making within the design phase, reflecting a critical innovation in addressing communication challenges. However, it primarily focuses on design, leaving gaps in other construction phases. The study [74] applies cooperative game theory to streamline resource management among subcontractors, highlighting the importance of effective communication for short-term partnerships. This underscores the need for improved communication strategies across various stakeholders. These papers collectively demonstrate strides in addressing communication issues but also reveal the necessity for comprehensive approaches throughout the construction lifecycle.



(e) Network visualization for key terms in 2018



(f) Network visualization for key terms in 2019



(g) Network visualization for key terms in 2020

Fig. 12. (*continued*).

In 2015, researchers in the study [75] signifies a pivotal step in communication efficiency within construction, automating the briefing process through AI, promising streamlined information dissemination. Furthermore, its implementation of ICT-based logistics systems highlights strides in team coordination, accentuating the growing importance of real-time communication. Nevertheless, both studies underscore the persistent challenge of practical application and the imperative for validation in the intricate contexts of construction projects.

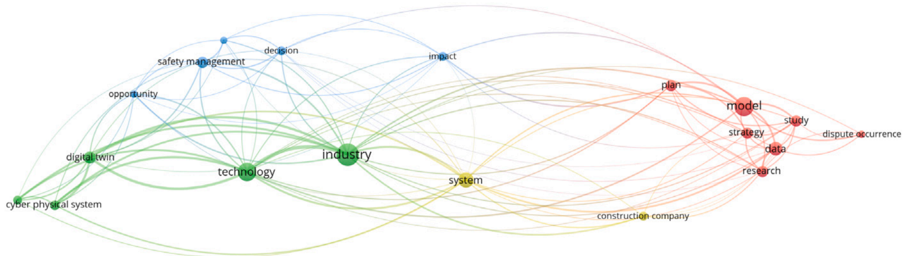
In 2016, the demonstration of real-time technology in tasks are highlight in [76], including lift-thickness monitoring marks a shift towards practical, tech-driven solutions, enhancing communication accuracy on operational fronts. However, the study also underscores the ongoing hurdle of technology adaptability across diverse construction landscapes, warranting further exploration and refinement.

In 2017, the application of machine learning in the study [77] to classify accident narratives illustrates AI's potential in bolstering safety communication protocols, a crucial advancement for risk management in construction. Similarly, the study [78] examination of ICT's sustainability impact hints at broader technology integration for efficient project delivery. Despite these strides, challenges in practical implementation persist, emphasizing the necessity for ongoing research to optimize technology efficacy and address communication barriers.

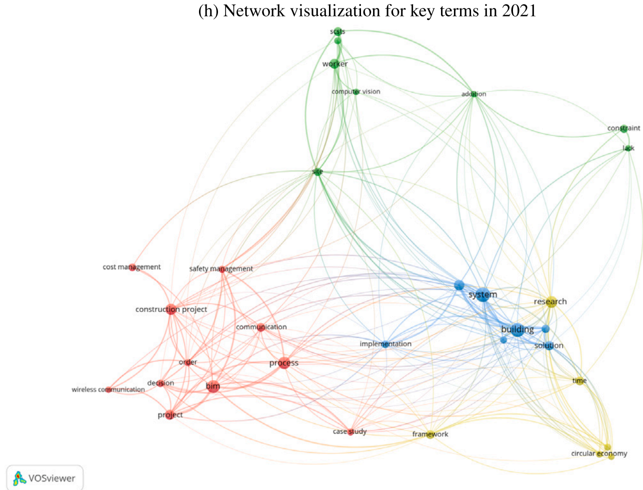
In 2018, the utilization of virtual reality for facility management underscores the transformative potential of immersive communication tools in construction contexts [79]. However, the study also sheds light on challenges related to user engagement and technology dissemination, highlighting the critical need to overcome communication barriers for effective technology adoption.

In 2019, papers such as [80] on BIM in railway projects and [81] on IoT applications underscore AI's pivotal role in enhancing project management and safety communication. While these advancements signify a shift towards more holistic approaches, persistent implementation challenges emphasize the ongoing importance of research in communication-focused AI applications within construction.

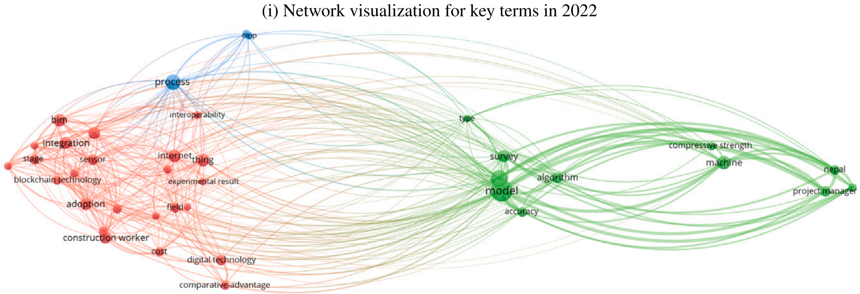
In 2020, the construction sector experienced a notable shift towards specialized AI applications focusing on communication. Innovations such as cognitive systems in building management [82] and



(h) Network visualization for key terms in 2021



(i) Network visualization for key terms in 2022



(j) Network visualization for key terms in 2023

Fig. 12. (*continued*).

deep learning for equipment monitoring [83] demonstrated a move towards precision and efficiency in industry operations. Additionally, remote electron microscopy for material monitoring [84] contributed to enhanced communication regarding material quality and performance. However, despite these advancements, challenges persisted in the widespread adoption and skill development necessary for effective implementation, underscoring the existing gap between technological potential and practical integration within the construction industry.

In 2021, AI research in construction communication witnessed notable advancements, particularly in enhancing communication via natural language processing [85]. This innovation aimed to streamline interactions between stakeholders and improve project coordination. However, these advancements also revealed limitations in the form of potential biases and inaccuracies inherent in AI-driven language processing systems, highlighting the need for ongoing refinement and validation. Additionally, while improved IoT security contributed to bolstering communication channels by addressing concerns regarding data protection and privacy in interconnected construction environments, it also raised awareness of the evolving cybersecurity threats facing digitally integrated construction projects. These innovations signify a growing emphasis on leveraging AI to facilitate seamless communication within construction projects, highlighting a shift towards more digitally integrated and efficient practices. However, addressing limitations and ensuring robust cybersecurity measures will be crucial for realizing the full potential of AI in construction communication in the future.

In 2022, the construction industry's focus on AI applications in communication significantly evolved. Notable strides were made in leveraging AI for blockchain implementation in smart contracts [86] and integrating edge computing for more efficient data processing on construction sites [70]. The emphasis on Industry 4.0 technologies [87] showcased AI's role in enhancing communication and data sharing for sustainable construction practices. This shift towards practical AI applications in communication and data management marked a notable progression from 2021's emphasis on digital twins and cyber–physical systems. However, the industry still faced challenges in adopting these advanced technologies, indicating a gradual but steady move towards fully embracing AI's potential in improving communication and project management in construction.

In 2023, the construction industry witnessed significant AI-driven advancements in communication, marking a progressive shift from previous years. Notably, the study [90] introduced a groundbreaking deep learning and signal processing approach that greatly enhanced audio clarity in noisy construction environments, addressing a longstanding challenge in on-site communication. This innovation stands out for its

Table 7
Timeline of AI evolution in construction industry communication.

Year	New developments	Consistency	Evolution	Limitations	References
2014–2015	Introduction of SimulEICon for sustainable decision-making and cooperative game theory for resource management.	Automation of briefing processes using AI.	Transition towards automated and real-time communication systems.	Challenges of practical application in real-world construction.	[73–75,88]
2016	Real-time tech applications like lift-thickness monitoring.	Integration of operational tech solutions into construction processes.	Shift towards practical, tech-driven solutions for communication accuracy.	Adapting technology across diverse environments.	[76]
2017	Use of ML to classify accident narratives and ICT's impact on sustainability.	AI applications focusing on safety and sustainability in communication.	Broader technology integration for efficient project delivery.	Challenges in practical application across construction scenarios.	[77,78]
2018	VR utilization for immersive communication tools in facility management.	Introduction of VR to enhance communication through immersive experiences.	Introduction of immersive communication tools.	User engagement and effective technology dissemination hurdles.	[79]
2019	IoT applications for project management and safety communication.	BIM usage in railway projects for comprehensive project management.	Holistic approaches in project management and safety communication.	Implementation and integration challenges.	[80,81]
2020	Innovations like cognitive systems in building management and deep learning for equipment monitoring.	Specialized and precise AI applications for construction operations.	Transition towards precision in construction operations.	Widespread adoption challenges and skill development needs.	[82–84]
2021	Advancements in NLP for project coordination and IoT security enhancements.	Focus on enhancing communication through NLP and bolstering IoT security.	Enhancement in communication via NLP and IoT security.	AI-driven language processing biases and cybersecurity threats.	[85,89]
2022	AI for blockchain in smart contracts and edge computing for data management.	Shift towards practical AI applications emphasizing efficiency and sustainability.	Integration of AI with blockchain and edge computing for efficient data management.	Challenges in adopting advanced technologies.	[70,86,87]
2023	Groundbreaking deep learning for audio clarity in noisy environments and real-time site monitoring with IoT and AI.	Sophisticated, AI-integrated communication systems for enhanced decision-making.	Targeted application of AI in communication for on-site decision-making.	Necessity for further refinement in AI applications.	[90–92]

practical application in improving worker safety and coordination efficiency. Meanwhile, the study [91] broadened the scope, highlighting AI's role in civil engineering to facilitate more effective data exchange and decision-making processes, underscoring the growing interdependence between AI and communication in construction. Additionally, the study [92] showcased the integration of IoT and AI for real-time site monitoring and risk assessment, revolutionizing how information is communicated and acted upon in construction settings. These advances reflect a trend towards more sophisticated, AI-integrated communication systems in the industry. Compared to 2022, these developments signify a more targeted application of AI in communication, moving beyond general data processing to specific, impactful enhancements in on-site communication and decision-making processes.

Overall, the timeline for the evolution of AI in addressing the communication aspects in construction studies is presented in Table 7. The progression of AI in enhancing construction communication from 2014 to 2023 marks a transition from basic automation to advanced AI integration, focusing on improvements in project coordination, safety messaging, and real-time decision-making. This progression includes the adoption of technologies such as VR for immersive communication, natural language processing for clearer coordination, and blockchain and edge computing for secure data management. Despite challenges in technology adoption and application, this decade has witnessed significant advances in construction communication through AI innovations.

3.4.3. The evolution of AI applications in maintenance issues

Based on the RIS file exported from the SCOPUS when searching for related studies in AI applications in maintenance area from 2014 to 2023, we created a map using VOSviewer, a threshold was set such that only terms appearing a minimum of 10 times were included. Out of 76 papers, which yielded 3006 terms, and 42 terms meet the threshold of minimum 10 occurrences. For each of the 42 terms, a relevance score will be calculated, then based on the score, the most relevant terms will be chosen. By using default choice is to select 60% of most relevant terms, it results 25 terms to be selected. The density visualization is presented in Fig. 13, and the network visualization is depicted in Fig. 14.

Fig. 13 is used to represent the concentration and clustering of terms related to AI applications in maintenance over a decade (2014–2023). Each term is a focal point that is part of a larger discourse in the field. The terms "building", "data", "construction", and "technology artificial intelligence" are prominent, suggesting these are key areas where AI has been applied in the maintenance sector. The bright spots on the map, like "building" and "data", likely indicate areas of high activity or interest, suggesting significant research and application in these areas.

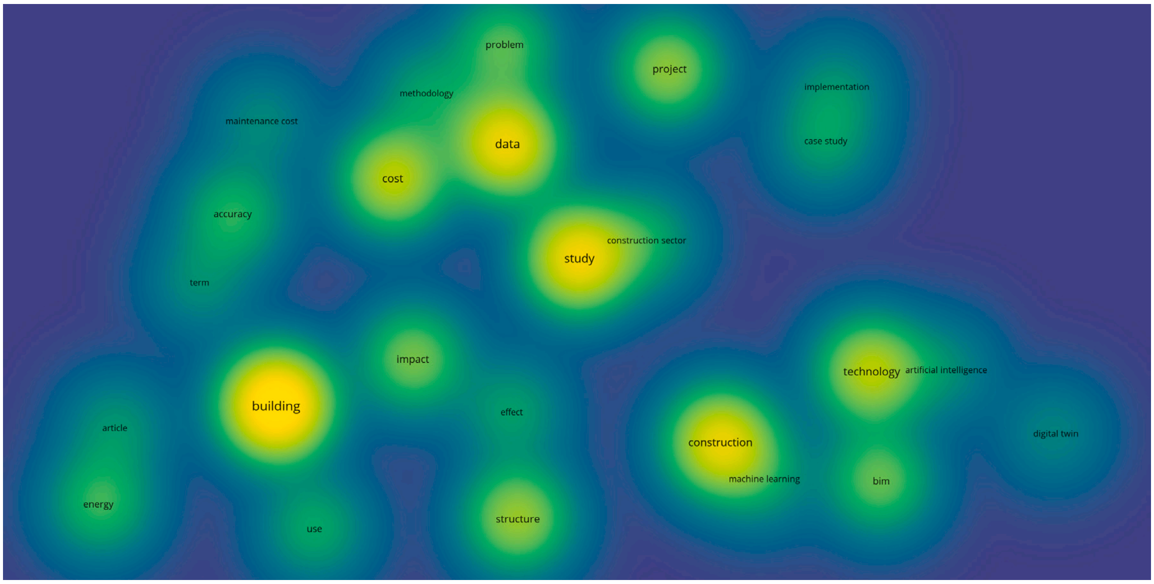


Fig. 13. Visualization of keyword density for AI construction maintenance studies (2014–2023).

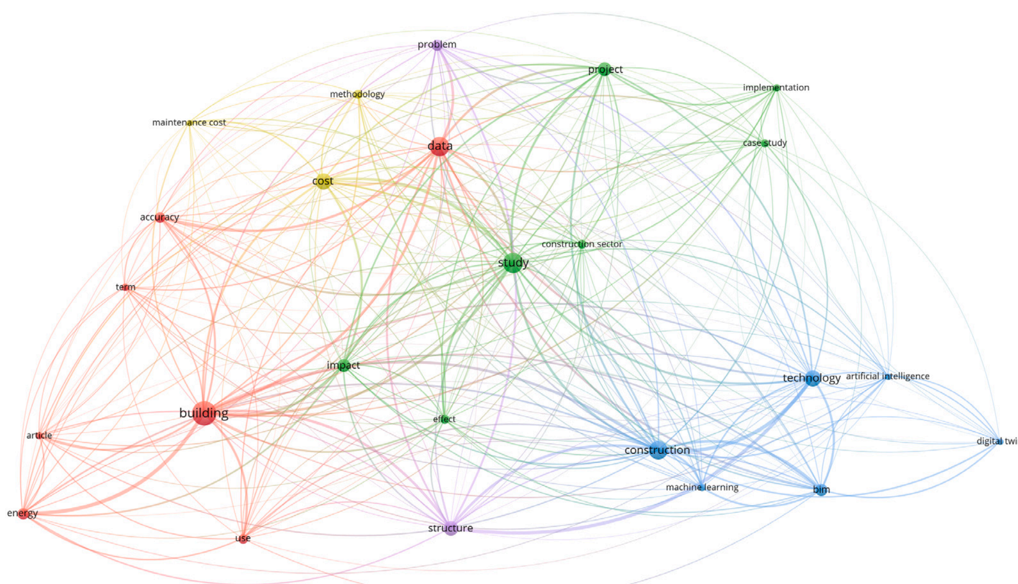


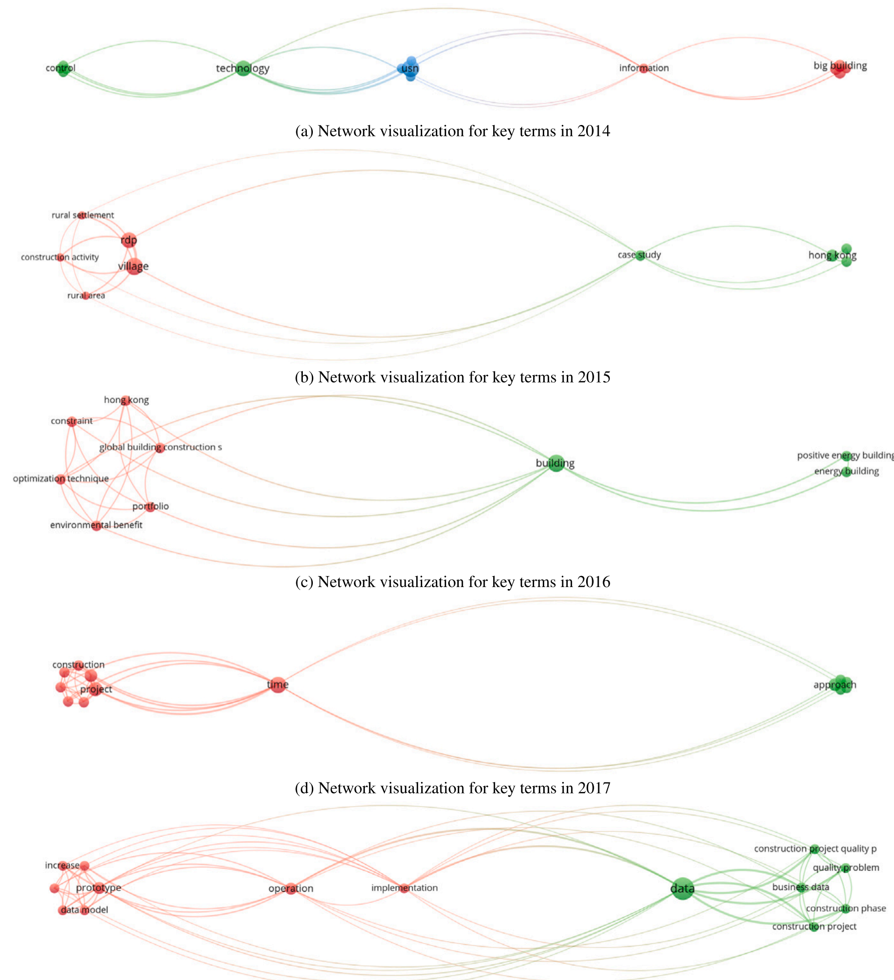
Fig. 14. Network visualization of keywords for AI in construction maintenance studies (2014–2023).

The varying intensities of color denote the different levels of focus, with lighter areas possibly indicating emerging or niche topics. On the other hand, Fig. 14 the shows the relationships between different concepts or entities. This visualization is particularly useful for understanding the structure of the relationships between concepts, highlighting how advancements in one area may influence or be influenced by others, and how central themes are to the broader topic of AI in maintenance. For example, "building" is a central node with numerous connections, signifying its pivotal role in AI-driven maintenance. The layout of the network shows how concepts like "machine learning", "bim", and "digital twin" are interconnected, reflecting their co-development or co-application in the field.

The adoption of Artificial Intelligence (AI) in construction maintenance is revolutionizing predictive and operational maintenance strategies, enhancing equipment longevity and minimizing downtimes. AI's integration into maintenance modeling and management shows significant potential for improving maintenance strategies through predictive analytics and intelligent decision-making support systems [93]. Machine learning techniques are instrumental in predictive maintenance, optimizing equipment health status predictions and maintenance scheduling, contributing to sustainable manufacturing in Industry 4.0 [30].

AI's evolving role in construction engineering and management (CEM) emphasizes automating and refining maintenance tasks, pivotal for the industry's digital transformation [17]. It also plays a crucial role in mitigating uncertainties within the Architectural, Engineering, and Construction (AEC) sector, enhancing decision-making across project lifecycles, including maintenance [20].

Despite challenges like industry fragmentation and data acquisition issues, AI streamlines maintenance tasks, improving efficiency and



(a) Network visualization for key terms in 2014
(b) Network visualization for key terms in 2015
(c) Network visualization for key terms in 2016
(d) Network visualization for key terms in 2017
(e) Network visualization for key terms in 2018

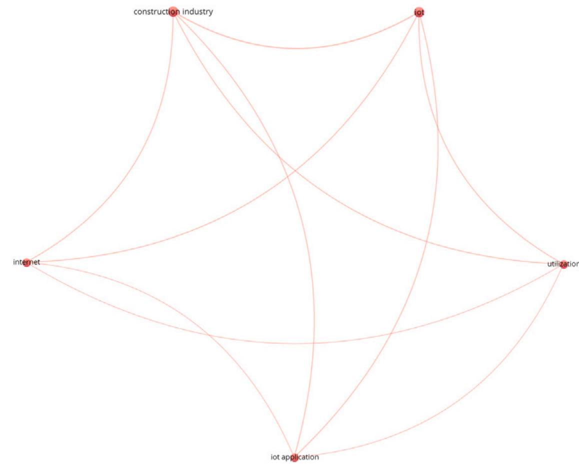
Fig. 15. Network visualizations for key terms extraction from AI construction maintenance studies (2014–2023).

operational effectiveness [18]. The development of innovative AI-based systems, such as the Mobile 2D Barcode/RFID-based Maintenance Management (M-BRMM) system, demonstrates AI's practical application in enhancing maintenance management and information sharing within construction labs [94]. In essence, AI's role in construction maintenance is transformative, offering predictive maintenance and intelligent decision support to improve operational efficiency. However, harnessing AI's full potential in maintenance requires addressing industry-specific challenges, including data management and algorithm optimization.

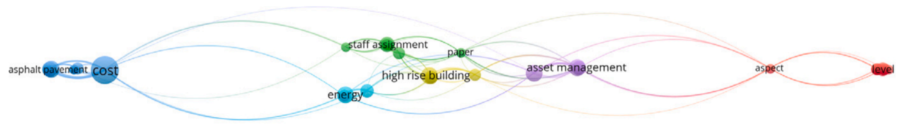
In the next part of this section, the study presents the improvement annually based on both visualization and deep mining content of related studies. In which, Fig. 15 visualizes the network of key terms in AI-driven studies related to construction maintenance from 2014 to 2023, illustrating the maturation of key themes and the integration of AI technologies. The initial visualization in 2014 is simple, indicating the infancy of AI in construction maintenance, with a focus on "control" and foundational "technology", as shown in Fig. 15(a). Moving into 2015 and 2016, as indicated by Figs. 15(b) and 15(c), terms like "information" and "USN" suggest an early adoption of IoT and data-driven maintenance. By 2017, there is a shift towards discussing broader "building" applications of AI, showing a trend toward scaling up AI tools for larger projects, as presented in Fig. 15(d). Turning to 2018 and 2019, as in Figs. 15(e) and 15(f), the appearance of "optimization techniques" and "environmental benefits" signals a focus on improving efficiency and sustainability in maintenance practices through AI. Significantly, from 2020 to 2022, the networks become denser with terms like "data model", "implementation", and "operation", reflecting a deeper integration of AI in the maintenance process and an emphasis on predictive analytics, as shown in the list of Figs. 15(g), 15(h), and 15(i). By 2023, the complex interplay of terms such as "assessment", "AIC industry", and "future" indicates a sophisticated ecosystem where AI is pivotal for the proactive and strategic maintenance of construction projects, streamlining workflows, and driving the industry towards intelligent automation and decision-making, as presented in Fig. 15(j). In summary, the network visualizations highlight the evolution from theoretical AI concepts toward tangible, data-centric solutions that optimize the maintenance lifecycle and contribute to smarter, more resilient building management practices.

Furthermore, a detailed dive into the content of related studies highlights the evolution of AI in construction maintenance research from 2014 to 2023 as follows:

In 2014, the construction industry saw significant improvements thanks to AI. Innovations included better ways to ensure bridge safety and new systems for monitoring construction sites in real-time. The use of Radio frequency identification (RFID) technology was a step forward in managing construction projects, although it was not fully integrated yet. Studies also looked at how building affects the environment and set new standards for keeping up with maintenance work. There were some challenges, such as outdated building codes and varying types of maintenance data. Looking ahead, these developments suggest that we

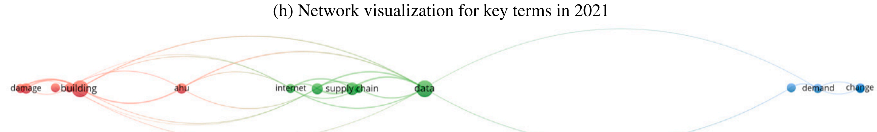


(f) Network visualization for key terms in 2019

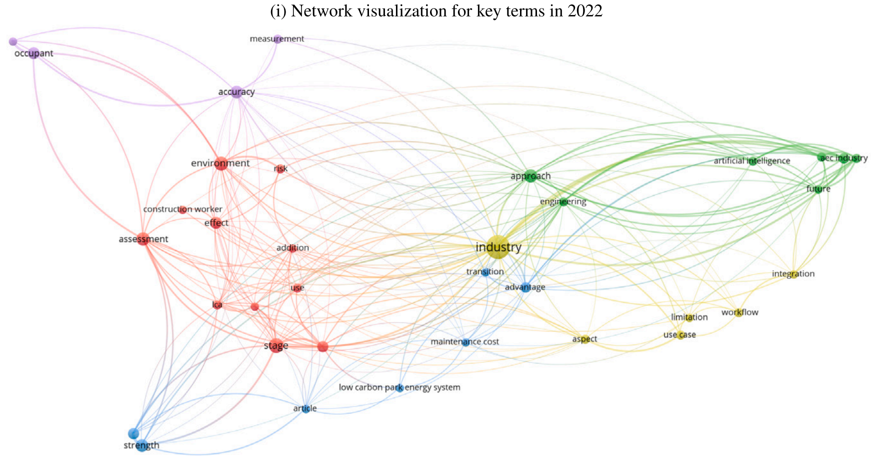


(g) Network visualization for key terms in 2020

(h) Network visualization for key terms in 2021



(i) Network visualization for key terms in 2022



(j) Network visualization for key terms in 2023

Fig. 15. (*continued*).

can expect safer construction methods, improved tracking technologies, and building practices that are better for the planet, leading to a smarter approach to maintenance [58,59,95].

In 2015, in the realm of sustainable building maintenance, the year marked a year of progressive innovation through the utilization of alternative materials aimed at reducing labor, costs, and carbon emissions, coupled with the enhancement of development plans to refine maintenance protocols. The advancements were underpinned by empirical data on labor and emissions and rural development studies, yet faced hurdles such as an aging workforce and the intricacies of optimizing construction plans. Future directions suggest a shift towards green technology and material optimization, as well as the evolution of maintenance and construction methodologies, signifying a transformative phase for sustainable practices in the industry [96,97].

In 2016, the sustainable building maintenance sector was marked by efforts to harmonize economic, social, and environmental impacts, evidenced by the evaluation of maintenance projects and the application of univariate models for output forecasting. Data-driven optimization techniques and analyses of material portfolios, along with historical construction output data, underpinned these advancements. However, the industry confronted the intricate challenge of maximizing these tripartite benefits concurrently and faced a dearth of quantitative data for precise forecasting. These issues notwithstanding, the progress laid a foundation for future enhancements in decision-making processes prioritizing sustainability and for the refinement of strategic planning in construction with improved output forecasting mechanisms [98,99].

In 2017, the construction industry continued to innovate with a focus on project efficiency and maintenance. The sector analyzed the effects of project acceleration on quality and profitability, developing techniques to ensure profitable returns without compromising maintenance quality. A significant technological leap was the introduction of a model for evaluating concrete structure performance using deep convolutional neural networks, using data from project acceleration studies and concrete surface imaging. Despite these advancements, the industry faced challenges in maintaining a balance between the rapid completion of projects and the quality and profitability of the work, as well as limitations in traditional non-destructive methods for assessing concrete durability, which spurred the need for more advanced imaging techniques. The future implications of these advancements include the potential for improved project management strategies that better balance time, quality, and profitability, and the development of more sophisticated maintenance systems for concrete structures using deep learning technology [100,101].

In 2018, the construction industry's drive towards sustainable and efficient maintenance crystallized in several key areas. Life-cycle assessments for bridges set a precedent for holistic maintenance planning, while big data became pivotal in refining quality management. The advent of virtual reality (VR) marked a leap in the management of facilities, and heritage buildings benefited from targeted vulnerability analysis. Each innovation, though promising, was met with its own set of challenges: achieving an economic-environmental balance in bridge maintenance, navigating data integration complexities, resolving VR system integration, and accurately predicting the service life of heritage structures. These steps forward anticipate not only enhanced bridge maintenance and quality management but also a new era of efficiency in maintenance through VR and more informed conservation of heritage buildings [79,102,103]

In 2019, the construction industry saw a shift towards advanced maintenance strategies through the optimization of technician teaming and routing, the implementation of the Internet of Things (IoT) for smarter construction and asset management, and the integration of AI for occupational health and safety. The data fueling these advancements were drawn from workforce analytics, IoT sensor outputs, and AI safety algorithms. However, the sector faced challenges in maintaining a balance between service quality and cost-efficiency, resistance to the adoption of digital technologies, and hurdles in embedding AI into existing safety protocols. Despite these challenges, the innovations of 2019 set the stage for improved efficiency in maintenance operations and the potential for significantly enhanced safety and construction processes through IoT and AI integration [81,104,105].

In 2020, it marked a watershed in the construction and maintenance industries, catalyzed by groundbreaking innovations that, while promising, are not without their limitations. The integration of robotics and high-pressure water-based window cleaning systems showcases significant advancements towards automation, yet the industry grapples with practical application challenges and implementation hurdles that temper the enthusiasm. Similarly, initiatives aimed at energy and resource optimization reflect a conscientious move towards sustainability but are mired in complexities surrounding the trade-offs between operating and embodied energy and reconciling environmental impacts with cost and quality objectives. The push towards digital transformation with BIM and digital twins, along with NLP for staffing, heralds a smarter approach to maintenance, although integration and efficacy issues persist. Furthermore, the commitment to sustainable labor practices and urban planning faces obstacles in ensuring labor safety and managing intricate urban data. The adoption of the stochastic annuity method for lifecycle cost planning also underscores the industry's movement towards economic sustainability, despite uncertainties inherent in forecasting and planning. These initiatives collectively steer the industry towards a future of enhanced operational efficiency and sustainability, yet they also underscore a present riddled with challenges that must be navigated with critical and innovative thinking [106–111].

In 2021, the focus on maintenance within the construction sector turned sharply towards sustainable practices, as evidenced by scholarly contributions that scrutinized the maintenance of wooden buildings, the application of Fiber Bragg Grating (FBG) sensors for road infrastructure, and the use of Building Information Modeling (BIM) in cultural heritage management. The commendation of wood for its environmental benefits in construction underpins a deeper environmental commitment, while the enhancement of structural health monitoring (SHM) through FBG sensors indicates an advance in resource optimization and infrastructural safety. Despite these advancements, the sector confronts significant challenges, such as the environmental impact assessment of wooden structures, the integration of sensor data into effective SHM systems, and the complexities inherent in the juxtaposition of preserving cultural heritage against maintenance costs. Looking forward, these studies propose a paradigm shift towards more sustainable maintenance practices that promise not only eco-efficiency in wooden construction but also improved safety and cost-efficiency in the upkeep of roads and cultural sites, indicating a future where maintenance strategies are both economically and environmentally sustainable [112–114].

In 2022, the construction industry's pursuit of sustainability through digitalization took a dual approach, encapsulating both the circular economy and structural health. The study underscores the pivotal role of AI, digital twins, and scanning technologies in fostering circular economy practices within social housing, from construction to demolition, while facing hurdles such as technological adoption and cultural resistance. Concurrently, predictive analytics emerged as a cornerstone for structural integrity, shown in [115,116] where researchers used CNN and SVM models, and the synergetic integration of Digital Twin, BIM, and IoT for predictive maintenance of Heating, Ventilation, and Air Conditioning (HVAC) systems. These efforts, despite grappling with the complexities of accurate damage prediction and technology integration, pave the way for advanced machine learning models to revolutionize maintenance management. Such innovations promise not only economic and environmental paybacks but also augur a new era of efficiency and longevity in building maintenance [117].

In 2023, the construction industry's maintenance domain was marked by a surge in digitization and eco-conscious practices, as studies highlighted the integration of computer vision and machine learning for asset management and cost prediction. Despite technological advances, the industry grappled with the complexity of digital adoption and circular economy transitions. Green lifecycle management efforts, such as using urban tree waste and optimizing energy systems, faced challenges in integrating green infrastructure with building materials and coping with building lifespan variability. Predictive analytics for structural health and HVAC systems showed promise for enhanced maintenance and energy efficiency, yet were hampered by the integration complexities and data accuracy dependence. Additionally, health and safety advancements in construction were constrained by the need for more accurate physiological response models. Collectively, these studies underscore an industry at the cusp of a digital transformation poised to revolutionize maintenance efficiency, though contingent upon overcoming present data and integration challenges [118–126].

Overall, the timeline for the evolution of AI in construction maintenance studies is illustrated in Table 8. AI-driven studies in construction maintenance have progressed from basic innovations in safety and real-time monitoring to sophisticated digitalization and eco-conscious practices. Beginning with the introduction of RFID technology and advancing through the adoption of VR, IoT, and advanced AI for project management and maintenance, the industry has experienced a significant shift towards sustainability, efficiency, and advanced monitoring

Table 8
Timeline of AI evolution in construction industry maintenance.

Year	New developments	Consistency	Evolution	Limitations	References
2014	Innovations in bridge safety, RFID for project management.	Early steps towards real-time monitoring, green practices.	Advancement of tracking tech for sustainability.	Outdated building codes, data diversity issues.	[58,59,95,127]
2015	Use of alternative materials for sustainability, new maintenance protocols.	Continued focus on real-time monitoring, new standards.	Shift towards green tech, evolution in maintenance methods.	Aging workforce, optimizing construction plans.	[96,97]
2016	Data-driven optimization focusing on sustainability, univariate forecasting models.	Reliance on empirical data for advancements.	Enhancements in decision-making prioritizing sustainability.	Lack of precise forecasting data.	[98,99]
2017	Techniques for project acceleration, AI for evaluating concrete structures.	Continued focus on data-driven techniques.	Improved management strategies using AI.	Balancing quality with profitability, traditional assessment limitations.	[100,101]
2018	VR for facility management, big data in quality management.	Ongoing tech innovation for efficiency.	New era of maintenance efficiency, conservation of heritage buildings.	Data integration issues, predicting service life of structures.	[79,102,103]
2019	Optimization of technician teaming, IoT and AI for asset management.	Big data refinement in maintenance.	Enhanced maintenance efficiency and safety through IoT and AI.	Service quality vs. cost efficiency, resistance to digital adoption.	[81,104,105]
2020	Robotics for automated tasks, BIM and digital twins for maintenance.	Advanced strategies from previous innovations.	Sustainable and efficient maintenance practices.	Robotics application challenges, environmental impact concerns.	[106,128–130]
2021	Maintenance of wooden buildings, FBG sensors for infrastructure monitoring.	Automation and enhanced monitoring tech.	Eco-efficient practices, improved safety in infrastructure.	Environmental assessments, integration of advanced monitoring tech.	[108,112–114]
2022	AI and digital twins for circular economy, predictive analytics for structural health.	Sustainable practices, BIM usage.	Advanced AI models enhancing maintenance efficiency.	Technological adoption barriers, cultural resistance.	[115–117]
2023	Integration of ML for asset management, green lifecycle management.	Development of predictive analytics and optimization technologies.	Industry at the cusp of digital transformation in maintenance.	Digital adoption complexities, predictive analytics integration.	[118–122,124,126]

techniques. Despite challenges in technology adoption and data integration, advancements toward circular economy practices, predictive analytics, and the integration of machine learning for asset management herald a new era in maintenance strategies. This evolution underscores a decade of progress toward more sustainable and efficient construction maintenance practices powered by AI.

In summarizing Section 3, it is clear that AI-driven research within the construction industry showcases varied levels of maturity across the domains of security, communication, and maintenance. The concept of "maturity" in this context is multifaceted, encompassing developmental, adoption, and impact maturity. In which, developmental maturity reflects the sophistication and complexity of AI methodologies, such as machine learning algorithms and neural networks, tailored to the unique challenges of the construction industry, while adoption maturity indicates the extent of AI integration and acceptance within construction processes. Impact maturity is measured by the tangible improvements AI applications contribute in reducing costs, enhancing safety, and boosting operational efficiency. Specifically, construction security demonstrates a notably advanced maturity level. This is substantiated by a robust volume of scholarly publications, a diverse range of AI techniques employed, and their significant impacts, such as the marked reduction in workplace accidents and the enhancement of site security protocols. Advanced surveillance systems and predictive analytics, for example, have seen widespread adoption, evidencing high impact maturity by substantially mitigating risks and refining safety management practices. Conversely, the domains of communication and maintenance, despite the well-established presence of foundational technologies like Building Information Modeling (BIM), digital twins, and the Internet of Things (IoT), have not reached a comparable maturity level. These areas are still in a phase of developmental evolution, focusing on creating AI tools that can fully exploit these technologies to streamline communication and optimize maintenance operations. Additionally, the progressive integration of blockchain technology to bolster privacy management exemplifies a strategic response to the maturity challenges associated with data security and privacy in AI applications. This marks a significant evolutionary advancement in addressing AI challenges, showcasing a strategic and comprehensive approach to augmenting the maturity of AI applications across the construction industry. This multi-dimensional understanding of maturity not only clarifies the current state of AI applications but also sets a framework for future research and development in these crucial areas.

4. Limitations and future research directions

4.1. Limitations

This study presents a comprehensive analysis of AI applications in construction, specifically focusing on security, communication, and maintenance. It offers a detailed review of literature up to the year 2023, capturing a solid snapshot of current trends and established technologies. While this temporal boundary provides a robust foundation for understanding well-established knowledge, it also marks a deliberate scope which may limit insights into the very latest AI advancements emerging post-2023.

The study's concentration on selected areas of the construction industry allows for an in-depth exploration of AI's impact in these critical sectors. This focused approach ensures that our findings are detailed and insightful, tailored to the areas that could benefit most immediately from AI technologies. However, it is recognized that this focus might not encapsulate the full spectrum of potential AI applications across the broader construction industry.

Additionally, the reliance on sources from technologically advanced regions ensures high-quality and rigorous research inputs, reflecting the leading-edge application of AI technologies. This geographic focus, while enhancing the credibility and applicability of the findings, may limit the generalizability to global contexts. Future studies are encouraged to include more diverse global perspectives, broadening the understanding and applicability of AI technologies across different regions and construction practices.

4.2. Future research directions

Looking forward, the research anticipates that the landscape of AI in construction will continue to evolve, driven by both technological advancements and increasing integration across various construction phases. Predictive analytics in security is poised for significant breakthroughs with the development of sophisticated algorithms capable of preempting risks and enhancing site safety. To maximize effectiveness, these technologies should integrate human expertise, ensuring that AI supports rather than supplants human decision-making processes. The potential integration of AI with nascent technologies such as quantum computing and augmented reality promises not only to fortify security measures but also to revolutionize real-time collaboration and stakeholder engagement in construction projects.

The study also identifies a pressing need for future investigations into the ethical implications and privacy concerns surrounding AI in construction. As AI systems become more autonomous, ensuring their responsible deployment will be crucial. This includes addressing issues of data privacy, algorithmic bias, and the ethical use of AI-driven decision-making systems. Moreover, exploring human–AI collaboration models could be pivotal in harnessing AI's capabilities while enhancing human judgment, particularly in complex security and maintenance tasks.

Future research should also aim to broaden the scope of AI applications studied, to include a more diverse array of construction activities and regions. This expansion would provide a more rounded view of the challenges and opportunities presented by AI in construction. It is imperative for future studies to delve into a cost–benefit analysis of AI implementations, assessing their return on investment to better inform policy and investment decisions within the sector.

In conclusion, while this study has laid a foundational understanding of AI's role in enhancing security, communication, and maintenance within the construction industry, the full potential of AI can only be realized through continued, expansive research efforts. These efforts should aim to not only address the gaps identified but also anticipate and shape the future trajectory of AI applications in construction, ensuring they lead to more efficient, safe, and sustainable construction practices.

5. Conclusions

This paper has demonstrated that the integration of AI in the construction industry over the past decade has been pivotal, significantly transforming security, communication, and maintenance domains. AI technologies such as RFID, autonomous systems, and predictive modeling have transitioned security practices from reactive to proactive, enhancing operational safety and risk management. The integration of AI with human expertise is underscored as essential for driving innovative, sustainable, and ethically sound practices in construction. Continued research into hybrid models that combine AI precision with human insights is advocated.

In communication, AI has facilitated a leap from basic manual processes to advanced, integrated systems. Tools such as SimulEICon, VR, BIM, and IoT have revolutionized project management by improving the flow of information and coordination, thereby addressing the traditional inefficiencies and ensuring projects are completed more efficiently and economically.

Maintenance has seen a shift towards sustainability and predictive analytics, with AI applications like deep learning and digital twins playing a central role in advancing maintenance practices. This transition supports more sustainable and efficient construction processes, vital for enhancing operational reliability and reducing environmental impacts.

Collectively, these developments indicate that AI has not only addressed critical vulnerabilities in the construction industry but also catalyzed a shift towards more innovative, sustainable, and efficient practices. These advancements have showcased AI's potential to further drive industry-wide changes. The findings underscore the necessity of continuing to explore AI integration, particularly in developing hybrid models that synergize human expertise with automated precision. Future research should also consider the ethical implications and scalability of AI technologies to ensure broad and responsible adoption.

By analyzing the evolution of AI in construction and proposing future research directions, our study contributes to a deeper understanding of how AI can enhance security, communication, and maintenance within the construction industry. We advocate for continued research efforts that anticipate and shape the future trajectory of AI applications in construction, leading to more efficient, safe, and sustainable construction practices.

CRediT authorship contribution statement

Thu Giang Mai: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Minh Nguyen:** Validation, Supervision, Project administration, Methodology, Conceptualization. **Akbar Ghobakhlou:** Supervision, Methodology, Conceptualization. **Wei Qi Yan:** Supervision, Methodology. **Bunleng Chhun:** Supervision, Project administration. **Hoa Nguyen:** Writing – review & editing, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Thu Giang Mai reports financial support was provided by MJ Realities Limited. Thu Giang Mai reports a relationship with MJ Realities Limited that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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