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Artificial Intelligence in Bridge Engineering and Management with Emphasis on Construction Phase

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Abstract: Civil infrastructure has increasingly adopted artificial intelligence, reshaping bridge engineering, and management practices, particularly during the construction phase. This review provides a comprehensive assessment of AI applications, specifically machine learning, deep learning, and computer vision, employed in bridge construction planning, scheduling, monitoring, quality assurance, and safety management. Given the growing complexity of bridge projects and the persistent demands for enhanced safety, efficiency, and cost-effectiveness, integrating intelligent, data-driven methodologies has become essential. Utilizing a mixed-methodology approach, this study combines scientometric and systematic literature reviews to critically analyze peer-reviewed publications spanning the years 2000–2025. The findings indicate substantial advancements in AI techniques, demonstrating notable improvements in resource optimization, risk prediction accuracy, and proactive safety management. However, the implementation of AI in bridge construction also faces challenges, such as high computational resource requirements, data quality issues, model scalability concerns, and integration complexities. By identifying key research trends, technological benefits, and existing limitations, this paper contributes valuable insights and proposes future research directions to enhance the practical integration of AI, ultimately aiming to improve the resilience, reliability, and longevity of bridge infrastructure.

Author keywords: Artificial intelligence (AI); machine learning (ML); deep learning (DL); computer vision (CV); bridges; construction phase

Introduction

Artificial Intelligence (AI) has emerged as a transformative force in civil engineering, offering powerful tools to address the complexities and challenges inherent in planning, constructing, and maintaining infrastructure. In recent years, AI techniques such as machine learning (ML) and evolutionary algorithms have been used to optimize structural designs, predict material behavior, and improve project outcomes.[1] The construction industry has likewise embraced AI for project management tasks, deploying algorithms for scheduling, resource allocation, risk assessment, and safety management on job sites. This broad adoption of AI in civil engineering is revolutionizing how civil engineers design, build, and maintain bridge infrastructure in the 21st century.

As the demands for cost-efficiency, safety, and sustainability in infrastructure projects grow, AI is increasingly seen as a critical enabler of smart and adaptive engineering solutions. In bridge construction engineering and management, AI plays a particularly vital role. The complexity of modern bridge projects presents pressing challenges that traditional methods struggle to meet.[2,3] In response, AI techniques, encompassing machine learning (ML), deep learning (DL), and computer vision (CV), have emerged as powerful tools to improve the efficiency, safety, and sustainability of bridge engineering. AI-driven approaches are being embraced across the project life cycle, from design and construction to maintenance and management, offering data-driven insights and predictive capabilities previously unattainable. For example, Kumar[4] introduces an innovative framework to enhance bridge deck deterioration modeling. This data-driven approach facilitates proactive maintenance planning, reducing costs, and improving the safety and longevity of infrastructure assets. Bridges, as critical components of transportation networks, stand to benefit enormously from these innovations. Recent studies show that integrating AI into bridge infrastructure can make the construction and management of bridges more information-based and intelligent.

A range of AI techniques have been applied to bridge construction and management, with the core areas being ML, DL, and CV. ML-based tools are utilized for tasks like load forecasting, optimization of construction processes, and maintenance decision support.[5] In fact, even relatively simple classifiers (e.g., support vector machines or decision trees) have shown success in identifying bridge component failures, highlighting that data-driven approaches can

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complement traditional engineering analysis in bridge management. DL, a subset of ML, uses multilayered neural networks capable of learning complex feature representations. In bridge engineering, researchers are employing DL for analyzing structural vibration patterns and modal properties; one study introduced a multitask deep neural network to automatically identify bridge modal frequencies from raw vibration data, demonstrating near-instantaneous performance in extracting structural features that would be difficult to obtain with conventional methods.[6] These examples illustrate how DL techniques enable more autonomous and insightful analysis of bridge behavior, from construction quality control to long-term health monitoring. CV techniques have become indispensable for modern bridge inspection and construction monitoring. High-resolution cameras and drones collect images or video of bridges, and AI vision algorithms then process this visual data to detect issues or track progress. During bridge construction, vision systems (often powered by DL models) are used for progress monitoring and quality assurance. For example, comparing as-built construction images against design models to ensure components are placed correctly, and flagging any deviations or safety hazards on site in real time.[1] By turning visual inputs into actionable information, CV greatly extends the reach and frequency of inspections. Notably, a recent study by Liu et al.[45] demonstrated an AI-enhanced "sensing skin" for crack monitoring: a network of flexible sensors applied to a steel bridge was coupled with AI algorithms to interpret sensor data, successfully detecting fatigue cracks under real traffic loads and providing large-area coverage that a human inspection could not easily achieve. This blend of CV (for image-based damage detection) and novel sensing technologies exemplifies the innovative AI techniques advancing bridge engineering. These advancements have made it possible to minimize human error, reduce construction delays, and extend the service life of bridge assets.

While AI receives significant attention in the context of operational bridge management, it is also profoundly transforming the construction phase of bridge projects. Construction of bridges is a complex process involving numerous tasks and stakeholders,[7] and AI helps streamline these activities in several ways. Project scheduling and logistics benefit from ML models that can optimize work sequences and predict delays or cost overruns before they happen.[1] By analyzing historical project data, AI systems can suggest more efficient resource allocation and improve risk management (e.g., identifying when a particular construction activity is likely to become a bottleneck). On the construction site, AI-driven tools improve quality control and safety. CV monitoring can automatically track the progress of construction in real time, comparing it against the project's four-dimensional building information model to ensure the bridge is being built to specifications. Deviations such as misaligned elements or improper installations can be detected early through image analysis, allowing for prompt corrections.[8] Additionally, AI-enabled cameras and sensors can monitor worker safety, ensuring proper use of protective equipment and alerting to hazardous conditions as well as equipment operation, which reduces the likelihood of accidents. By providing a continuous, data-driven overview of the construction site, AI helps project managers maintain schedule adherence and quality standards with fewer manual inspections. Overall, the infusion of AI into the bridge construction phase has been shown to enhance productivity and coordination, minimize human error, and facilitate real-time decision-making on site.[1] Early case studies in bridge projects demonstrate that AI-supported construction management leads to more efficient building processes and sets the stage for a smarter maintenance life cycle once the bridge is in service.

Recent advancements in digital twin technology have significantly impacted construction phase applications, particularly for bridge engineering and management. Digital twins enable real-time monitoring, enhanced predictive maintenance, and risk management during construction. Luo et al.[9] conducted an extensive review on digital twin applications specifically targeting safety risk management in construction projects. Their study revealed that digital twins, combined with AI and internet of things (IoT) sensors, provide comprehensive insights into real-time safety conditions, substantially improving risk forecasting and decision-making capabilities.[9] The integration of digital twins facilitates not only improved safety but also optimization of resource allocation and enhanced stakeholder communication. On the other hand, the use of robotics and autonomous equipment powered by AI is transforming traditional construction practices by enhancing operational efficiency, safety, and accuracy. Rabbi and Jeelani[10] reviewed the state-of-the-art integration of AI within construction robotics, highlighting substantial improvements in productivity, safety, and consistency. Autonomous robotic systems, powered by AI-driven algorithms, can perform repetitive or hazardous tasks like precise structural component placement, welding, and concrete finishing. This reduces human exposure to high-risk activities and enhances overall construction quality. Additionally, recent practical implementations of robotic technologies have shown promising results. For example, autonomous construction robots equipped with advanced sensing and AI-based control systems have successfully executed complex structural assembly tasks, demonstrating notable efficiency gains and error reductions compared to manual approaches.[11] However, significant challenges remain, including high initial costs, operational complexity, and integration difficulties with existing construction practices, all of which require further research to overcome fully.[12]

Given the fast-growing body of research and applications of AI in bridge construction engineering and management, this review paper aims to provide a comprehensive overview of the state-of-the-art in this field. The scope of the review encompasses the use of AI during the bridge construction phase. This paper specifically focuses on the core AI techniques of ML, DL, and CV, examining how each contributes to various tasks such as construction planning. The review draws on recent peer-reviewed studies and innovations to highlight key achievements of AI in improving bridge performance and longevity. Furthermore, the impact of AI on construction practices and project delivery is discussed,

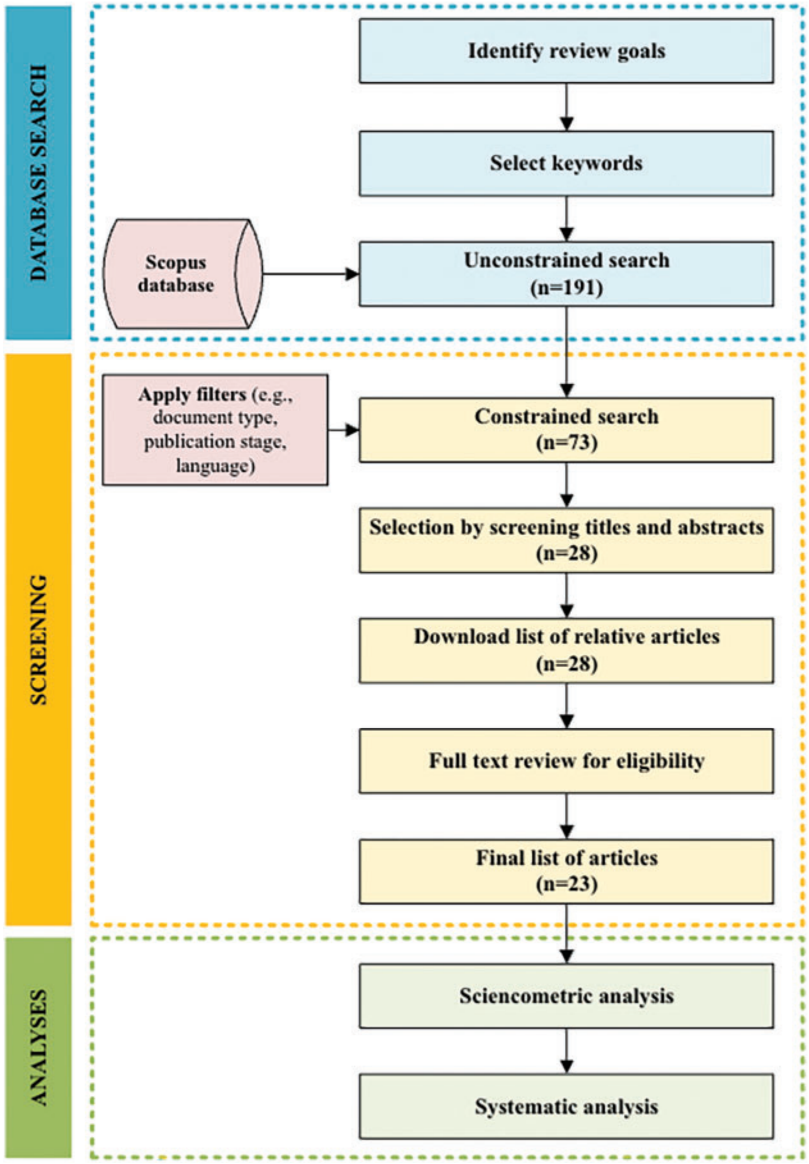


Figure 1. Research methodology

illustrating how intelligent systems are changing traditional workflows in bridge projects. The objectives of this review are: (1) to examine current applications of AI during the construction phase of bridge infrastructure, (2) to evaluate the benefits and limitations observed in practice, and (3) to identify knowledge gaps and future research directions for integrating AI more fully into bridge engineering. By clarifying the advancements so far and the challenges ahead, the review intends to guide both researchers and practitioners in leveraging AI technologies to build and maintain bridges that are safer, more durable, and more efficient to operate.

Methodology

This study adopted a mixed-method approach, combining scientometric and systematic analyses, to investigate the application of AI in bridge engineering and management, focusing specifically on the construction phase. The systematic analysis addressed key aspects such as construction planning and scheduling, monitoring and quality assurance, and safety management. To clearly define the research scope and gather an adequate number of relevant publications, a preliminary search was performed to identify pertinent research studies and prior reviews on the topic. Fig. 1 illustrates the steps conducted in three main stages: (1) database search, (2) screening, and (3) analysis. Each of these stages is described in detail in the subsequent sections.

Database search

This stage consisted of three primary steps: identifying research goals, selecting relevant keywords, and conducting an initial, unconstrained database search. First, the research scope was established, concentrating specifically on the bridge construction phase and examining advancements in computational intelligence techniques, including AI, ML,

Table 1. Keywords used to search for the related articles

Category	Keywords	Reason
Bridge-specific	"bridge infrastructure," "bridge engineering," "bridge management," "bridge construction"	Captures studies specifically addressing bridges.
Computational intelligence	"artificial intelligence," AI, "machine learning," ML, "deep learning," DL, "neural network," NN, "computer vision"	Ensures the results include studies explicitly employing these computational methods.
Construction phase	"planning," "scheduling," "resource allocation," "risk analysis," "monitoring," "quality assurance," "safety management," "hazard detection," "accident prediction," "wearable devices," "emergency response," "construction phase"	Limits articles strictly to the construction phase of bridges, excluding design, in-service, or end-of-life phases.

DL, and CV. Based on this scope, a comprehensive set of primary and alternative keywords was generated to facilitate an effective database search, as presented in Table 1. The Scopus database was selected due to its extensive coverage of multidisciplinary research articles compared to other databases. Using these identified keywords, the unconstrained search in Scopus returned 191 relevant articles.

Screening

The first step in this stage involved establishing clear inclusion and exclusion criteria to refine the search results. The inclusion criteria were defined as follows: (1) studies focusing specifically on bridge applications, (2) studies utilizing computational intelligence techniques, and (3) studies addressing the bridge construction phase. In contrast, the exclusion criteria included: (1) articles not written in English, (2) articles not published in peer-reviewed journals, and (3) articles published outside the defined timeframe (i.e., 2000–2025). These criteria were applied in the "Constrained search" step, reducing the total number of articles from 191 to 73.

Following this step, the titles and abstracts of each of the 73 articles were reviewed to determine if they aligned with the research scope. The inclusion criteria were applied to assess the relevance of the titles and abstracts. After screening the titles and abstracts, the number of articles was reduced to 28. These 28 articles were subsequently downloaded, and their full texts were reviewed thoroughly to verify their relevance to the defined research scope. Following the full-text review, 23 articles were identified as directly related to the three targeted research areas and were included in the final list for analysis. The remaining 5 articles were excluded, as they either covered broader topics in bridge engineering (such as structural health monitoring unrelated to construction, theoretical studies, or approaches not explicitly involving AI) or did not directly apply AI techniques within the bridge construction phase.

Analysis

This study applied a mixed review methodology, integrating scientometric and systematic analyses, an approach widely recognized for delivering comprehensive insights into research domains.[13–15] The scientometric analysis was utilized to examine annual publication trends, relationships among journals, citation patterns (including highly cited articles and influential journals), and frequently used keywords. The scientometric review was supported by text-mining software (e.g., VOSviewer), helping to enhance objectivity and minimize subjective bias in the findings.

Despite the advantages of the scientometric approach in handling large volumes of articles, it lacks the capacity to offer detailed insights into specific aspects of the research area, such as the strengths and weaknesses of the applied AI. To address this limitation, the systematic review method was employed to extract essential characteristics of the research domain, highlight existing gaps, and propose future research directions. The systematic review approach is widely adopted across various research fields due to its effectiveness in providing deeper analyses and structured guidance.[16] Detailed findings from both scientometric and systematic reviews are presented in the subsequent sections.

Scientometric Review and Analysis

Scientometric reviews provide objective outcomes compared to qualitative approaches, primarily due to their reliance on advanced text-mining algorithms.[17] Consequently, this analytical method has become increasingly popular among researchers.[13,18] In this study, the open-source text-mining software VOSviewer was utilized to conduct the scientometric analysis.[19] VOSviewer has previously been employed effectively in review studies by several researchers.[20,21] The bibliometric data of relevant articles were imported into VOSviewer to visualize and analyze relationships among different networks, such as journal interactions, co-authorship collaborations, and keyword co-occurrences, in the form of nodes and links. In these scientometric networks, the proximity between nodes represents their similarity, while thicker lines indicate stronger connections between nodes.

Annual publication trend

The selected articles were categorized by publication year to examine trends in publication rates. As illustrated in Fig. 2,

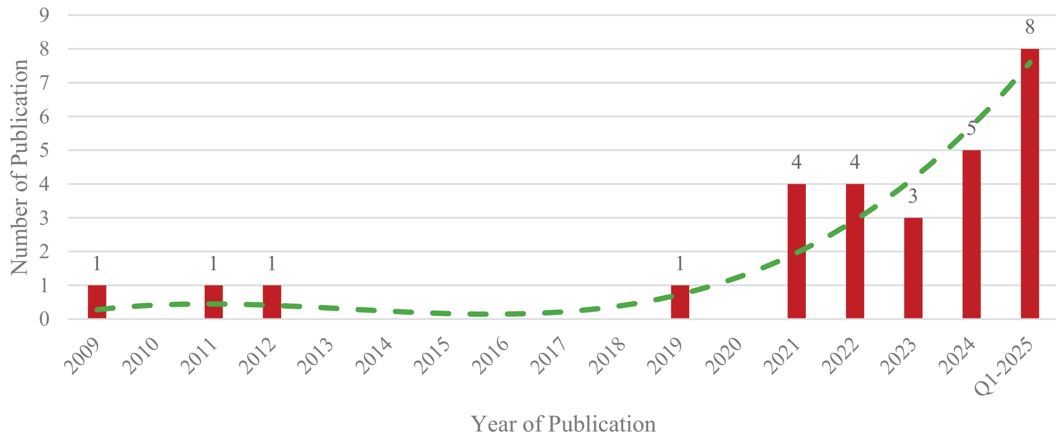


Figure 2. Number of documents published over the years

Table 2. Bibliometric ranking of journals based on citations

Source	Number of documents	Total citations	Total link strength
Archives of Computational Methods in Engineering	1	276	2
Journal of Construction Engineering and Management	3	195	1
Structures	1	98	0
Buildings	3	35	0
Automation in Construction	4	20	0
Journal of Management in Engineering	1	8	1
Scientific Reports	1	151	0
Mathematical Problems in Engineering	1	12	0
International Journal of Recent Technology and Engineering	1	11	0
Advances in Multimedia	1	9	0
Applied Sciences (Switzerland)	1	9	0
Mathematics	1	5	0

there has been a notable rise over the past decade in the number of publications focused on AI applications during the construction phase of bridge infrastructure. The trend line in the figure indicates that research interest in this field has significantly increased, especially within the past 2 years.

From 2009 to 2020, the average annual publication rate on this research topic was below one article per year. It is worth noting that before 2009, no publication meeting the specified criteria was found. However, during the recent 5-year period (2021–2025), there has been a notable increase, with an average of nearly five articles published annually. Despite occasional fluctuations in specific years, the overall upward trend clearly demonstrates the growing significance of AI techniques in bridge engineering and management (Fig. 2). This rise in interest aligns with the broader variety of methodologies being explored by researchers, as discussed in detail in section "Systematic Review and Analysis."

Journals network analysis

The scientometric review process involves analyzing the journals that publish articles related to the researched topic. This analysis is crucial for identifying high-impact journals and directing readers to the most significant journals in the field.[15] Researchers can use this list to select the best journals for their publications, and it also helps institutions and libraries with limited resources subscribe to key journals.[22] Table 2 provides quantitative statistics related to the journal network analysis. It ranks the 12 most influential journals based on three criteria: the number of articles published, citation counts, and total link strength. The total link strength represents the extent of each journal's connections with other journals. As indicated in Table 2, *Archives of Computational Methods in Engineering* is identified as the most influential journal, with a total of 276 citations.

Figure 3. Network of collaborating countries/regions

Table 3. Top countries collaborating to the studied research

Country/region	Number of documents	Total citations	Total link strength
China	19	460	4
Australia	1	276	1
United States	4	215	4
United Kingdom	2	100	5
South Korea	3	24	2
Pakistan	1	13	1
India	2	12	0
Hong Kong	2	7	5
Taiwan	1	6	0
Norway	1	2	4
Switzerland	1	2	4

Co-authorship analysis

The co-authorship network, developed using bibliometric analysis, highlights the contributions and collaborative relationships among key researchers in the studied field. Understanding these collaboration networks is essential, as it fosters enhanced partnerships in joint funding opportunities and facilitates effective communication between institutions. Specifically, co-authorship analysis identifies and visualizes collaboration patterns among researchers from different institutions and countries. The following sections present and discuss the co-authorship networks among researchers affiliated with various nations and institutions in this research domain.

Active countries in the research

To emphasize the contributions of different countries and regions within this research domain, a co-authorship network was generated using VOSviewer. Specifically, the analysis type was set to "co-authorship," and the analysis unit was set to "countries." The thresholds for inclusion were defined by setting the minimum number of documents per country to 2 and the minimum number of citations to 12. Although there are no standard guidelines for these thresholds, five out of 11 countries met these criteria and are illustrated in Fig. 3. Understanding international collaboration networks can promote future partnerships and knowledge exchange. Additionally, examining the geographical distribution of research activities provides insights into the field's global significance and versatility; broader international engagement typically indicates greater global recognition and relevance.

In Fig. 3, the size of each node corresponds to the number of articles published by each country. For example, China (19 documents), the United States (4 documents), and South Korea (3 documents) are represented by larger nodes compared to others. The color groupings in the bibliometric networks indicate distinct clusters of international collaboration. Table 3 summarizes the contributions of all 11 countries analyzed, highlighting the five countries with the highest citation counts: China, Australia, the United States, the United Kingdom, and South Korea. This table provides additional insights into the global collaboration networks and the international significance of the studied research area.

Active institutions in the research

Table 4 summarizes the leading institutions contributing significantly to this research field. Understanding the collaborative networks among these institutions is valuable for both industry professionals and researchers seeking innovative approaches to address challenges related to AI techniques in bridge engineering and management. The institutions listed in Table 4 were selected based on a threshold of at least 50 citations. Although no standardized criteria exist for setting citation thresholds in network analyses,[23] 11 out of 70 institutions met this criterion and are presented accordingly.

Keywords analysis

Keywords play a crucial role in highlighting the core concepts, methods, and essential aspects of a research field, providing concise descriptions of the main topics covered. To gain a thorough understanding of the research domain, a co-occurrence network of keywords was developed, setting the minimum keyword occurrence threshold to "3." Fig. 4 illustrates the resulting keyword network, comprising 15 keywords meeting this threshold. In this figure, each keyword is depicted as a node whose size reflects its frequency

Table 4. Top institutions publishing articles in the studied research

Rank	Institution/university	Country/region	Total citations
1	Curtin University	Australia	276
2	Deakin University	Australia	276
3	Western Sydney University	Australia	276
4	The University of Melbourne	Australia	276
5	East China Jiaotong University	China	276
6	Virginia Tech	United States	178
7	Columbia University	United States	178
8	University of Michigan	United States	178
9	Southeast University	China	98
10	Canterbury Christ Church University	United Kingdom	98
11	University of Liverpool	United Kingdom	98

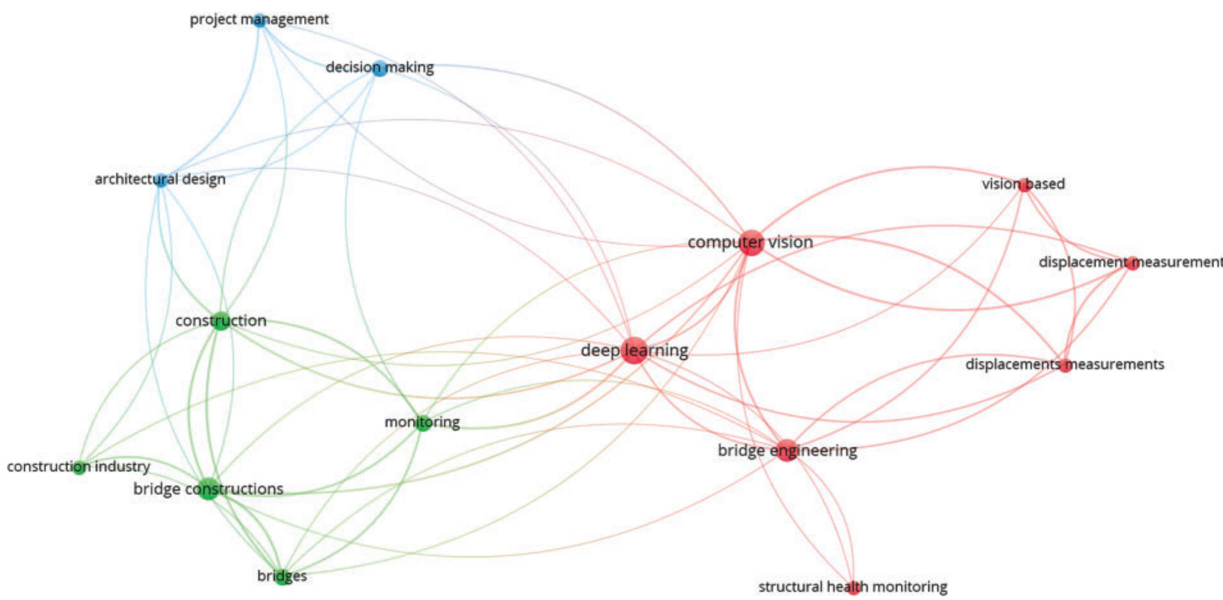


Figure 4. Co-occurrence network of keywords

of occurrence. The distances between nodes represent the strength of their relationships; smaller distances indicate stronger connections, while larger gaps signify weaker associations. Additionally, keywords are grouped into color-coded clusters based on their frequent co-occurrences. For example, keywords such as "deep learning," "computer vision," "bridge engineering," and "displacement measurement" frequently appear together, demonstrating their strong interrelatedness.

Systematic Review and Analysis

While scientometric analysis provides valuable insights, it cannot alone offer a comprehensive understanding of specific topics, especially when it comes to the utilization of AI. The application of computational intelligence, including AI, ML, DL, and CV, has advanced considerably in recent years. To achieve an in-depth understanding, a systematic review was performed on each selected article. The systematic analysis was categorized into three main areas, accompanied by qualitative discussions based on the extracted data. This structured review provides a thorough overview of the development and progression of computational intelligence applications in bridge engineering and management, with a particular focus on the construction phase.

AI in construction planning and scheduling

The complexity of bridge construction necessitates efficient resource management, precise scheduling, and comprehensive risk assessment. AI techniques, such as ML and DL, have significantly enhanced these planning activities. AI-driven optimization models facilitate effective resource allocation, minimizing idle times and costs by dynamically managing equipment and labor usage.[24,25] Advanced AI algorithms enable accurate prediction of project timelines, incorporating historical data and real-time site conditions

Table 5. AI in construction planning and scheduling

Reference	Year	Paper title
Pan[25]	2009	Hybrid Optimization for Dynamic Simulation of Moving Scaffolding System
Kim et al.[24]	2021	Automatic Creation of Heuristic-Based Truck Movement Paths
Moon et al.[29]	2022	Application of Neural Networks for Predicting Stress and Strain in Concrete Bridge Decks
Chatrabhuj and Meshram[28]	2024	Satellite Image Analysis for Sustainable Construction Site Identification
Wu et al.[27]	2024	Risk Assessment of Bridge Construction Using Random Forest
Taiwo et al.[26]	2025	Generative AI in Construction: Delphi Framework and Case Study

to forecast and continuously refine construction schedules.[26] Additionally, AI-supported risk analysis proactively identifies potential hazards and evaluates contingency strategies, allowing project managers to mitigate risks early and ensure smoother project delivery.[27,28] These AI applications collectively contribute to more efficient, reliable, and resilient bridge construction processes. The state-of-the-art literature review proposed by researchers for AI in construction planning and scheduling is presented in Table 5.

During the construction phase, AI techniques are leveraged for optimizing plans, allocating resources, and managing risks in bridge projects. Several papers address this phase. Pan[25] introduced a hybrid simulation-based optimization for scheduling a moving scaffolding system in bridge construction. By combining neural networks, genetic algorithms, and fuzzy logic, this approach optimizes equipment utilization and sequence, improving efficiency in formwork operations. Similarly, Kim et al.[24] developed a heuristic-based path planning method for construction trucks, using AI search algorithms to automatically generate efficient haul routes on site. This reduces idle time and enhances coordination of equipment movements. Generative AI is emerging as a tool for construction planning. Taiwo et al.[26] conducted a Delphi study to develop a framework for generative AI in construction, outlining how tools like ChatGPT and generative adversarial networks can assist in schedule generation, design optimization, and decision support. Their case study demonstrates AI-generated construction scenarios and schedules, showing that large language models and reinforcement learning can iteratively refine plans in response to real-time data. This highlights AI's potential in automatically producing and adjusting project timelines. The framework that construction professionals and firms can follow to develop tailored GenAI models using their proprietary data is illustrated in Fig. 5. The key steps include data collection, dataset preprocessing, training of custom GenAI models or implementing retrieval-augmented generation systems, evaluation of the models, and deployment.

AI is also applied to predict and mitigate risks during bridge construction. Wu et al.[27] employed a ML approach (random forest) to assess collapse risk in bridge construction, identifying key factors contributing to failures. By training on past accident data, their model can predict the probability of construction-stage failures, allowing project managers to proactively adjust plans or reinforce methods to prevent accidents. Such AI-driven risk analysis supports contingency planning by highlighting high-risk activities and suggesting preventive measures. Chatrabhuj and Meshram[28] proposed an AI-based approach for selecting sustainable construction sites. They designed a satellite image analysis model using convolutional neural networks (CNN) to classify terrain and land use and a Q-learning algorithm to account for continuous environmental monitoring. The system identifies optimal bridge locations with minimal environmental impact and monitors subsidence risks, integrating planning with long-term sustainability considerations. This AI-driven planning tool helps allocate resources to sites that ensure structural stability and environmental compliance.

AI in construction monitoring and quality assurance

AI has significantly enhanced bridge construction through advanced monitoring and quality assurance capabilities. Real-time monitoring of construction processes is increasingly achieved by integrating CV and drone technologies, providing rapid, continuous, and accurate assessment of site conditions and construction progress.[30,31] AI-driven methods facilitate automated detection of construction defects and deviations, employing DL models to quickly identify anomalies such as structural misalignments, cracks, or inadequate material placements.[32,33] Furthermore, AI-powered predictive analytics using ML algorithms analyze sensor data and historical records to anticipate potential quality issues, enabling proactive interventions and ensuring compliance with quality standards.[34,35] These innovations contribute substantially to reducing manual inspection efforts, minimizing errors, and enhancing overall structural reliability and durability. Table 6 summarizes the AI models used in construction monitoring and quality assurance.

AI techniques play a crucial role in real-time monitoring of construction processes and in assuring the quality of the bridge as it is built. The papers in this area predominantly leverage CV and sensor data to track construction progress, structural behavior, and defects. Multiple studies apply CV to monitor bridge structures during construction.

Figure 5. Framework for building custom GenAI model in the construction industry[26]

Table 6. AI in construction monitoring and quality assurance

Reference	Year	Paper title
Fan et al.[35]	2021	Machine Learning Applied to Design and Inspection of Reinforced Concrete Bridges
Li et al.[37]	2022	Signal Identification of Wire Breaks in Bridge Cables Using Machine Learning
Wang et al.[38]	2022	Visual Relationship-Based Identification of Key Construction Scenes
Choi et al.[36]	2023	Imaging Technology in Smart Bridge Inspection: Application Study
Chen and Zhang[32]	2024	Efficient and Lightweight Crack Monitoring Network with Adaptive Perception
Tang et al.[31]	2024	Computer Vision-Based Real-Time Monitoring of Pose for Bridge Cable Lifting
Cheng et al.[39]	2025	Real-Time In-Tube Concrete Level Tracking via Thermography and Vision
Hou et al.[30]	2025	Anti-Occlusion Vision-Based Method for Structural Motion Estimation
Liao et al.[34]	2025	Channel-Attention-Based LSTM Network for Temperature-Induced Response Modeling
Tian et al.[33]	2025	Noncontact Vision-Based Deformation Measurement Under Object Occlusion
Shi et al.[40]	2025	Computer Vision-Based Monitoring of Bridge Vibration During Incremental Launching

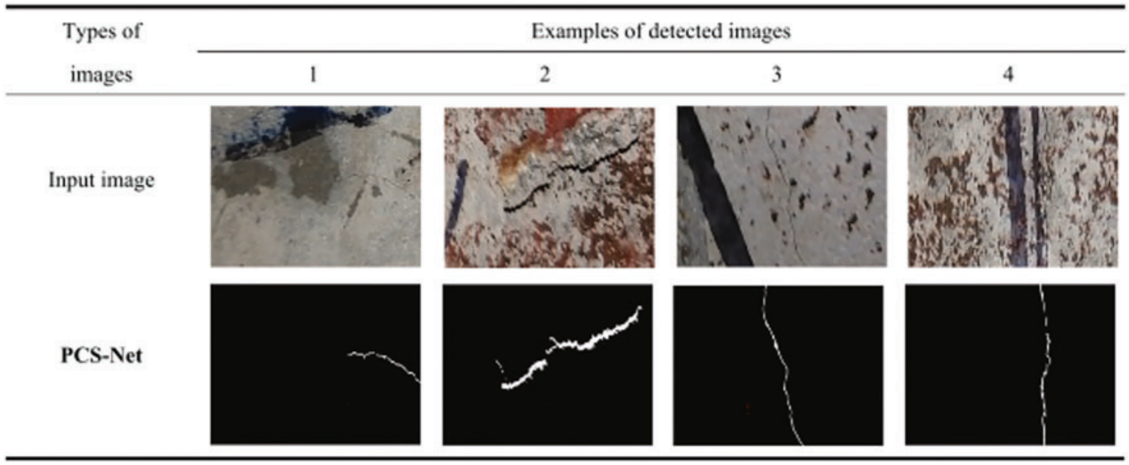


Figure 6. Visualized result of the PCSNet deep learning model[32]

Hou et al.[30] developed an anti-occlusion vision-based method to measure structural displacements. Their system uses correlation filters and a Gaussian mixture model to track targets on the bridge even when objects (workers, vehicles) temporarily block the view, achieving sub-pixel accuracy in deflection measurement. Building on vision techniques, Tian et al.[33] integrated DL in a noncontact deformation monitoring system for a long-span rigid-frame bridge under construction. By incorporating a CNN with attention mechanisms to handle occlusion and illumination variability, they improved the accuracy of deflection measurements during the incremental launching of bridge segments (a critical phase requiring symmetric deflection control). Tang et al.[31] focused on real-time monitoring of cable lifting operations using CV. They developed a monocular vision system to continuously track the pose (position and rotation) of bridge cables during installation. This real-time CV system helps ensure cables are lifted and positioned correctly, addressing safety issues since misalignment can lead to instability (a concern raised by past crane accidents). By providing immediate feedback on the cable geometry, the system supports on-site decision-making and quality control during the erection of suspension or cable-stayed bridges.

Ensuring concrete quality and detecting defects are vital QA tasks. Chen et al.[32] proposed an adaptive perception crack monitoring network for complex backgrounds. They designed a lightweight DL model (denoted "PCSNet") to segment and quantify cracks in images of concrete surfaces, even amid noise from rebar or formwork. The network efficiently identifies crack patterns and tracks their evolution over time, as demonstrated in a case where dynamic crack growth was monitored over 2 weeks. This AI-driven crack detection enables early remedial actions to maintain structural integrity. A visualized result of the PCSNet DL model is shown in Fig. 6. Similarly, Choi et al.[36] evaluated the use of imaging technology in a smart bridge inspection system. In their study, drones capture high-resolution images of the bridge under construction, and image analysis (photogrammetry and CV) is used to detect structural anomalies or misalignments. This approach verifies that modern imaging can reliably replace or augment manual inspections, improving coverage and objectivity in quality assurance. Their system primarily uses automated image processing; any critical findings can then be reviewed by engineers.

AI enhances traditional sensor monitoring by modeling complex structural responses. Liao et al.[34] developed a channel-attention bidirectional long short-term memory network to model temperature-induced responses in cable-stayed bridges. By training on long-term sensor data (strain and displacement) along with temperature readings, the DL model predicts how the bridge will deform due to thermal effects, distinguishing these from load-induced changes. Such predictive analytics help in separating normal thermal movements from potential issues during construction (e.g., differentiating heat effects from overstress). In another study, Cheng et al.[39] combined infrared thermography with CV to track concrete fill levels inside steel tubular arches in real time. Thermal cameras monitored the rising concrete in the arch ribs, while a vision algorithm interpreted temperature gradients to determine the fill height. This ensured complete filling of arch segments and detected any blockages or anomalies, thus guaranteeing quality in this critical construction step. Li et al.[37] tackled the issue of cable wire break detection in suspension bridge cables by using ML on heterogeneous sensor data. They employed a pattern recognition approach to identify the signal signature of wire fractures amidst strain and acceleration data, achieving timely detection of internal cable breaks that are invisible externally. This contributes to quality assurance by monitoring the health of tension elements during tensioning and service.

AI can also interpret construction progress from visual data. Wang et al.[38] introduced a visual relationship-based method to identify key construction scenes on highway bridges from site photos and videos. Their approach uses object detection (via CNN) to recognize equipment, materials, and personnel, and then infers the construction activity (e.g., formwork installation, concreting) by analyzing spatial relationships between detected objects. Fig. 7 shows that the detection result for workers wearing helmets in Fig. 7a is

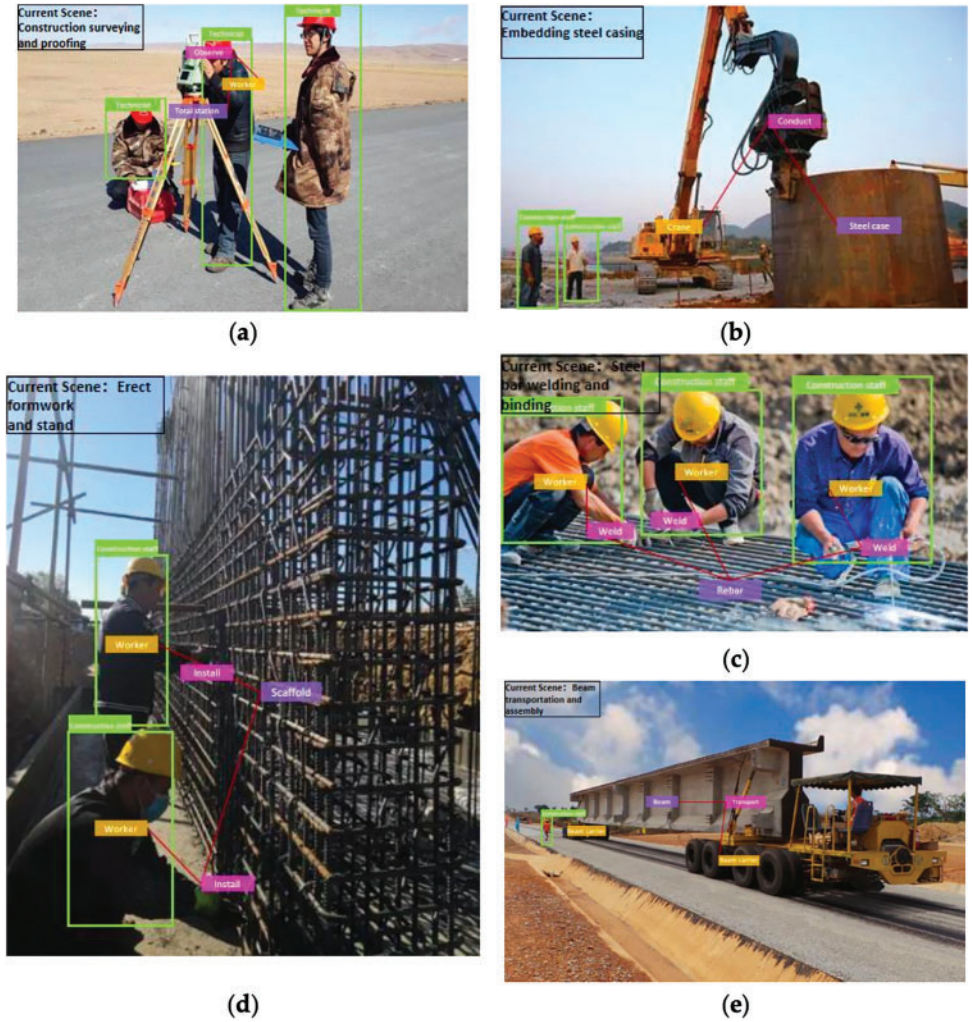


Figure 7. Partial results of the bridge key construction scene identification method[38]

a "technicist," while the workers wearing yellow helmets in Fig. 7b–e are detected as "construction staff." In particular, the method proposed in this paper can still accurately detect the type and location information of the relatively small-sized workers appearing on the left side of Fig. 7e. By automatically pinpointing when major milestones or critical activities occur, this technique enables more objective progress tracking and quality checks (e.g., confirming that each stage's requisite components are in place). Fan et al.[35] provide a broader overview of how ML aids design and inspection of concrete bridges. They summarize resilient methods for structural design optimization and emerging applications for inspection (such as CV for crack detection and digital twin simulations), highlighting that integrating AI during construction can improve both the structural performance and the quality control processes.

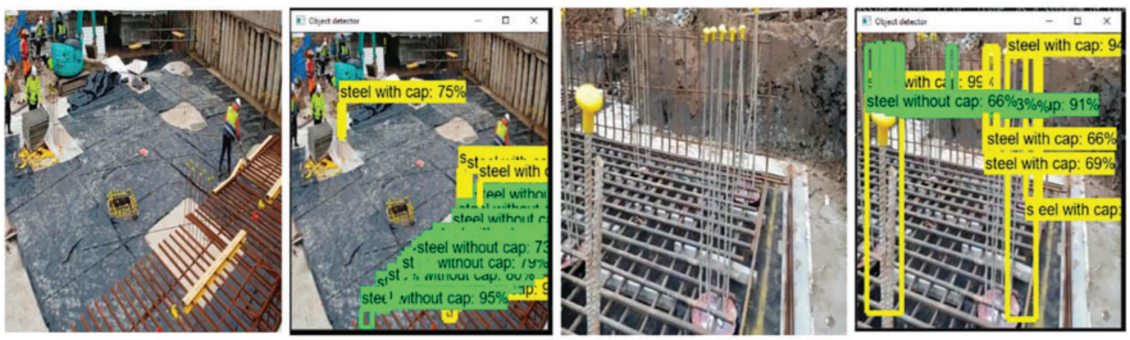
Shi et al.[40] developed a CV-based system to monitor girder vibrations during incremental launching construction of a bridge. Using high-frame-rate cameras, they tracked the vibration amplitudes of the bridge deck as each segment was jacked forward. The system could detect abnormal vibration patterns in real time, functioning as an early warning for potential issues like resonant excitation or support instability. By ensuring vibration levels remain within safe limits, this vision-based monitoring contributes to both quality assurance and safety during the launching process.

AI in safety management

Safety remains a paramount concern during bridge construction, and AI technologies offer significant advancements in hazard detection, worker safety monitoring, and emergency response planning. AI-based systems, particularly using CV and ML, enable real-time hazard detection by continuously monitoring site activities and identifying potential risks, such as improper equipment operation or lack of personal protective equipment (PPE).[31,41] Additionally, the integration of wearable technologies with AI algorithms helps in monitoring workers' health, fatigue, and unsafe behaviors, thereby preventing accidents before they occur. Furthermore, AI-driven predictive models assist in accident forecasting and emergency response planning, providing insights into possible high-risk scenarios and enabling proactive mitigation strategies.[27] These innovative applications significantly enhance construction safety,

Table 7. AI in safety management

Reference	Year	Paper title
Khan et al.[41]	2023	Construction Work-Stage-Based Rule Compliance Monitoring Framework Using Computer Vision (CV) Technology
Chen and Zhang[32]	2024	Efficient and Lightweight Crack Monitoring Network with Adaptive Perception
Tang et al.[31]	2024	Computer Vision-Based Real-Time Monitoring of Pose for Bridge Cable Lifting
Wu et al.[27]	2024	Risk Assessment of Bridge Construction Using Random Forest
Taiwo et al.[26]	2025	Generative AI in Construction: Delphi Framework and Case Sudy



(a) (b) (c) (d)

Figure 8. Detection results for two cases: "steel with cap" and "steel without cap"[41]

reduce incident rates, and promote a safer working environment on bridge construction sites. Ensuring safety on the construction site is a critical aspect where AI is increasingly applied for hazard detection, accident prevention, and emergency preparedness. The following works demonstrate how AI techniques enhance safety management during bridge construction. Table 7 provides a summary of the AI models utilized in safety management.

Khan et al.[41] proposed a work-stage-based rule compliance monitoring framework using CV to improve safety. Their system automatically checks if safety rules such as wearing PPE, proper scaffolding setup, and restricted zones are followed at each stage of construction. It uses DL-based object detection to identify workers, equipment, and safety gear in video feeds, and then applies predefined safety rules for each construction activity. For example, during deck concreting, the AI can flag if a worker enters an exclusion zone or if someone lacks a harness at height. This real-time hazard detection allows site managers to intervene before an accident occurs. Fig. 8 shows examples of true-positive prediction for steel with cap and steel without cap. The framework effectively uses ML to serve as an ever-vigilant "safety inspector," reducing the likelihood of human oversight errors. Wu et al.[27] leveraged AI for predictive safety analytics, focusing on the risk of bridge collapses during construction. By training on historical incident data, their random-forest-based model can predict the probability of collapse or major structural failure for ongoing projects under various conditions. The model considers factors like construction stage, temporary support configuration, weather, and crew experience. A high-risk prediction can trigger an early warning, prompting additional bracing or a review of construction methodology. Such AI-driven accident prediction tools are invaluable for emergency response planning, as they enable teams to allocate emergency resources (e.g., shoring materials, evacuation routes) in advance for high-risk operations and to develop contingency plans for worst-case scenarios.

Tang et al.[31] (mentioned earlier in monitoring) contributes to safety by preventing lifting accidents. Their vision-based cable lifting monitoring not only ensures quality but also averts hazards by detecting any misalignment or excessive sway in a lifted bridge cable. The system alerts operators to pause and correct issues, thus avoiding potential cable drops or tower strikes. This is an example of AI aiding real-time hazard mitigation. The system effectively functions as an automated safety officer specific to a high-risk activity (heavy lift). Likewise, Chen and Zhang's[32] crack monitoring system has safety implications. By catching crack propagation early, it prevents catastrophic failures during construction that could endanger workers. AI can also assist in preparing for and managing emergencies on site. Generative AI tools and simulations (as discussed by[26]) can be used to run what-if scenarios for emergency situations. For example, simulating a scaffold collapse or a crane failure and optimizing the response plans. While this review paper does not specifically detail an emergency response AI system, the risk assessment models (like Wu et al.'s) inherently support emergency planning by identifying the most vulnerable stages of construction. In practice, an AI system could integrate sensor data (structural monitoring, weather forecasts, etc.) and project metadata to forecast when and where an emergency is most likely, and recommend evacuation routes, stabilization measures, or alternative construction sequences to minimize harm.

Another emerging aspect of safety management is the use of wearable sensors combined with AI to monitor worker health and behavior. Although none of the reviewed papers is dedicated to wearables, related research indicates the potential. For instance, a study by Jebelli et al.[42] validated a gait-stability metric from wearable motion sensors to assess fall risk for ironworkers. Wearable devices integrated with AI and IoT technologies represent a transformative approach to proactive safety management on construction sites. Ibrahim et al.[43] highlighted the numerous benefits of wearable safety technologies, including continuous monitoring of worker health, fatigue detection, and real-time hazard alerts. Complementing these findings, Kim et al.[43] systematically reviewed wearable devices and data analytics within the construction industry, emphasizing how AI-driven analytics significantly enhance the predictive capabilities of wearable systems, thereby improving overall site safety management. Dobrucali et al.[45] also underscored the critical role of wearable technologies in boosting safety performance, stressing that the combined use of IoT and AI analytics can lead to substantial reductions in accident rates and improved health outcomes on construction sites. In general, AI algorithms can analyze data from smart helmets, vests, or boots to detect fatigue, slips, or abnormal vital signs, enabling proactive interventions. This area complements vision-based monitoring by focusing on the individual worker's condition and is an active avenue of AI-driven safety research.

Discussion

The integration of AI in construction planning and scheduling has significantly advanced resource optimization, schedule automation, and risk mitigation strategies. Hybrid approaches, such as the simulation-optimization model developed by Pan,[25] which incorporates fuzzy logic, genetic algorithms, and neural networks, have demonstrated strong capabilities in balancing time and cost objectives in bridge construction workflows. Similarly, the use of generative AI models, as illustrated by Taiwo et al.,[26] enables automated document processing and planning support, showing high potential in accelerating early project decision-making. Risk analysis methods, including ML-based predictive models like the random forest approach employed by Wu et al.,[27] enhance the early identification of structural and project risks. Despite these advances, challenges persist regarding data dependency, expert system configuration, and limited scalability of some models across different project types.[24,28] These limitations highlight the necessity for more adaptable and context-aware AI frameworks.

In the domain of construction monitoring and quality assurance, AI—particularly through CV, DL, and digital twins—has facilitated more efficient and accurate inspections of structural performance during the construction phase. Vision-based systems developed by Hou et al.,[30] Tian et al.,[33] and Tang et al.[31] enable real-time displacement and alignment tracking, enhancing the reliability of on-site decision-making. DL models for defect detection, such as the adaptive crack monitoring network proposed by Chen and Zhang,[32] offer high precision in identifying surface-level damage. Predictive analytics based on sensor data, as seen in the work of Liao et al.,[34] further support quality assurance by forecasting performance deviations under varying conditions. However, these methods face practical challenges, including sensitivity to environmental factors (e.g., lighting, occlusion), high computational demands, and technical complexity that may limit their widespread application on smaller projects.[35,38] Therefore, while AI contributes substantially to construction monitoring, its implementation must be matched with adequate infrastructure and domain expertise.

From a safety management standpoint, AI technologies have enabled proactive and automated detection of on-site hazards and unsafe behaviors. For instance, Khan et al.[41] developed a rule-based safety compliance framework using CV and DL to monitor adherence to safety protocols in real time. Similarly, Tang et al.[31] demonstrated how vision-based systems could support safe cable lifting by monitoring movement patterns and detecting anomalies. ML-driven risk prediction models, as shown by Wu et al.,[27] have proven effective in identifying high-risk construction scenarios before incidents occur. Wearable sensor integration and predictive response planning, as explored in the generative AI framework by Taiwo et al.,[26] show further promise in enhancing worker safety and emergency preparedness. Nevertheless, widespread deployment of these systems is often hindered by limitations in training data diversity, infrastructure requirements (e.g., camera and sensor networks), and the need for continuous system updates to reflect evolving site conditions.[32] Addressing these issues is critical to maximizing the reliability and acceptance of AI in construction safety practices.

In advancing the analytical depth, this discussion highlights comparative evaluations across various AI techniques, particularly focusing on their effectiveness, scalability, and practical integration into construction tasks. Within construction planning and scheduling, comparative analysis reveals that ML-based models excel in predictive accuracy and adaptability, outperforming traditional optimization methods in dynamically adjusting schedules. Conversely, genetic algorithms demonstrate superior capabilities in resource optimization when faced with fixed constraints but may be less flexible in handling real-time adjustments. Generative AI techniques, while powerful in scenario planning and decision support, often demand significant computational resources and extensive data training, posing scalability challenges. For construction monitoring and quality assurance, CV techniques demonstrate considerable advantages in precision, real-time processing, and automation capabilities, surpassing conventional manual inspection methods. However, CV models are highly sensitive to environmental conditions such as lighting and weather, potentially limiting their reliability and generalizability. In contrast, ML and DL models, when integrated with sensor data, provide robust defect detection capabilities under diverse environmental conditions but require extensive datasets for training and high computational infrastructure, influencing their scalability. Thus, a balanced hybrid approach combining CV with ML could address individual limitations and enhance overall system robustness and scalability. In construction safety management, comparative evaluation suggests that wearable devices and IoT systems equipped with AI analytics offer superior continuous monitoring and real-time alerting compared to traditional manual oversight. Yet, these systems face challenges such as user acceptance, data privacy concerns, and the unpredictability of human behavior, impacting real-world deployment effectiveness. Conversely, CV-based monitoring provides immediate hazard detection and compliance enforcement, but its practical deployment often requires significant infrastructure investment and complex system integration. Overall, this comparative synthesis underscores the necessity of strategically selecting and integrating AI techniques based on specific project requirements, environmental constraints, and scalability considerations to maximize their effectiveness and practical applicability in bridge construction and management.

Conclusion and Future Research Opportunities

This paper provides an in-depth analysis of the application of AI in bridge engineering and management, specifically addressing construction phase applications through ML, DL, and CV technologies. Drawing from 191 research articles retrieved from the Scopus database, it is evident from the review that significant advancements have been made, particularly in improving predictive accuracy for planning and scheduling, enhancing real-time monitoring for quality assurance, and establishing proactive safety management practices. However, despite these technological advancements, practical readiness varies significantly across different AI tools. CV systems and wearable technologies have demonstrated substantial practical utility due to their immediate impact on monitoring safety and quality in real time. Conversely, complex generative AI and DL models, while powerful, often encounter practical deployment hurdles related to computational demands, extensive data requirements, and specialized expertise for model maintenance. Key research gaps identified include the need for more generalized and scalable AI models that can adapt effectively across diverse project conditions and environments. Further, there is a notable absence of comprehensive frameworks for seamlessly integrating multiple AI methodologies into cohesive operational workflows. Addressing these gaps offers fertile ground for future research endeavors.

Emerging research opportunities encompass the refinement of hybrid models that combine the predictive strengths of ML with the detailed analytical capabilities of DL and CV. There is also significant potential in advancing digital twin technologies to enhance real-time decision-making and predictive maintenance during bridge construction, leveraging real-time data integration and analytics. Barriers to industry adoption primarily involve high initial investment costs, challenges associated with managing and interpreting vast amounts of generated data, and resistance due to limited awareness or trust in AI capabilities among construction practitioners. Strategic approaches such as improving the explainability of AI decisions, simplifying user interfaces, and ensuring compatibility with existing industry processes and regulations will be critical to overcoming these adoption barriers. In conclusion, continued research should strategically focus on overcoming integration challenges, enhancing model scalability and generalizability, and fostering practical adoption through improved usability and clearer demonstrable benefits. Such targeted efforts will significantly contribute to the broader integration and acceptance of AI in bridge construction practices, ultimately enhancing the efficiency, safety, and sustainability of bridge infrastructures.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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