JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

THE ROLE OF AI IN ENHANCING ENERGY EFFICIENCY IN MODERN CONSTRUCTION: INNOVATIONS AND TRANSFORMING CONSTRUCTION AND DESIGN PRACTICES FOR A GREENER FUTURE

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Abstract: This article delves into the transformative impact of artificial intelligence (AI) on energy efficiency within the modern construction sector. It highlights various AI-driven innovations that are revolutionizing the industry by optimizing design processes, improving construction methodologies, and integrating sustainable practices. Through a detailed examination of practical applications, the paper elucidates how AI enhances energy efficiency by employing smart design software, predictive analytics, and automated construction technologies. Furthermore, it discusses the benefits of these advancements, such as reduced energy consumption, minimized material waste, and the seamless incorporation of renewable energy sources. The article also addresses the challenges and future prospects of AI in construction, including cost implications, skill gaps, and data privacy concerns. By providing a comprehensive analysis, this paper underscores AI's pivotal role in fostering a greener, more sustainable future for the construction industry (Sawhney, Riley, & Irizarry, 2020; Bock & Linner, 2015; Dallasega, Rauch, & Matt, 2018; Esmaeili & Hallowell, 2012; Brynjolfsson & McAfee, 2014).

Keywords: Artificial Intelligence (AI), Energy Efficiency, Modern Construction, Sustainable Building Practices, AI Innovations in Construction, IoT

1. Introduction

The construction industry is currently navigating an era of heightened scrutiny and regulatory demands for sustainable practices. This shift is driven by the urgent need to address environmental concerns such as climate change, resource depletion, and the overall ecological footprint of construction activities. As governments and regulatory bodies impose stricter guidelines, the industry is compelled to innovate and adopt more sustainable methodologies (Sawhney, Riley, & Irizarry, 2020).

Artificial intelligence (AI) has emerged as a key enabler in this transformation, offering tools and technologies that can drastically improve energy efficiency across various aspects of construction. AI's ability to process vast amounts of data, identify patterns, and make predictive analyses positions it as a powerful catalyst for change in an industry traditionally resistant to rapid technological shifts (Brynjolfsson & McAfee, 2014).

This paper delves into the multifaceted ways AI is being harnessed to optimize construction processes, enhance building designs, and integrate renewable energy sources, thereby contributing to a more sustainable and energy-efficient future. The integration of AI in construction not only promises to reduce energy consumption but also aims to streamline operations, reduce waste, and improve overall project efficiency (Bock & Linner, 2015).

1.1 Optimization of Construction Processes

AI's impact on construction processes is profound, particularly through the use of automation and predictive analytics. Automated construction machinery, such as AI-driven robots, can perform repetitive and precise tasks more efficiently than human workers. These machines reduce material waste and energy consumption by optimizing resource use and minimizing errors. Additionally, AI-powered predictive analytics enable project managers to foresee potential issues, optimize schedules, and allocate resources more effectively, leading to substantial energy savings (Esmaeili & Hallowell, 2012).

1.2 Enhancement of Building Designs

AI is revolutionizing the design phase of construction projects. Advanced AI-powered design tools allow architects and engineers to create highly energy-efficient buildings by simulating various design scenarios and assessing their impact on energy use. These tools take into account factors such as natural light, ventilation, and thermal performance, helping to develop designs that maximize energy efficiency. Furthermore, AI aids in the selection of sustainable materials, ensuring that buildings are constructed using resources that offer optimal energy performance and minimal environmental impact (Dallasega, Rauch, & Matt, 2018).

1.3 Integration of Renewable Energy Sources

Incorporating renewable energy sources into building designs is another significant area where AI proves indispensable. AI algorithms can optimize the placement and performance of solar panels, wind turbines, and other renewable technologies, ensuring that buildings are capable of generating and utilizing clean energy effectively. This integration not only decreases dependence on non-renewable energy sources but also significantly reduces the carbon footprint of construction projects (Bock & Linner, 2015).

1.4 Challenges and Future Prospects

While the potential benefits of AI in construction are substantial, several challenges need to be addressed. The high initial costs associated with implementing AI technologies, the need for a skilled workforce capable of managing these systems, and concerns over data privacy are significant barriers to widespread adoption. However, as technology continues to advance and the industry gains more experience with AI applications, these challenges are expected to be mitigated (Sawhney, Riley, & Irizarry, 2020).

Looking to the future, the ongoing development and integration of AI in the construction industry hold tremendous promise. The potential for AI to drive energy efficiency and promote sustainable practices is vast, making it a crucial component of the construction industry's strategy to achieve a greener, more sustainable future.

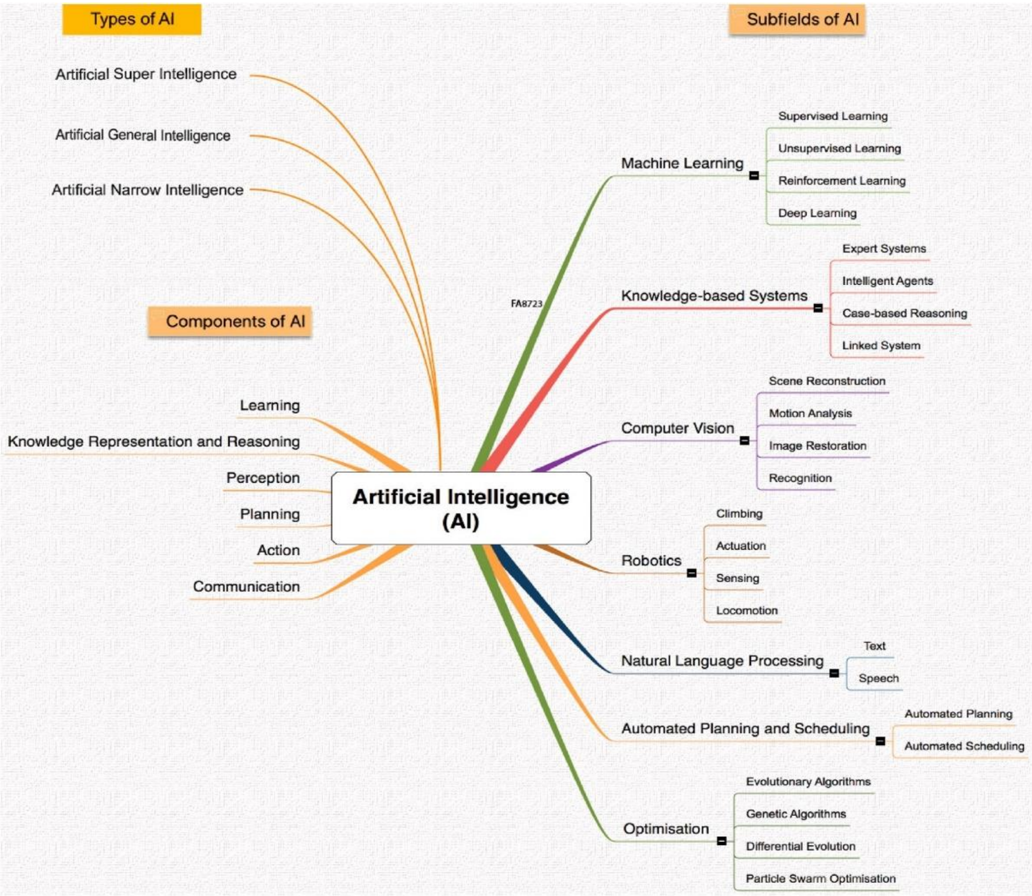
2. Literature Review

The concept of creating machines with human-like intelligence has roots in various fields, including philosophy, fiction, imagination, computer science, electronics, and engineering inventions. A significant milestone in AI was Alan Turing's test for intelligence, which surpassed traditional theological and mathematical perspectives on the potential for intelligent machines. Sixty years later, AI has evolved to outperform humans in numerous domains such as learning, driven by advancements in big data and computational power. AI is defined as "the study of how to make machines do things which, at the moment, people do better", capturing the essence of AI's goals.

AI can be categorized into three types: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, also known as weak AI, is designed to perform specific tasks, such as playing chess, predicting sales, suggesting movies, translating languages, and forecasting weather. AGI, or strong AI, aims to create machines that can operate at the same level as humans, capable of solving complex problems across different domains, autonomously controlling themselves, and possessing their own thoughts, feelings, and dispositions, although this remains a challenging goal. ASI focuses on developing machines that surpass human capabilities across various domains.

The primary components of AI, depicted in Figure 1, include: (1) learning, (2) knowledge representation, (3) perception, (4) planning, (5) action, and (6) communication. Some studies classify these components as tasks that AI can perform, akin to human senses.

Understanding the current state of AI in the construction industry requires identifying its major subfields, as shown in Figure 1. The advancement of AI applications in industry has led to the emergence of several well-known subfields, including (a) machine learning, (b) computer vision, (c) natural language processing, (d) knowledge-based systems, (e) optimization, (f) robotics, and (g) automated planning and scheduling. An overview of each subfield is provided below.



2.1. Machine Learning

Machine Learning (ML) focuses on designing and using computer programs to learn from experience or past data for modeling, control, or prediction using statistical techniques without explicit programming. ML methods include:

Supervised Learning: Involves machines making decisions based on labeled datasets, categorized into classification and regression.

Unsupervised Learning: Involves machines learning structures from unlabeled datasets, categorized into clustering and dimension reduction techniques.

Reinforcement Learning (RL): Defined as "learning a mapping from situations to actions to maximize a scalar reward or reinforcement signal", involving learning from interactions with the environment.

Deep Learning: Represents the state-of-the-art in ML, providing more accurate predictions than conventional techniques.

2.2. Computer Vision

Computer Vision is a multidisciplinary field focused on simulating the human visual system. Its goal is to enable machines to achieve a high-level understanding of digital and multidimensional images by capturing images through appropriate devices, processing them with advanced algorithms, and analyzing them to facilitate decision-making.

2.3. Automated Planning and Scheduling

Planning is a subfield of AI that enables intelligent systems to achieve desired goals by carefully selecting and sequencing actions based on expected outcomes. Scheduling involves selecting plans and allocating time and resources to achieve goals based on available resources. Planning and scheduling techniques are adopted to provide solutions to complex applications, using heuristics, optimization techniques, and genetic algorithms.

2.4. Robotics

Robotics involves designing, manufacturing, operating, and maintaining robots, which are highly automated devices that perform physical tasks in the real world. Robots interact with their environment using sensors and actuators and are typically used for specialized tasks. Most learning problems in robotics are reinforcement learning problems.

2.5. Knowledge-Based Systems

Knowledge-based systems (KBS) involve machine decision-making based on existing knowledge, consisting of a knowledge base, an inference engine, and a user interface. The knowledge base stores expert knowledge, past cases, or other relevant sources. KBS are classified into:

Expert Systems: Use task-specific knowledge from experts to imitate human decision-making.

Case-Based Reasoning (CBR) Systems: Use past experiences or cases to explain or critique new situations.

Intelligent Tutoring Systems: Use AI to provide tailored tutoring.

Database Management Systems (DBMS) with Intelligent User Interfaces: Driven by AI, these systems allow easy traversal of complex information networks.

2.6. Natural Language Processing

Natural Language Processing (NLP) focuses on creating computational models that mimic human linguistic capabilities. NLP applications include machine translation, text processing and summarization, user interfaces, multilingual information retrieval, speech recognition, and expert systems. NLP tasks include part-of-speech tagging, chunking, named entity recognition, and semantic role labeling.

2.7. Optimization

Optimization involves making decisions that yield the best outcomes within given constraints. Originating as a mathematical discipline, optimization now includes evolutionary algorithms (EA) developed alongside AI, such as evolutionary strategies (ES), evolutionary programming (EP), genetic algorithms (GA), differential evolution (DE), and particle swarm optimization (PSO).

3. Methodology

A comprehensive review of the literature was conducted to explore the existing applications of artificial intelligence (AI) in the construction industry. To achieve this, database queries were executed on the SCOPUS database, with additional validation from other sources such as the Institute of Electrical and Electronics Engineers (IEEE), the Association for Computing Machinery (ACM), and Science Direct, covering the period from 1960 to 2020. This timeframe was selected to trace the evolution of AI adoption in the construction industry, beginning from the 1950s when modern AI research emerged. The objective was to identify trends, research gaps, opportunities, and challenges in the field.

The chosen databases (SCOPUS, IEEE, ACM, and Science Direct) were selected due to their extensive collections of high-impact publications in construction, engineering, and computer science. SCOPUS, being the largest citation database of research literature and web sources, served as the primary data source, while the other databases were utilized for downloading full articles and validating data.

The initial observations indicated that most studies concentrated on specific AI techniques to achieve their goals. Consequently, the search focused on these techniques. Twenty-nine free-text keywords representing AI subfields and the construction industry were used, including "Robotics," "Computer Vision," "Machine Learning," "Expert Systems," "Knowledge-based Systems," "Optimization," "Natural Language Processing," "Artificial Intelligence," "K-Means Clustering," "Hierarchical Clustering," "Fuzzy Clustering," "Model-based Clustering," "Linear Discriminant Analysis," "Monte Carlo," "Deep Belief," "Deep Boltzmann," "Deep Learning," "Convolutional Neural Network," "Stacked Autoencoders," "Recurrent Neural Network," "Deep Neural Network," "Speech Processing," "Evolutionary Computing," "Evolutionary Algorithms," "Swarm Intelligence," "Discrete Optimization," "Convex Optimization," "Automated Planning," and "Automated Scheduling" combined with "Construction Industry."
The search was restricted to English-language articles. For keyword searches yielding over 100 articles, conference papers were excluded, based on the premise that the domain is well-established in construction, and many conference papers have already been expanded into journal articles. This approach was particularly effective for the domains of optimization and knowledge-based systems, which each yielded over 500 papers. For subfields with further classifications, such as machine learning, knowledge-based systems, and optimization, additional searches were conducted using the same method.

Out of 1800 publications assessed, 1272 were deemed relevant and included for further analysis. The main inclusion criteria were the description or evaluation of an AI subfield and its practical application in the construction industry, based on the abstract, title, or full-text article when necessary. For each article, data were extracted on the following aspects: (i) application area in construction, (ii) methodology/techniques used, and (iii) findings.

4. State-of-the-Art and Future Opportunities of AI Applications in the Construction Industry

4.1. Trends of AI Application in the Construction Industry

Figure 2 highlights the growing trend of publications in the field of artificial intelligence from the 1960s onwards. In the 1960s, AI use was in its infancy, with very few publications focusing on optimization techniques. Over time, optimization has become a primary research interest in applying AI subfields to the construction industry, likely due to the industry's longstanding struggle with low productivity levels. Another notable trend is that machine learning has surpassed knowledge-based systems as a focal area in the construction industry over the last decade, driven by the need to address labor and skill shortages. Additionally, robotics has gained prominence in AI applications within the construction sector, particularly with the introduction of 3D printing, exoskeletons, and UAV technologies. Conversely, natural language processing remains the least researched AI subfield in construction.

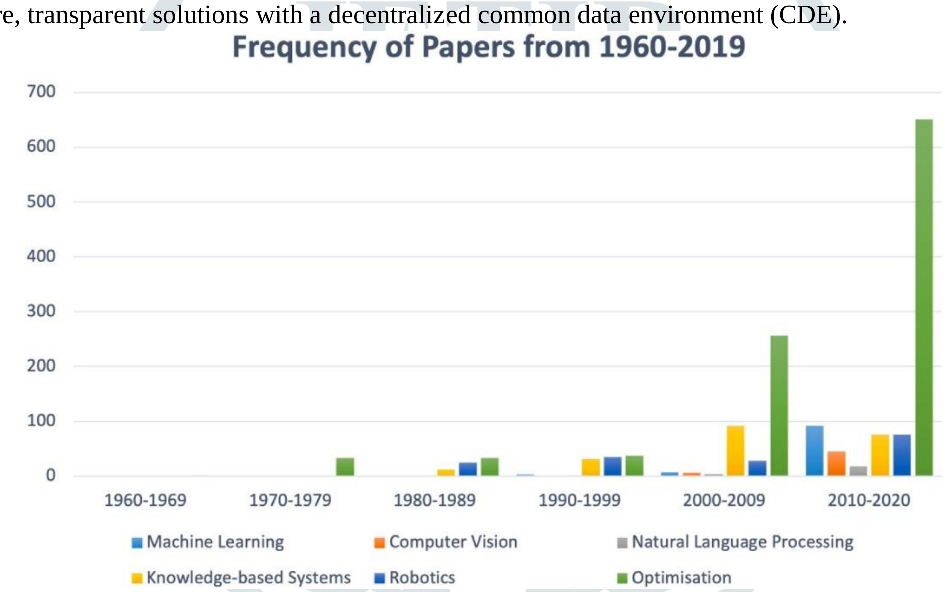
Over 60% of AI application research in construction has occurred in the past decade, contributing to or enhancing advanced technologies such as: (1) Quantum computing, (2) Internet of Things (IoT), (3) Cybersecurity, and (4) Blockchain. Quantum computing offers the potential to solve specific computational tasks more efficiently than classical computers, with quantum algorithms proving more effective than traditional ones. AI can leverage quantum computing capabilities to accelerate problem-solving and optimize solutions.

The internet has evolved from facilitating human communication to enabling interaction between objects and humans, creating a smart environment. This shift has been driven by advances in sensors, actuators, wireless technologies (e.g., RFID), cloud computing, and more powerful, cost-effective devices. In construction, IoT integration with AI has facilitated various applications, such as intelligent building energy monitoring for energy savings, IoT-enabled building information modeling (BIM) platforms for real-time visibility and traceability in prefabricated construction, and dynamic safety barriers for hazard energy on underground construction sites.

However, the benefits of increased internet access and interconnected systems are threatened by evolving cyber threats, including malware, social engineering, and phishing. Although the construction industry has not been a primary focus in cybersecurity discussions, the adoption of level 3 BIM and growing reliance on virtual environments will likely increase vulnerability to cybercrime. Integrating BIM with external data sources makes it particularly susceptible to cyber-attacks. Any digital technology used in construction, including AR/VR, IoT, and AI technologies like robots, is at risk without proper network security and response plans.

Since its invention in 2008, Blockchain technology has rapidly grown in adoption, particularly in cryptocurrency, risk management, IoT, and public, social, and financial services.

Blockchain technology ensures transaction legitimacy, prevents double-spending, and enables high-value transactions in distrustful environments using cryptography and a consensus mechanism for verification. Recent applications of blockchain in construction include logistics of construction materials, integration with IoT and BIM to manage building lifecycle data, and enhancing manufacturing supply chains in the composite materials industry. These applications are significant and have the potential to address many of the trust, communication, and transparency issues in the construction industry. Integrating AI with blockchain technology could develop secure, transparent solutions with a decentralized common data environment (CDE).



4.2 Application of AI Subfields in the Construction Industry

Tables 1 and 2 present the applications, advantages, and limitations of various AI subfields within the construction industry. Across all subfields, common advantages include increased cost and time savings, improved safety, better accuracy, and overall increased productivity. However, some limitations include incomplete data, high initial deployment costs, and challenges in data and knowledge acquisition.

4.3 Common Application Areas and Future Opportunities for AI in Construction

Table 3 identifies fourteen subdomains where AI is applied in the construction industry, highlighting state-of-the-art advancements and potential future opportunities. These subdomains include resource and waste optimization, value-driven services, supply chain management, health and safety, AI-driven construction contract analytics, voice user interfaces, and AI-driven audit systems for construction financials.

4.3.1. Resource and Waste Optimization

The rapid development in construction generates significant amounts of construction and demolition waste (C&DW) annually, impacting environmental, natural, and human resources globally. There is a shift from reactive waste management to proactive data-driven approaches like waste analytics (WA), aiming to minimize waste through design. BIM is increasingly used as a virtual, cost-effective environment to enable construction design that minimizes waste generation. Advanced data analytics techniques can produce detailed waste generation profiles, suggesting the use of AI techniques for effective waste management. Combining AI techniques with BIM can optimize design for offsite construction, material selection, reuse and recovery, waste-efficient procurement, deconstruction, and flexibility.

4.3.2. Value-Driven Services

This section discusses various non-core services that can benefit from emerging AI trends in the construction industry.

4.3.2.1. Estimation and Scheduling

AI-based estimation models have wide applicability in construction, particularly for early predictions of construction costs and durations, which are critical for project success. Unreliable cost and time estimates can have significant economic and financial implications. BIM, the current state-of-the-art in construction, enhances the reliability of cost and time estimates by integrating time (4D) and cost (5D) to BIM enables better planning at the early design stage for project scheduling and cost estimation (Jrade & Lessard, 2015; McCuen, 2018). However, despite the significant benefits of BIM, evidence suggests that its automation advantage only encompasses information within the model, overlooking external subjective factors, additional materials, and resources (Golaszewska & Salamak, 2017). Therefore, applying BIM for cost and time estimation still demands extensive work for the cost estimator.

This underscores the need for integrating advanced AI techniques such as deep learning with BIM for cost and time prediction to capitalize on enhanced accuracy. Deep learning techniques can also enhance predictions of other relevant factors like bankruptcy, success, energy, carbon efficiency, and waste.

4.3.2.2. Emerging Trends in Construction Site Analytics

Construction sites are rapidly evolving into smart working environments with the increasing prevalence of IoT sensors and other digital technologies (Lin & Golparvar-Fard, 2019). Construction site analytics involves generating, collecting, storing, and analyzing construction site data to derive deep insights for visualization (Lin & Golparvar-Fard, 2019). A vast amount of data, including images, videos, and reports, is generated on construction sites, mostly unstructured. This data can be aggregated in BIM and analyzed using advanced AI techniques to optimize site performance in key areas such as planning, design, safety, quality, schedule, and cost (Schwabe et al., 2020).

For instance, there is a need to develop a holistic site analytics tool using AI for real-time, cloud-powered analytics of data generated on the construction site. This tool will enhance productivity, and quality control, and help achieve performance targets. Additionally, a construction site AI Chabot providing real-time updates about site activities would be invaluable for project managers and other stakeholders.

4.3.2.3. Impact on Job Creation in Construction

Construction jobs rank third highest at risk of automation in the next decade due to the increasing prevalence of automation technologies like AI and IoT (Lin & Golparvar-Fard, 2019). However, the adoption of such technologies could also lead to the creation of entirely new roles to assimilate and reskill displaced workers in the industry.

For example, the advent of BIM has created new roles such as BIM project manager, director, coordinator, and designer. Similarly, the adoption of digital technologies like AI will give rise to new types of jobs such as construction AI researchers, trainers, and engineers. These researchers will drive AI adoption in the construction industry through continuous research and innovation, while engineers will focus on developing and deploying cutting-edge AI solutions tailored to the construction sector. Trainers and testers will also be essential to ensure the effective deployment of AI solutions, with displaced workers potentially serving as trainers and testers for systems replacing them.

4.3.2.4. Integration of AI and BIM with Industry 4.0 Tools

BIM represents the current state-of-the-art in the architecture, engineering, and construction (AEC) industry, with global adoption (Lin & Golparvar-Fard, 2019). For instance, the UK government has mandated BIM level 2 for all publicly procured projects. However, despite efforts to establish BIM as the global standard, its adoption rate remains low [112]. Therefore, it is crucial to conduct research on methods to enhance BIM adoption. For instance, some studies have combined BIM applications with AI subfields like NLP to improve the navigation of BIM interfaces. Styhre et al. (2006) highlighted the reliance of construction practice on direct verbal and symbolic communication for sharing expertise and information. Given that speech is one of the oldest and most natural forms of communication, integrating voice interaction with BIM can make it feel more intuitive and aligned with the nature of construction. Additionally, other studies have integrated AI and BIM with Industry 4.0 tools such as the Internet of Things (IoT), smart cities, augmented reality, blockchain, and quantum computing (Please refer to Table 3).

4.3.3. Revolutionizing Supply Chain Management with AI

A recent study by Luo et al. [113] explored factors affecting supply chain excellence and outcomes, revealing issues such as SCM knowledge education and supply chain culture. Major barriers include lack of top-level buy-in, understanding of the supply chain, high cost of advanced IT for SCM, absence of unique performance measurement frameworks, and lack of organizational trust and effective communication channels between partners [114,115]. AI techniques can address these hindrances to supply chain excellence.

For instance, Tsang et al. [89] developed an IoT-based real-time risk monitoring system for controlling product quality and occupational safety risks in cold chains. Real-time integration in decentralized supply chains is a priority for European institutions and industries [90]. Xiong et al. [91] developed a process specification language to enhance supply chain communication for offsite construction. This study advocates for the development of a decentralized supply chain knowledge management and monitoring system. The combination of blockchain for transaction transparency and legitimacy, along with AI-powered analytics, has the potential to resolve organizational trust and communication issues in construction supply chains. For example, Mondragon et al.

[62] explored blockchain's applicability to enhance manufacturing supply chains, demonstrating a tamper-proof history of product manufacturing and storage. AI can manage the entire supply chain process, detecting potential issues and ensuring timely and quality project delivery. Moreover, AI chatbots for supply chain management systems can streamline information access.

Aspect	Description	AI Applications
Demand Forecasting	AI algorithms improve accuracy in predicting product demand by analyzing historical data, market trends, and external factors.	Machine learning models for predictive analytics, time series analysis
Inventory Management	Optimizes stock levels to reduce overstock and stockouts by continuously monitoring inventory and adjusting based on real-time data.	Automated stock replenishment systems, real-time tracking
Supplier Managemen	Enhances supplier selection, evaluation, and relationship management by analyzing performance data and market conditions.	AI-driven supplier risk assessment, performance analytics
Innovation and Development	Accelerates innovation in product development and supply chain processes by leveraging AI for research and development, and process improvements.	AI for R&D insights, process innovation tools

4.3.4. Prioritizing Health and Safety Analytics

Health and Safety analytics (HSA) utilizes advanced data analytics techniques to predict and prevent occupational accidents in the workplace. The construction industry experiences significantly higher rates of occupational injuries and deaths compared to other industries [116]. Due to onsite dangers like working from heights, getting trapped, falling objects, and equipment hazards, proactive measures facilitated by AI-driven analytics are essential for mitigating risks and ensuring worker safety.

Conclusion

AI stands poised to revolutionize numerous industries, offering innovative solutions to enhance productivity and tackle challenges. The construction sector, plagued by productivity issues and various hurdles, stands to benefit significantly from AI advancements. With the exponential growth of data throughout the building lifecycle and the emergence of complementary digital technologies, AI holds the potential to harness this data and synergize with other technologies to streamline construction processes.

In addressing the research questions of this study, we delved into the extent of AI utilization within the construction domain. Our exploration spanned the latest research as well as relevant publications from the past six decades across various construction application areas. We provided a concise explanation of AI concepts, types, components, and subfields, along with insights into works utilizing these subfields. Additionally, we offered a succinct overview of the application areas, advantages, limitations, and benefits associated with each AI subfield in construction.

Employing a qualitative approach, we reviewed publication trends for AI and its subfields using databases such as SCOPUS, Science Direct, IEEE, and ACM spanning six decades (1960–2020). These databases were chosen for their robustness and integrity to minimize bias. Our findings categorized AI subfields into emerging, ripe, and mature fields in construction research. Notably, computer vision, robotics, and NLP were classified as emerging technologies, while ML, automated planning, and scheduling were deemed ripe, and KBS and optimization were considered mature.

Based on our analysis, we designed a hype cycle to predict the maturity duration of each subfield. Despite the application of various AI technologies in construction research, recent advancements in these technologies have been underutilized, with the slow adoption of newer, more powerful AI technologies such as deep learning.

Furthermore, we identified and discussed additional opportunities and open research issues for AI in construction. The growing relevance of AI is bolstered by emerging trends like BIM, IoT, quantum computing, augmented reality, cybersecurity, and blockchain. We addressed challenges hindering AI adoption in the industry and provided recommendations.

This study serves as a valuable resource for researchers and practitioners alike, offering insights into relevant AI applications and research in the construction sector. It provides a clear understanding of the inherent opportunities and potential barriers associated with AI application subfields. Construction stakeholders, including regulatory bodies, decision-makers, skilled workers, and technology enthusiasts, can leverage the information presented herein to chart a clear path to AI implementation and mitigate potential risks.

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