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## Article

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Article

# Opportunities and Adoption Challenges of AI in the Construction Industry: A PRISMA Review

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**Abstract:** Artificial intelligence (AI) is a powerful technology with a range of capabilities, which are beginning to become apparent in all industries nowadays. The increased popularity of AI in the construction industry, however, is rather limited in comparison to other industry sectors. Moreover, despite AI being a hot topic in built environment research, there are limited review studies that investigate the reasons for the low-level AI adoption in the construction industry. This study aims to reduce this gap by identifying the adoption challenges of AI, along with the opportunities offered, for the construction industry. To achieve the aim, the study adopts a systematic literature review approach using the PRISMA protocol. In addition, the systematic review of the literature focuses on the planning, design, and construction stages of the construction project lifecycle. The results of the review reveal that (a) AI is particularly beneficial in the planning stage as the success of construction projects depends on accurate events, risks, and cost forecasting; (b) the major opportunity in adopting AI is to reduce the time spent on repetitive tasks by using big data analytics and improving the work processes; and (c) the biggest challenge to incorporate AI on a construction site is the fragmented nature of the industry, which has resulted in issues of data acquisition and retention. The findings of the study inform a range of parties that operate in the construction industry concerning the opportunities and challenges of AI adaptability and help increase the market acceptance of AI practices.

**Keywords:** artificial intelligence (AI); construction industry; construction technology; construction ecosystem; innovation ecosystem; AI opportunities; AI adoption challenges; industry 4.0; technology adoption; open innovation



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## 1. Introduction

In a rapidly urbanizing world, the construction industry innovations are critical to aid in addressing urban sustainability challenges [1–3]. Nonetheless, in recent decades, the construction industry continued to be one of the low innovation sectors with limited productivity and growth [4]. This is evident, as the construction industry is one of the least digitalized industries in the world in comparison to manufacturing, retail, and telecommunication. The productivity growth in the construction industry has only increased by 1% annually over the past two decades and consequently has raised questions about the industry's efficiency [5–8]. The fundamental rules and characteristics of the construction industry have contributed to the slow performance growth.

In response to this slow performance growth, companies are beginning to explore artificial intelligence (AI) to streamline processes and increase productivity [9,10]. The benefits include prevention of cost overruns, improvements in site safety, increased management efficiency of project plans, and productivity growth on sites [11]. The use of AI technologies has enhanced automated processes and provided a competitive advantage [12].

Nevertheless, applying AI on construction sites is challenging, as most algorithms require accurate data for training. Collecting large datasets is costly and time-consuming for most construction companies [13,14]. Additionally, outdoor environment conditions and non-standardized building designs cause even more complications in adopting AI on sites [10]. Consequently, the industry is gradually incorporating AI technologies into everyday practices, as it needs to transform a traditional hierarchy to a digital and more autonomous one.

A limited number of studies have reviewed the potential of AI in the construction industry, such as modular construction and robotics [15]. Nevertheless, there remain grey areas towards future barriers and opportunities that technologies and robotics may bring on a construction site. In addition, the existing literature does not provide a comprehensive understanding of how AI tools and technologies are applied and used in the entire construction project lifecycle, i.e., planning, design, and construction stages—besides some limited number of studies partially covering the big picture view [16,17]. Moreover, there are limited review studies that investigate the reasons for the low-level AI adoption in the construction industry. This study aims to bridge this gap by identifying the adoption challenges of AI, along with the opportunities offered for the construction industry.

To deliver the abovementioned aim, the current study conducts a systematic literature review with the objectives of (a) identifying the prominent AI technologies that are used in the construction industry; (b) comprehending AI technologies and how they are applied throughout various construction stages; (c) determining AI opportunities and challenges in construction projects, and; (d) acknowledging new concepts, perceptions, and approaches that can lead to a research agenda for prospective studies. The findings contribute to the knowledge base in the AI opportunities and constraints in the construction industry and inform the industry on the opportunities and challenges regarding an increase in market acceptance of AI practices.

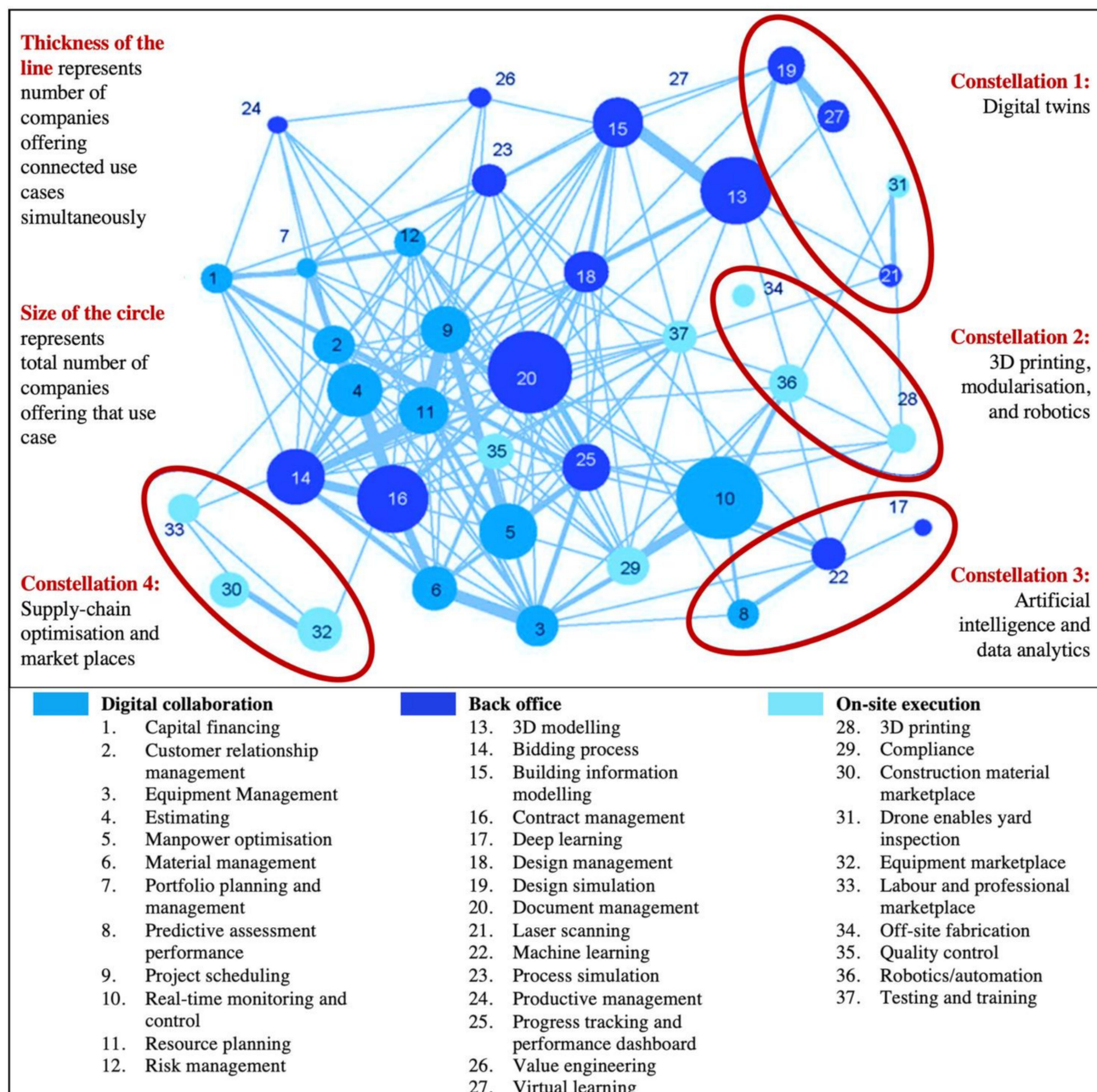
## 2. Literature Background

### 2.1. Global Construction Industry

The international construction market is forecasted to grow by 85% to USD 15.5 trillion by 2030, and AI could potentially raise productivity from 0.8% to 1.4% annually [18]. Most of this forecast growth is based on technological advancements in all phases of a construction lifecycle, i.e., planning, design, and construction stages [5]. Nonetheless, as mentioned earlier, the annual productivity of the construction industry worldwide has only seen an average increase of 1% over the past couple of decades. This also relates to low technology uptake in the construction industry (Figure 1).

The construction industry has already experienced significant changes through industrialization, globalization, and digitalization. The subsequent major changes that the industry will encounter within the next five years include product-based approach, specialization, value-chain control and supply chains, consolidation, customer centricity, investment in technology, human resources, internationalization, and sustainability [19]. These shifts will change current project-based construction processes to a product-based approach. This new approach will consolidate numerous stages in the value chain either digitally or through vertical integration. Instead of building structures on-site, companies will produce them offsite [5]. The process may resemble other manufacturing activities.

The construction process in the future is envisaged to be more standardized, consolidated, and integrated. This process will be increasingly product based, meaning that structures and products will be manufactured offsite. Furthermore, the value chain will be consolidated, increasing the degree of internationalization [20]. Data and analytics on customer behavior will be used to optimize future designs. The future of the construction ecosystem will be greatly reliant on the advancement of AI technologies. Digitalization is required to shift towards a more data-driven decision-making process and consolidate the value chain [21,22].

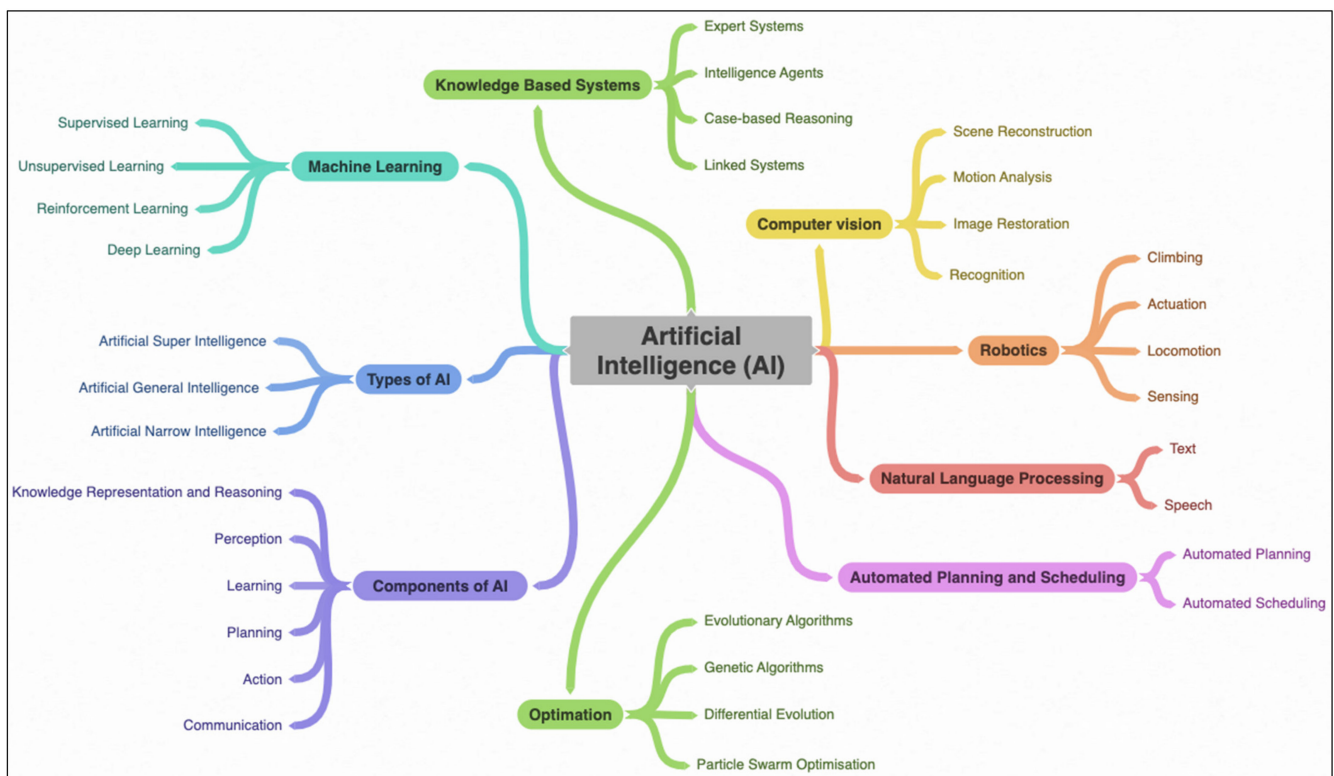


**Figure 1.** Construction technology map, derived from [5].

### 2.2. Artificial Intelligence and the Subfields

The definition of AI states that “tasks that can be operated automatically using self-governing mechanical and electronic devices that use intelligent control”. There are three types of AI conceptualizations. The first one is Artificial Narrow Intelligence (ANI). This existing AI type is used in language translation and weather forecasts. The second one is Artificial General Intelligence (AGI), and this future AI type will be able to solve complex problems with its own thoughts and disposition. The last one is Artificial Super intelligence (ASI), and this futuristic AI type, if it can ever be developed, will exceed human capabilities across several domains [23]. As seen in Figure 2, the major subfields of AI in construction are: (a) machine learning; (b) knowledge-based systems; (c) computer vision; (d) robotics; (e) natural language processing; (f) automated planning and scheduling, and (g) optimization [24].





**Figure 2.** Components, types, and subfield of AI, derived from [25,26].

### 2.3. Overview of Artificial Intelligence in Construction

While there are various definitions of AI, it is commonly accepted that AI in the built environment involves “making intelligence machines and programs that mimic cognitive systems to learn or solve problems” [27]. There has been a large expenditure on the research and development (R&D) of AI technologies in construction. From 2014 to 2019, the global construction industry has invested USD 26 billion into engineering and construction technologies, including AI, up from USD 8 billion over the previous five years [6]. Despite an increase in expenditure on construction technologies, construction methods for various core construction processes have not changed over the last four decades. There are insufficient skills, inadequate business models, and knowledge of AI for the construction industry. Thus, the application of AI for construction works remains time-consuming, costly, and error-prone, leading to slow AI adoption in the construction processes [8,28,29].

In addition, the large amount of unstructured data on sites implies that many platforms cannot analyze these datasets and function effectively. It is essential to standardize the data collected and tracked across the organization and project lifecycle to achieve useful analytics [18]. The global construction industry has only recently started to invest in the research and development of digital technologies. Firms are becoming more aware of these technologies’ benefits, operational and productivity advantages [30]. All these positive attributes that technologies may bring to a construction company will help the urban built environment overcome safety concerns, labor shortages, and cost and schedule overruns [8].

The construction industry is a growing interconnected ecosystem of hardware and software solutions, as seen in Figure 2. The concept of different “constellations” of connected solutions emerges around the established use cases, indicating what technologies are gaining the most traction [31]. In addition, there is a potent combination between the technologies under the same “constellation”, as they increase the number of solutions when used together. The most prominent constellations include 3D printing, modularization,

robotics, digital twin technology, AI, analytics, and supply chain optimization. Three of the constellations—digital twins, 3D printing, and AI and its analytics—will be transformational for the industry. The fourth constellation, supply chain optimization, is also expected to be notable shortly [32]. This is due to the increasing importance of supply chain optimization during the COVID-19 era and beyond.

The fundamental technologies that will impact the construction industry in the short term are the following: information communication technology (ICT), internet-of-things (IoT), big data analytics, blockchain, and AI [6]. The popular AI technologies currently being used in the construction industry worldwide are presented in Table 1. In addition to those listed in Table 1, digital twins allow for AI technologies to integrate with various projects. It captures real-time activity and supports predictive intelligence for decision making [33]. It enables project managers to create a virtual construction site that can be accessed remotely using network technologies. Moreover, it lays the ground for intelligent 3D models that provides insight and tool to plan, design, and manage building and infrastructure efficiently [34]. The system uses historical figures and evaluates millions of alternatives to create an accurate project schedule for project delivery. At the same time, image recognition can identify unsafe works and allow future training of workers [5].

**Table 1.** Common AI technologies used in the construction industry, derived from [19].

Application	AI Technology	Purpose
Big data and data analytics	Machine learning	Risk detection and assessment are improved by using new technologies that predict incidents and issue early warnings. Smart wearables can collect data for analytics, and AI algorithms address possible issues on-site and create new strategies that increase efficiency. In addition, data analytics can be used for decision making and strategy building.
Robotic and automation	Machine learning	Robotics is becoming more apparent on construction sites and will be highly specific (e.g., bricklaying, painting, and loading). The technology will benefit sites, as it reduces the time spent on repetitive tasks and helps protect workers from dangerous building environments. Aerial drones are frequently used to survey sites and collect data that allow surveyors to generate 3D models of buildings.
Data and system integration	Pattern recognition	Digital automated approaches can enhance safety management by stepping in related education, planning, and inspection processes. When combined with virtual reality, these become even more powerful as they ensure personnel safety in real-time.
Mobility and wearable	Automation	Smart wearable technologies detect movement, spatio-temporal activity, and thoracic posture of workers. These systems provide real-time data on-site, which reduces the risk of collisions between workers and heavy equipment.

#### 2.4. Disruption of Artificial Intelligence

Although the industry is changing slowly to digitalize and automate construction processes to improve productivity, safety, and quality [35], AI is beginning to gain attention as businesses are beginning to release the benefits that AI-powered algorithms may bring to a construction site [20]. In addition, AI increases accuracy in data analysis and formulates better strategies that benefit all actors involved [36]. It is essential that construction firms implement AI technologies to increase efficiency and competitiveness and realize the potential of AI on a construction project.

AI technologies transform the construction structures to increase efficiency, enhance business models, and bring new services to the market [37]. Furthermore, as projects are temporary and multi-organizational that rely on planning and scheduling models, the construction industry would benefit more than other industries to incorporate technologies [38].

AI can assist the construction industry by automating operation and digitalizing processes to improve productivity, safety, and quality [39]. This independence will make the development of buildings more evidence based and depend less on implicit knowledge. This will reduce unforeseen changes that may impact the time and cost.

Although AI in the construction industry is an emerging subject, it lacks “applied knowledge” and “tacit knowledge” [40]. Most of the literature focuses on one unique algorithm during the entire construction process, and research that analyses all the algorithms is restricted in the construction stage only. The use of AI in the construction industry remains uncertain, and there is a lack of understanding due to the lack of research and development (R&D) in AI [41]. The major difficulty of measuring the benefits of AI is the uncertainty of the gift from insurmountable investments. This uncertainty is being magnified as large construction companies are still implementing a traditional process that could be automated, and small subcontractors are following a similar business model [42].

In sum, compared to other sectors, the acceptance of AI in the construction industry is rather limited. Despite AI being a trendy topic in built environment research, there are limited review studies investigating the reasons for low-level AI adoption in the construction industry. To bridge this knowledge gap, this study identifies the adoption challenges of AI and the opportunities offered for the construction industry through a systematic literature review.

### 3. Methodology

This study intends to provide a summary of a full array of AI technologies and identify the key challenges involved in their applications and key opportunities these technologies will bring to the construction industry. To achieve this, a systematic literature review was conducted. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol is adopted in this systematic literature review to offer the replicability of the study (see <http://prisma-statement.org>). The literature on AI was collected from academic peer-reviewed journals. The searches included current technologies and those developing through R&D projects, as a review of the current technologies will provide a reference point on the current landscape of the construction industry and analyze the development, adaption, and application of AI in the construction industry [43]. The study has implemented a similar three-stage methodological approach [44] by following the PRISMA protocol, as follows:

Stage 1 (planning stage) includes research objectives that answer the research question, keywords, and a set of exclusion and inclusion criteria. The aim is framed to identify predominant AI technologies in the construction industry and identify the opportunities and challenges these technologies may impose over the construction lifecycle from project initiation to completion. While there are research papers that use bibliometric software to analyze AI in construction, there is no research that manually reviews the challenges and opportunities based on AI in the planning, design, and construction phases of construction activities.

The following broad concepts were used to develop an initial search criterion: “Industry 4.0”, “Construction AI”, “Construction algorithms”, “Construction neural networks”, “Construction robotics”, and “Construction machine and deep learning”. Based on the findings from the literature review, keywords co-occurrences for AI in construction and robotics in construction were established and outlined 57 broad technology themes currently being used in the industry. Additional keywords were analyzed, but they did not establish or identify any additional technology areas. Eight out of these fifty-seven key AI algorithms were frequently mentioned in journal articles, namely, neural networks, fuzzy cognitive

maps, genetic algorithms, Bayesian model, support vector machine, fast messy genetic algorithm, bootstrap aggregating neural networks, and adaptive boosting neural networks. These keywords defined the boundaries of the research areas and gave an overview of AI technologies that are currently used in the industry.

The keyword search was conducted in February 2022 and obtained 886 results that satisfied search criteria. After removing duplicated ones, 793 papers were retained, including research papers that go beyond the university library databases. The search engine covered over 400 different bibliographic repositories, including Scopus, ScienceDirect, Web of Science, Web of Science, Directory of Open Access journals, and Wiley Online Library. This initial search did not restrict specific periods. Furthermore, as shown in Table 2, the criteria were developed to effectively decrease the number and difficulty of review and helped screen articles.

**Table 2.** Exclusion and inclusion criteria, derived from [44].

Primary Data		Secondary Data	
Inclusionary	Exclusionary	Inclusionary	Exclusionary
Journal articles Peer-reviewed Full-text available online Published in English Government reports Conferences	Duplicate records Books and chapter Industry reports	AI in construction Opportunities and challenges in construction Relevant to the research objective	Not AI in construction-related Irrelevant research objectives

In Stage 2 (conducting the review stage), relevant articles were searched during February 2022. The use of AI in construction has mostly gained momentum over the last two decades, and the adaptation has increased during the previous decade. The initial search was then filtered to choose articles only published from January 2000 to February 2022, and it reduced the number of articles from 793 to 705. The remaining 705 articles were then assessed against the category formulation, as seen in Table 3, and the number of relevant articles was reduced to 379. The title, abstract, and keywords of the remaining 379 articles were screened out according to the exclusion criteria, and the number of relevant articles was eventually reduced to 72.

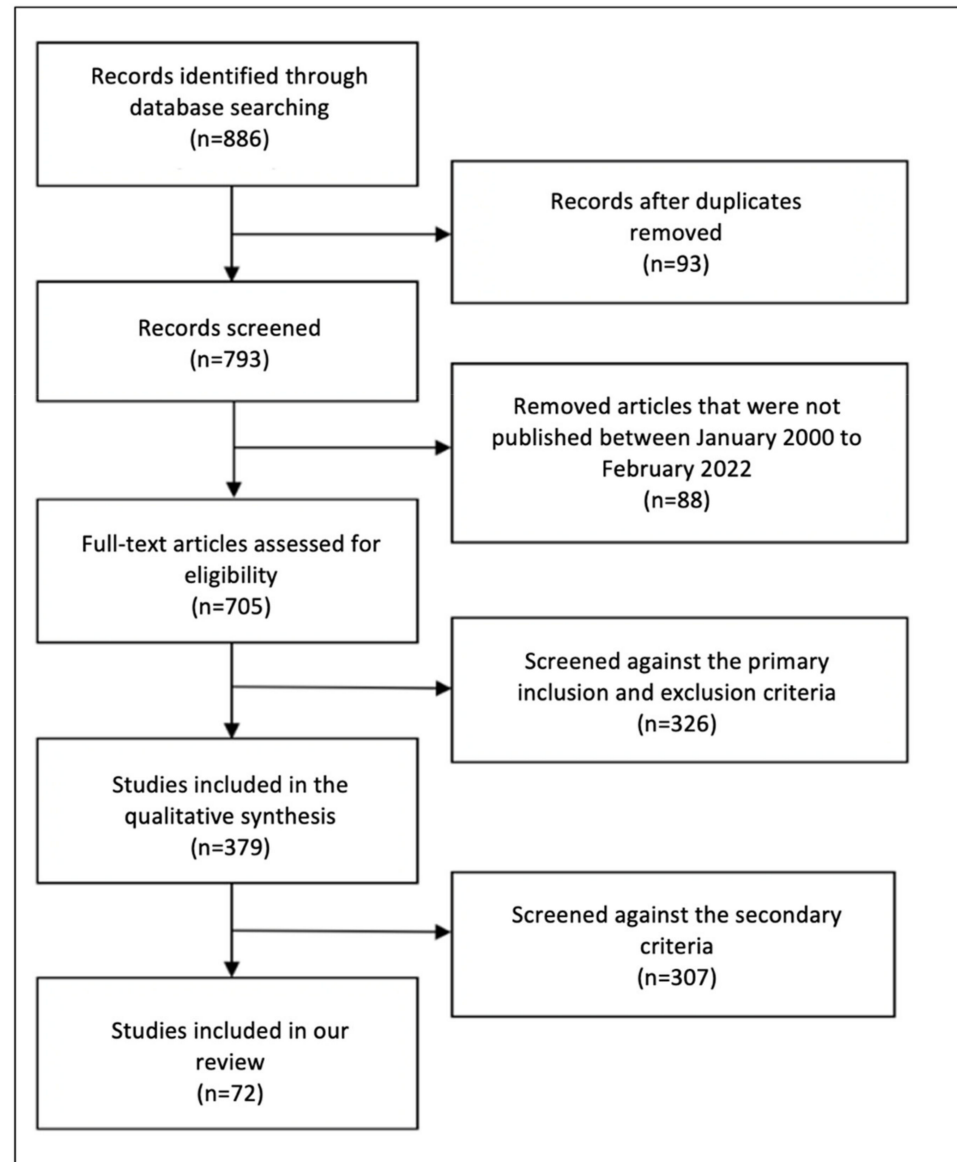
**Table 3.** Category formulation criteria, derived from [43,44].

Selection Criteria
<ul style="list-style-type: none"> <li>■ Identify the key authors that are relevant to AI in the construction industry by using qualitative data</li> <li>■ Determine the barriers of AI technologies implementation throughout a project lifecycle</li> <li>■ Identify the challenges and opportunities that AI technologies may impose throughout the construction process</li> <li>■ Categorize similar opportunities and challenges</li> <li>■ Group AI technologies relating to a particular construction stage and form categories</li> <li>■ Check the consistence and AI categories against other literature</li> <li>■ Shortlist categories and analyze recent literature reviews</li> <li>■ The final categories are verified, classified, and finalized</li> <li>■ Relevant categories are distributed and selected under the most pertinent categories</li> </ul>

In Stage 3 (reporting), 72 articles were analyzed using the descriptive techniques of explanation building and pattern matching [43]. The objectives of these screening processes were to analyze the selected articles according to some pre-defined categories to assess similarities and differences [44]. The four-step process was then used to classify the reviewed literature into specific themes [43,44]. The first step highlighted significant



challenges in the reviewed literature and critiques raised on AI in construction. Secondly, the most important themes were then categorized and reviewed concerning the research aims. The third step was to cross-check the categories with other review studies and identify further challenges. Lastly, the themes were categorized and finalized in planning, design, and construction phases under common themes. Figure 3 displays the overview of the process of selecting papers.



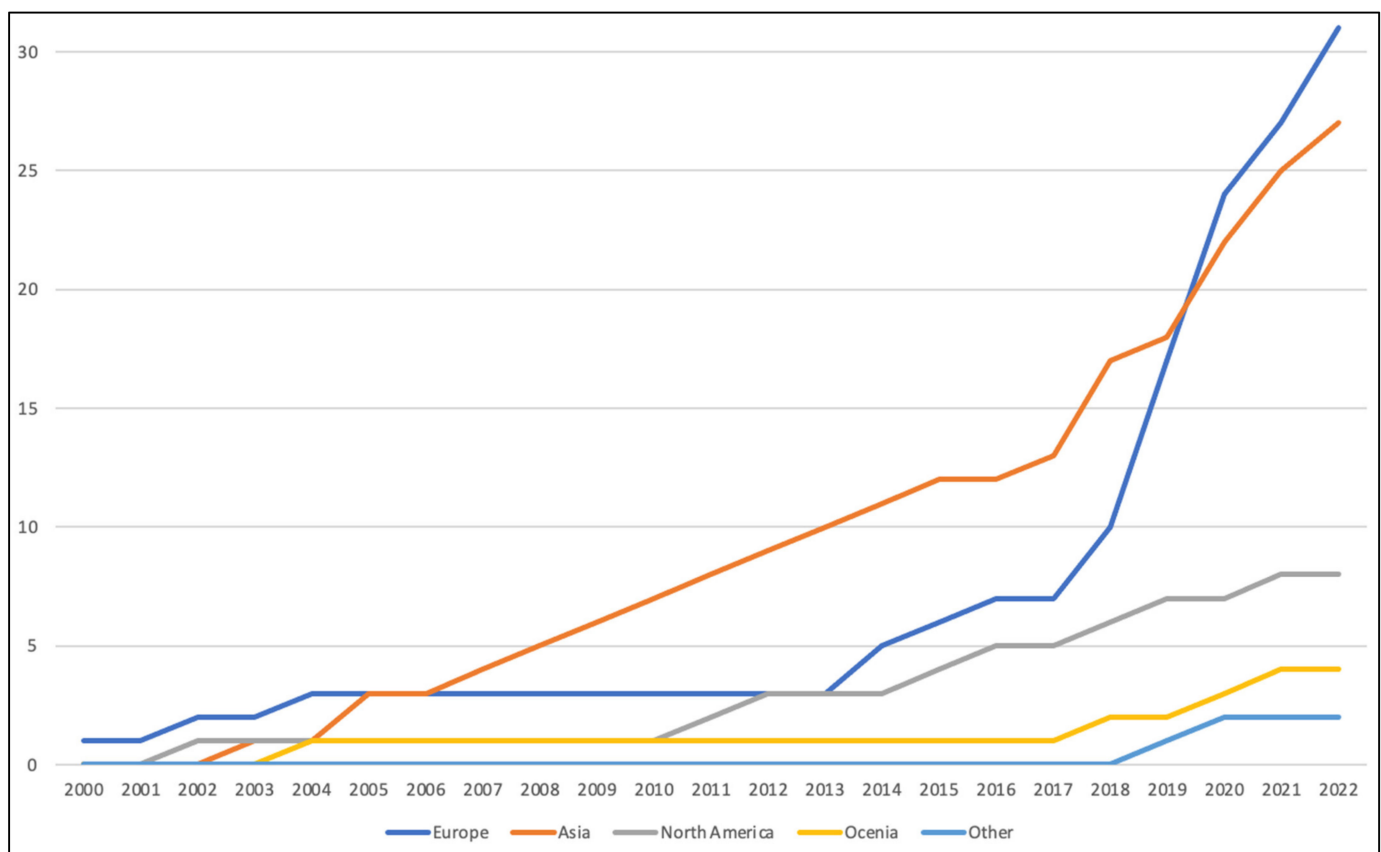
**Figure 3.** The PRISMA selection process of relevant literature.

After that, selected papers were reviewed to form the opportunities and challenges of embracing AI in the planning, design, and construction phases. AI technologies were categorized under the three subset themes of “machine learning” ( $n = 38$ ), “neural networks” ( $n = 27$ ), and “deep learning” ( $n = 8$ ). These themes were then assessed against other peer-reviewed studies. Furthermore, the selected articles were categorized into “planning stage” ( $n = 34$ ), “design stage” ( $n = 15$ ), and “construction stage” ( $n = 24$ ). Each stage involves similar and dissimilar AI technologies that result in different opportunities and challenges.

## 4. Results

### 4.1. General Observations

The publication date reflected the rapid growth of interest in artificial intelligence in the construction industry as 47% of 72 articles were published in the last three years (7 in 2019, 15 in 2020, and 20 in 2021). Many leading authors were affiliated with academic institutions in Asia ( $n = 32$ ), reflecting a substantial interest in Asia, where the industry has quickly adopted AI in construction processes. Furthermore, there is also a tremendous interest in Europe ( $n = 26$ ). However, there are only a limited number of studies from North America ( $n = 9$ ), Oceania ( $n = 3$ ), and others ( $n = 2$ ). As shown in Figure 4, the growth of AI literature concerning publication year and the region has recently increased.



**Figure 4.** Distribution of publications by region and year.

Of the 72 articles, the following authors had the most published articles: Chen Lu ( $n = 2$ ), Hao Wang ( $n = 2$ ), Reza Hosseini ( $n = 2$ ), Tao Yu ( $n = 2$ ), Yuzhu Cai ( $n = 2$ ), Carlos Balaguer ( $n = 2$ ), and Wolfgang Eber ( $n = 2$ ). No single author has dominated the literature on AI in construction. Given that automation is a subset of AI and signifies a new concept in construction, it was not surprising that most articles were published in Automation in Construction ( $n = 19$ ). These papers focused on BIM in the planning and design stages. The remaining 53 articles were published in Advances in Engineering ( $n = 9$ ) and Engineering Management ( $n = 3$ ). The remaining 41 articles were published in 41 different journals, focusing on neural networks, fuzzy cognitive maps, genetic algorithms, Bayesian model, support vector machine, fast messy genetic algorithm, bootstrap aggregating neural networks, and adaptive boosting neural networks.

In total, 72 articles reviewed the topics of construction innovations ( $n = 14$ ), intelligent systems ( $n = 19$ ), engineering management ( $n = 4$ ), and information systems ( $n = 28$ ). The remaining seven papers analyzed large construction companies that used technology to improve construction efficiency. These papers adopted qualitative methods such as focus

groups, interviews, and workshops to collect research participants' opinions. While these papers provide valuable insight into stakeholders' perceptions, these methods can create complications as AI and robotics are relatively new concepts in the construction industry.

Some studies revealed the limited experiences of professionals in the industry with these technologies. Even for studies collecting data following automation models and robotics ( $n = 5$ ), problems exist, as sample participants' perception of AI cannot represent the generally built environment professionals. However, they may represent a segment that already has an intrinsic curiosity with the services and, therefore, is more likely to hold a positive judgment. This is evident as large construction firms employ the sample participants, and smaller firms cannot utilize these new technologies. Consequently, these smaller firms hold a more neutral and/or negative opinion towards AI.

#### 4.2. Artificial Intelligence Adoption Opportunities and Challenges

There is a range of opportunities and challenges that AI may impose throughout a project, and firms must recognize these opportunities and challenges. Without a clear short-term objective, businesses will have inefficient AI platforms and lose the momentum to adopt AI-related technologies [15]. Companies need to prioritize their research, development, and investment in AI platforms when opportunities for AI outweigh challenges. They also need to identify the risks that may affect AI implementation to better planning and an efficient business transition [37]. Table 4 lists the opportunities and challenges that AI may impose on a project, and they are created based on common discussion principles as seen in the ( $n = 72$ ) reviewed articles.

**Table 4.** AI opportunities and challenges in the construction industry.

No	Opportunities	Challenges
1	Provide a competitive advantage to businesses that use AI, as it will reduce economic costs	AI applications are highly specialized and need constant algorithms training to identify patterns
2	Increase productivity and efficiency of on-site personnel	The fragmented nature of the construction industry may result in data scarcity
3	Reduce the time spent on repetitive tasks by using big data	High initial costs in the research and development of AI platforms
4	Identify high-risk issues and automatically classify them into actionable categories	AI platforms need investment constantly to keep data up to date
5	Improve current work processes	Implementation of AI requires businesses to move away from traditional ideas
6	Increase the consistency in project related work that will result in higher quality	Security and reliability of a large amount of data
7	Avoid possible delays through predictive modeling	Multi-point responsibility between stakeholders may reduce accountability
8	Extract data from the complex document and categorize them based on patterns easily	Non-standardization of a construction project makes it difficult to implement AI
9	Reduce the probability of on-site accidents and mitigate safety risks	Require an AI expert that will involve additional costs
10	Increase accuracy of plans and allow for better verification	High resistance from industry bodies
11	Produce outcomes that can be easily understandable by all stakeholders, which enhances efficient communication	Ethical, moral, and legal issues that are yet to be addressed by the government or institutional bodies
12	Enhance consistency and reliability, as AI is highly unlikely to make mistakes (provided data are correct)	High impact on traditional skills and may impact job availability

##### 4.2.1. Opportunities

There is a range of opportunities that new technologies bring to a construction project. It gives companies a competitive advantage by lowering costs and increasing efficiency. Adaptive manufacturing is a growing concept that introduces flexible machines capable of customizing part productions and enabling new cost-effective building methods [45,46]. This new method leads to the potential modification of jobs by combining planning, design, and construction tasks. It is critical that users acknowledge the benefits and performance

enhancement that AI may bring to a construction site to adopt new technologies into their projects [47] effectively.

#### Waste Management and Resources

The amount of resource waste is growing rapidly on a yearly basis due to rapid development [48]. Companies are becoming more waste aware and are implementing proactive data-driven approaches that minimize waste through analytics [49]. Waste analytics is dependent on different sources of data, such as building design, material properties, and construction strategies. AI technologies are needed to turn information into relevant waste management strategies. These strategies include the optimization of offsite construction, material selection, reuse and recovery, waste-efficient procurement, deconstruction, and flexibility [50,51].

#### Estimation and Scheduling

AI application models are important to accurately forecast construction costs and project timeline. Projects that do not have accurate costs and time estimation have large financial implications. The use of AI allows for the integration of 4D and 5D visualization to BIM and reduces the risks of unforeseen costs and project milestones. In addition, using enhanced technologies such as deep (neural) learning—which is a subset of machine learning that uses statistics and predictive modeling to act like a human brain—can increase time accuracy and cost predications in construction projects [52].

#### Construction Site Analytics

Construction sites constantly transform and incorporate new technologies to become smarter working environments. IoT sensors and other digital technologies are becoming more apparent on sites to generate valuation data. A large volume of data is generated from construction sites and is mostly unstructured. The use of AI can structure the data generated and analyze the data to optimize site performance in all key areas such as planning, design, safety, quality, scheduling, and costs [53].

#### Job Creation

Based on the literature review, construction jobs that require low to medium education are at a higher risk of becoming redundant. This is evident as, by 2030, 38–45% of these jobs will be completed by automated analytics or robotics [54]. However, the adoption of AI can also create new jobs such as construction AI researchers, trainers, and engineers to assimilate and reskill the displaced workers in the industry.

#### Supply Chain Management

There are common supply chain management (SCM) issues evident in the construction industry. The SCM is a costly and complex process, and the lack of specific performance measurement frameworks, organization trust, and communication channels risks its success [55]. AI can play an important role in reducing this limitation and increasing supply chains' efficiency. Incorporating both AI and IoT can develop real-time risk monitoring systems that control product quality and site safety. Furthermore, AI has the possibility to resolve organizational trust and communication issues that have hindered the use of SCM in recent years. AI can detect potential issues and ensure efficient delivery by managing the entire supply chain [56].

#### Health and Safety

Advanced analytics can reduce the risk of workplace accidents by using predictive analytics. The construction industry records a significant number of injuries compared to other industries [57]. This is due to construction personnel being highly exposed to onsite dangers such as heights, falling objects, equipment, tools, and toxic materials [58]. Therefore, construction companies need to take a proactive approach by using AI to reduce

the risk of accidents before they occur and to prevent them. AI and BIM can improve safety using sensor-based technologies and wearable technologies for safety monitoring. These technologies can identify dangers on a construction site and notify managers.

#### Construction Contracts

Construction management can be complex, as it involves multiple contracts, and mistakes can have costly implications. AI can diminish the risk of human errors by automating the efforts of contract managers to ensure that processes are faster and more accurate [59].

#### 4.2.2. Challenges

The construction industry is behind manufacturing and transportation to adopt AI, as it is still in the initial conceptual phase of development [60]. Technology challenges vary, depending on the project's size, labor and capital intensity, industry sector, technologies used for projects, and the types of firms that use the technology [61]. According to Mohammadpour et al. [21], a significant barrier for businesses to embrace AI is the complexity of tasks performed by analytics. This is potentially caused by the higher variability and volatility of construction sites and the urban environment. AI requires large amounts of data to train algorithms and identify patterns in which only a limited number of people can interpret data from these platforms, resulting in limited economies of scale, impeding innovation and digitalization [62,63].

#### Cultural Issues

Construction sites are constantly changing and require AI to learn and adapt to these new environments. Traditional methods are prioritized over un-trusted technologies due to the risk associated with construction, as mistakes can lead to high financial implications. The disjointed nature of the construction industry makes it difficult to change. Successful transition from traditional to future models requires compatible design, management, labor practices, and site operation practices [64]. Consequently, as construction is performed and requires multi-point responsibility from different project disciplines, individual organizations control construction phases. It is difficult for AI technologies to be effective without these disciplines sharing common interests throughout the project cycle [65–68]. Therefore, it would be beneficial to take advantage of technologies such as blockchain to improve trust and transparency [69].

#### Security

Despite the improvement in AI security, it can still be targeted by cyber criminals. This is a critical issue, as it can have financial implications and comprise the safety of construction works. For example, a computer vision system can be hacked to mislabel a construction worker working at height. Construction companies will need to implement machine learning (ML) techniques that reduce the exposure of high-level sensitive data [70].

#### Higher Initial Costs

The benefits that AI may bring to a construction site are indisputable. However, AI technologies require high initial costs to obtain accurate data. This may be unaffordable for most subcontractors and small firms that make up the majority of the construction industry. The high upfront costs require a considerable financial commitment for R&D and application purposes, and these investments will be at increased risk and taking this risk in a highly competitive market. Small to medium-sized business firms cannot invest in system-level technology and thus cannot benefit from technological breakthroughs [71]. In addition, there is a high cost of owning and using these AI technologies as they are not fully developed and need investment constantly to keep up to date with the advancement of the technology [72]. Therefore, it is imperative that firms determine the cost saving that AI may bring to a project and decide whether it is feasible. As AI in construction continues



to expand and becomes more prevalent in construction, the process is expected to lower and become more affordable for smaller businesses.

#### Project Uniqueness

Another challenge for the construction industry to implement AI technologies is that nearly every project is unique. The work process is complex, non-repetitive, and depends on the weather, labor, and local building regulations [73]. Consequently, non-standardization hinders automation and robotics efficiency, as it is difficult to control, and it also challenges maintaining these technologies in an unstructured environment [74].

#### Robotics

The development of construction robots is technologically challenging due to the constantly changing environment of the construction process. Furthermore, these robots need to be robust, flexible, highly mobile, and versatile [75]. As construction sites are an unstructured environment, robots must be reprogrammed according to conditions at each site when they move around the site [76]. To overcome this challenge, the repetitive planning, design, and construction of buildings are needed to provide an organized operating and structured environment [20].

#### Institutional Barrier

There is a solid institutional barrier in the construction industry, as technology may replace workers, resulting in higher unemployment rates. Nevertheless, construction robotics can take a significant amount of time to set up and need constant monitoring by skilled workers [77]. Therefore, for an efficient transition to incorporate robotics on a construction site and become more ordinary, a new construction profession with a strong background with specific training in robotics, algorithms, and software needs to be created [21,22].

#### Information Sharing

The construction industry has created standards that make it difficult to share information between companies due to intellectual property issues [20]. These companies have no framework to follow, and there is no guidance on implementing these technologies on sites [22]. There is also a concern about the security, reliable storage, efficiency, and interpretation of big data on sites [20–22].

### 4.3. Prominent Artificial Intelligence Technologies in Construction

#### 4.3.1. Planning Phase

Planning is a critical phase in a construction lifecycle, as it determines the success of a project in terms of time, cost, quantity, and quality [18]. Inaccurate planning will result in project failure [78]. The planning stage involves many stakeholders who spend considerable time in scheduling, cost analysis, and understanding the risk of a project [28,33]. AI is crucial in a project's initial stages as the cloud-based application can be used for deeper analysis and what-if scenarios increase projects profitability. This stage has seen a high investment from the private sector to conduct research and develop new AI software to increase efficiency and productivity [26]. McKinsey [5] published a report indicating that through real-time data analysis, construction firms could increase productivity by 50%. This has prompted construction firms to invest in AI and data sciences [79]. The opportunities and challenges in the planning phase can be found in Table 5 and are set out as follows.

**Table 5.** Opportunities and challenges of adopting AI in the planning phase.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges	Abioye Sofiat	2021	Building Engineering	Machine learning	1,2,4,5,6,8,10,11,12	1,3,5,8,9
Towards a semantic construction digital twin: directions for future research	Calin Boje	2020	Automation in Construction	Machine learning	2,3,4,5,6,11	1,4,7,9
Comparison of artificial intelligence techniques for project conceptual cost prediction: a case study and comparative analysis	Haytham Elmousalami	2020	IEEE Transaction on Engineering Management	Neural networks	1,2,3,5,6,7,9,12	1,2,3,4,9,10,12
Potentials of artificial intelligence in construction management. organization, technology and management in construction	Wolfgang Eber	2020	Organization, Technology, and Management in Construction	Deep learning	1,2,3,5,6,10,12	1,2,9
Application of artificial intelligence in construction project management	Venkata Nagendra	2018	International Journal of Research in Engineering, Science and Management	Machine learning	1,2,3,4,5,6,8,11,12	1,4,7,8,9
Fintech: the next generation of the capital projects technology roadmap	William John O'Brien	2017	Journal of Construction Engineering and Management	Neural networks	1,2,3,5,6,7,8,9	1,3,7,9
Understanding the implications of digitisation and automation in the context of Industry 4.0: a triangulation approach and elements of a research agenda for the construction industry	Thuy Duong Oesterreich	2016	Computer in Industry	Machine learning	1,2,3,4,5,6,8,10,11,12	1,7,9,11
A multi-agent model to manage risks in construction project (SMACC)	Franck Taillandier	2015	Automation in Construction	Neural networks	1,2,5,6,8	1,2,3,6,8,9
Automation in construction scheduling: a review of the literature	Vahid Faghihi	2015	International Journal of Advanced Manufacturing Technology	Neural networks	2,3,4,5,7,9	1,8,9
Interval estimation of construction cost at completion using least squares support vector machine	Min-Yuan Cheng	2014	Journal of Civil Engineering and Management	Machine learning	2,3,5,6,7,10	1,2,3,5,9

Table 5. Cont.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Using intelligent techniques in construction project cost estimation: 10-year survey	Abdelrahman Osmann Elfaki	2014	Automation in Construction	Machine learning	1,2,3,5,12	1,2,3,4,6,9
Automated vision tracking of project related entities	Ioannis Brilakis	2011	Advanced Engineering Informatics	Machine learning	2,4,5,8	1,2,3,9
Construction virtual prototyping: a survey of use	Ting Huang	2009	Construction Innovation	Machine learning	1,2,3,4,5,6,8,11	1,2,6,7,9
An augmented framework for practical development of construction robotics	Khaled Zied	2007	Advanced Robotics Systems	Neural networks	2,3,5,6,7,10	1,2,3,5,9
An optimal construction resource leveling scheduling simulation model	Sou-Sen Leu	2002	Canadian Journal of Civil Engineering	Neural networks	2,5,6,7	1,2,3,4,8,9,12
An industry foundation classes web-based collaborative construction computer environment: WISPER	Ihsan Faraj	2000	Automation in Construction	Neural networks	2,3,5,7,9,10,12	1,2,6,9

*Automated project schedule:* Project schedules have already been used throughout the construction industry. Kwant.ai is a leading software that uses AI predictive analytics and sensors to increase productivity and safety. The software helps predict risks and alert project managers when there is a possibility of project delay [80]. Furthermore, it can perform permutations and analyze different ways to deliver projects efficiently and enhance project planning [81]. The software analyses past schedules and determines the project timeline, personnel required, and a list of materials that will be needed to complete the project [82]. In a construction project, the schedule is mainly affected by changes in the scope, project complexity, design variation, inaccurate engineering estimates, and inadequate planning [83]. Unforeseen parameters can be attributed to the software and create an alternate schedule within minutes. This ability to forecast and schedule the entire project accurately will result in substantial productivity gains [32]. It also reduces the risk of information not being adequately communicated due to changes. According to Rene Morkos, CEO of Alice Technologies, the productivity gain of implementing AI scheduling programs will see an average of 16% shorter duration and 11% lower labor costs [84].

*Determine risks by predictive modeling:* The planning phase needs to determine project risks and measures if an adverse event occurs. Therefore, analytics that can predict events based on historical data will be critical in project success [48,52]. The industry has already used AI and machine learning solutions that optimize supply chain logistics, identify the effect of weather trends on project scheduling, and manage budget overages by analyzing the team's experiences and contract types [53]. A growing platform called AI Builder records data from inspection and on-site observation and creates a matrix of leading indicators that help predict future risk in real-time [47]. The algorithms will train consistently when the new data are added. Therefore, the predictive models will become more intelligent and determine the most effective process to reduce project uncertainty [85].

*Data accessibility:* The demand for highly personalized projects continues to rise, and the accessibility of data in real-time has become paramount. Stakeholders can solve

problems more efficiently by communicating with multiple project teams and meeting changing customer anticipations using real-time data [86]. Furthermore, the growth of IoT increases the ability to record data passively through portable devices [52,86]. This allows project managers to automatically prioritize issues and rate subcontractors according to a risk score so that construction managers can work closely with high-risk teams to mitigate risks [40]. The reinforcement learning AI algorithm is currently under development and will give project managers additional support from current matrixes. The algorithm will evaluate limitless combinations and alternatives based on comparable projects and optimize the best path and correct itself over time [87].

*Prevent cost overruns:* AI technologies can prevent cost overrun and predict unforeseen costs based on project size, contract type, and a project manager's competence level [58]. Various algorithms have been programmed for predictive modeling to foresee a realistic timeline of future projects [88]. In addition, machine learning can analyze complex tasks and establish variables that may adversely affect a project. According to Eber [49], artificial neural networks are applied to analyze start dates, employee performance, material costs, etc. However, the platform's efficiency depends on the accuracy of previous projects and may not be feasible for smaller construction companies [22]. 3D scans on a construction site can increase efficiency, as that is done autonomously, and images downloaded for a deep neural network can categorize the completion of specific tasks in real-time. This allows the project manager to step into delayed jobs and deal with more minor issues before they become significant issues.

*Health and safety:* A major driver of construction interruptions and cost overruns are accidents on sites. Computer vision and pattern recognition can identify unsafe sites by utilizing spatial and temporal information [89]. AI detects and identifies workers' actions using deep learning methods [40]. The plans include combining convolutional neural networks (CNN) with long-short term memory architectures [90], as it enables accurate motion detection in unsafe operations [91]. The leading software is Versatile nature AI and BIM 360 Project IQ, transforming any site into a smart data collection point. The platforms create a matrix that analyses project status and can assist firms in improving health and safety. It is essential to reduce on-site accidents, as they affect personnel's well-being and impact the cost and time of a project [37]. Another AI algorithm that is currently developed in Boston can analyze photos from job sites, scan the safety hazards, and compare images with its accident reports. It can calculate a risk rating for projects and alert project managers to have a safety briefing when there is an imminent threat on site.

*Labor shortages and low productivity:* Labor shortages and low productivity are growing concerns in the construction industry. The retirement of aging professionals will drain the talent pool. For example, about 41% of the current US construction workforce is expected to retire by 2031 [5]. Artificial intelligence and machine learning algorithms will help distribute labor across projects more efficiently [37]. This requires an autonomous vehicle to constantly evaluate job progress and tell instantly which jobs are falling behind schedule and require additional labor force.

#### 4.3.2. Design Phase

The design phase uses various automated tools such as the 4D AutoCAD interface to streamline traditional processes. The transition from automation to AI and machine learning systems has commenced as firms notice that the current platform cannot handle a large amount of data [92]. Every job site has become a potential data source for AI where firms can learn and improve previous traditional methods [20]. Data generated from images, drone videos, security sensors, and building information modeling (BIM) have become a pool of information in the design phase. AI in this phase can provide necessary project support by maintaining, storing, and evaluating complex design data [47]. Cost reduction of these programs has increased the viability for businesses to implement these platforms [62].

AI tools will increase the communication and collaboration on design functions and improve current management and control in all aspects of architectural practices. In addition, various projects can be managed more efficiently by incorporating information and knowledge repositories [93]. This will ensure parties access up-to-date data and share information efficiently [46]. The areas of AI use at the design phase are elaborated below, and relevant literature is listed in Table 6.

**Table 6.** Opportunities and challenges of adopting AI in the design phase.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Digital twinning of the built environment: an interdisciplinary topic for innovation in didactics	Wissam Wahbeh	2020	ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences	Machine learning	1,2,3,5,8,10,12	1,2,4,8
Artificial intelligence in the AEC industry: scientometric analysis and visualization of research activities	Amos Darko	2020	Automation in Construction	Machine learning	1,2,3,4,5,6,8,9,11,12	1,2,3,4,7,8
Artificial intelligence and robotics in smart city strategies and planned smart development	Oleg Golubchikov	2020	Smart Cities	Neural networks	1,2,5,6,8,9,12	1,2,4,6,9,10,11,12
Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions	Purva Grover	2020	Annals of Operations Research	Machine learning	1,2,3,5,6,7,8,11,12	1,2,3,4,5,6,8,12
BIM-based visualization research in the construction industry: a network analysis	Zezhou Wu	2019	International Journal of Environmental Research and Public Health	Neural networks	1,2,3,4,5,8,11,12	1,2,3,4,5,6,8,9,10,11,12
Integration of BIM and GIS in sustainable built environment: a review and bibliometric analysis	Hao Wang	2019	Automation in Construction	Machine learning	1,2,3,5,8,9,10,12	1,2,3,7,8
A review of artificial intelligence-based risk assessment methods for capturing complexity-risk interdependencies	Farman Afzal	2019	International Journal of Managing Projects in Business	Machine learning	1,2,3,4,5,7,8,9,10,11,12	1,2,3,4,9



Table 6. Cont.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Building information modeling (BIM) for structural engineering: a bibliometric analysis of the literature	Tatjana Vilutiene	2019	Advances in Civil Engineering	Machine learning	1,2,4,5,8,10,11,12	1,2,3,7,9
Open innovation of new emerging small economies based on university-construction industry cooperation	Zane Rostoka	2019	Open Innovation: Technologies, Market and Complexity	Neutral networks	1,2,5,6,8,9,12	1,2,4,6,9,10,11,12
Integration of BIM and GIS in sustainable build environment: a review and bibliometric analysis	Hao Wang	2019	Automation in Construction	Machine learning	1,2,3,5,8,9,10,12	1,2,3,7,8
Knowledge-based system for resolving design clashes in building information models	Hesieh-Chih Hsu	2015	Automation in Construction	Machine learning	1,4,5,7,9,12	1,2,3,4,8,9
Complex assessment model for advanced technology deployment	Simona Kildiene	2014	Journal of Civil Engineering and Management	Machine learning	1,5,6,8,9,12	1,2,7,8,9
Technology development in construction: a continuum from distant past into the future	Mirosław Skibniewski	2013	Journal of Civil Engineering and Management	Neural networks	1,2,3,5,7,10,12	1,2,6,9

*Building information modeling (BIM)*: BIM is becoming apparent on construction sites. It is easily accessible to purchase and provides an effective way to collect data and monitor a site's progress in real-time [94]. The potential of BIM will allow firms to manage a digital representation of the physical characteristics of construction projects. In addition, it increases flexibility on the design that is evident throughout the building stage process and prevents on-site hazards by creating an identification and prevention system. Ribeirinho et al. [63] found that contractors' expected use of BIM could increase by 50%. In addition, they were planning to significantly invest in expanding their BIM programs in the coming years. Such capabilities will change project risks and question traditional engineering, procurements, and construction models.

*Internet-of-things (IoT)*: IoT is a crucial technology that enables the link of BIM with real-time data. Major IoT companies in the market are SmartSite, SiteSense, Indus.AI, and Caido. These platforms process data from every phase of a construction process into valuable method instruction. Furthermore, blockchain technologies automatically record real-time data to provide on-site managers with reliable data to communicate and increase safety. Integrating smart homes/buildings and IoT will increase data availability and enable more efficient operation and new business models, such as performance-based contracting. IoT sensors will allow companies to create a virtual 3D model, which can increase efficiency and reduce maintenance costs [95].

*Generative design:* Most construction companies are still comparing planning documents from different stakeholders on-site. Consequently, it necessitates numerous reworks and reassessments that consume time and money [96]. Dassault systems EXALED and NETVIVES are leading generative design platforms that aggregate data from multiple sources and deliver accurate strategies. Recent studies have found that 35% of architects and engineers incorporate generative design in their projects [97]. The software allows for a simplified design that considers spatial requirements, performance, materials, and cost constraints [94]. The software explores all possible solutions and generates a design alternative that meets all the specific requirements [98]. Another AI technology GenMEP can automatically design the routing of an electrical system within the building model [16]. GenMEP also considers complexity in different building shapes and geometrics to ensure that cables do not end up in the same route [47]. It is expected that generative design will continue to grow and be applied by the AEC industry, given the potential benefits. Nevertheless, it will only be available for large construction companies shortly as the license is expensive and skilled workers are needed.

*Visualization:* Computer integrated construction (CIC) is another tool that is transitioning to incorporate AI capabilities. Combining CIC and machine learning can be powerful as it shapes data and analyses variability and underlying data patterns [48]. Therefore, both technologies work together, enhance information sharing, and reduce uncertainties. This will provide stakeholders with a proper understanding of where the construction project stands at any stage [32].

*Clash detection:* Clash detection is essential in the design phase and needs to be simplified and accelerated by AI. Technologies such as BuildingSP and GenMEP are in development, which detects clashes in real-time without the need to export files to other platforms [59].

*Surveying:* Various regular surveying processes such as point layout and soil deformation monitoring can benefit from innovative software and hardware [43–45]. Implementing a vision-based concept can leverage information obtained by the inspection or monitoring process.

#### 4.3.3. Construction Phase

The construction phase in a project is currently undergoing the most significant changes from traditional methods. Construction robots and automation enhance existing construction plants, equipment, and task-specific dedicated robots, while cognitive machines are still in the preliminary phase of development. The major robotics applied for the construction industry are KIST floor robotics, WASEDA construction robot, Interior wall painting robots, mobile robot, four-leg locomotion robot, and ASRERRISK robot. An integral technology to operate robots is using numerous sensors that provide feedback to the site manager [28,33,51]. The areas of AI use in the construction phase are elaborated below, and relevant literature is listed in Table 7.

**Table 7.** Opportunities and challenges of adopting AI in the construction phase.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Quantitative review of construction 4.0 technology presence in construction project research	Pia Schonbeck	2020	Buildings	Machine learning	1,2,5,6,10,11,12	1,2,5,7

Table 7. Cont.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Lean thinking and industrial 4.0 approach to achieving construction 4.0 for industrialisation and technological development	Lekan Amusan	2020	Buildings	Neural networks	1,2,3,4,5,7,9,11,12	1,2,4,5,6,7
Automation and robotics in the construction industry: a review	KN Narasimha Prasad	2019	Future Engineering and Technology	Neural networks	1,2,5,12	1,2,3,8,10,11
Artificial intelligence for construction safety: mitigation of the risk of fall. advances in intelligent systems and computing	George Bigham	2019	Intelligent Systems and Applications	Machine learning	1,2,3,4,5,6,10,11,12	1,2,3,4,5,7
How does artificial intelligence help to avoid disputes in construction?	Mathis Catelain	2019	PM World Journal	Machine learning	1,2,4,5,6,8	1,2,6,9,12
Robotics and automated systems in construction: understanding industry-specific challenges for adoption	Juan Manuel Davila Delgado	2019	Journal of Building Engineering	Neural networks	1,2,5,6,8,10	1,2,3,8,9,12
Digital skin of the construction site: smart sensor technologies towards the future smart construction site	Ruwini Edirisinghe	2018	Engineering Construction & Architectural Management	Machine learning	1,2,3,4,5,6,7,10,11,12	1,2,4,9,12
Safety leading indicators for construction sites: a machine learning approach	Clive Poh	2018	Automation in Construction	Neural networks	1,2,3,5,7	1,2,8,12
Unified resources marking system as a way to develop artificial intelligence in construction	Alexander Ginzburg	2018	Material Science and Engineering	Deep learning	1,2,5,12	1,2,5,9
Digital skin of the construction site: smart sensor technologies towards the future smart construction site	Ruwini Edirisinghe	2018	Engineering, Construction and Architectural Management Journal of Intelligent and Robotic Systems	Machine learning	1,2,4,5,6,8	1,2,6,9,12
Automation and robotics in construction and civil engineering	Mi Jeong Kim	2015		Machine learning	1,2,3,4,5,6,10	1,2,7,9
“Human-robot cooperation technology” an ideal midway solution heading toward the future of robotics and automation in construction	Chang-soo Han	2011	Automation in Construction	Machine learning	1,2,5,6	1,2,6,8

Table 7. Cont.

Title	Lead Author	Year	Journal	Subset of AI	Opportunities (See Table 4)	Challenges (See Table 4)
Trend analysis of research and development on automation and robotics technology in the construction industry	Hyojoo Son	2010	Journal of Civil Engineering	Neural networks	1,2,4,5,6,7,10,11,12	1,2,3,6,9,12
Study of information technology development for the Canadian construction industry	Thomas Froese	2007	Canadian Journal of Civil Engineering	Machine learning	1,2,3,5,9,11	1,2,4,6
Construction automation and robotics in the 21st century	Yukio Hasegawa	2006	Engineering Construction & Architectural Management	Machine learning	1,2,5	1,2,3,4
Experience with the management of technological innovations within the Australian construction industry	Mary Hardie	2005	Journal of Building Engineering	Machine learning	1,2,5,7	1,2,4,6,9
Robotics and automation in construction	Ernesto Gambao	2002	IEEE Robotics & Automation Magazine	Neural networks	1,2,3,5,6,8,12	1,2,3,4,5

*Construction monitoring:* Monitoring the current advancement of construction projects and the structural integrity of buildings is conducted by modal parameters using a speeded-up robust application (SURF). These parameters include natural frequencies, damping ratios, and model shape. Data analytics used for the SURF application can also correspond to the Bayesian method for dynamic structural characteristics identification. Artificial neural networks have also been used to predict and estimate the compressive strength of concrete. This platform analyses the five constituents of concrete, which clarifies firms on the quality of the concrete and if any more composite materials are required to increase durability.

*Image processing:* Construction buildings can be monitored by collecting data from placed sensors located around the site. Data streams using RGB cameras can collect data like workers' activities, location of raw materials, and earthworks. This is useful as it increases efficiency and reduces greenhouse gases emission [99].

*Modular construction:* Offsite production automation enhances industrialization by taking a product-based approach. The process involves planning, designing, and building in a controlled offsite building. The building incorporated various materials, scales, and systems, innovative manufacturing methods, digital software, and modern assembling techniques. The next step in the transition to efficient offsite manufacturing involves integrated automated production systems.

*Autonomous vehicles:* A central platform can control autonomous vehicles and direct these modes of transport on a construction site to assemble buildings. A currently under development technology is a set of aerial robots that work together to achieve a specific goal. This can be achieved by using digital twin technologies that can accurately schedule and plan individual robotic actions [100].

*Autonomous excavation:* Another growing technology is autonomous excavation, where the machine is positioned adjacent to its working area, and digging can be done automatically by sensors and control. Komatsu, a leading equipment manufacturer that focuses

on data-driven and machine learning enhanced analysis, launched its Smart Construction in 2015. The analysis improves efficiency, accuracy, and quality by extracting information via reliable automated systems [50]. INSITE's technology is currently under development to combine computer vision, deep learning, and aerospace algorithms [58], making the machines smarter by estimating the machine position and visual perceptions [49]. These technologies will ensure construction processes are reliable, productive, and efficient.

*Task-specific robots:* Task-specific robots have been used in Japan since 2018; they work under teleoperation or program control, and the operative is positioned near the machine [51]. The primary tasks that these robots can complete are structural work, finishing, inspection, and maintenance [61]. Robots are usually used for a specific construction process to reduce possible failures [33]. Another robotic technology being used is a smart system that automates the prefabrication process and reduces the need for on-site construction that may be exposed to unforeseen weather conditions [101]. According to Mohammadpour et al. [21], the roofing erection process of jacking towers and forming the work platforms takes approximately six weeks to set up. It may take an additional 6–12 weeks for automated technology to erect and weld steel frames, place precast concrete floors, interior and exterior wall panels and install prefabrication units. However, workers are still needed on-site to supervise and manage the assembly work processes. Another tool in development is Obayashi's Big Canopy system, where a temporary roof limits the implication of unforeseen weather conditions [102]. The primary function of this temporary structure is to shorten the project periods due to adverse weather conditions and improve the safety and productivity of personnel.

*Smart wearable technologies:* Wearable technologies provide an ecosystem where safety and other information can be easily accessible. Smart watches are used on a construction site in which workers receive information of context-relevant format from a removed AI module and deliver it to them in a location [103].

*Robotic equipment:* Many construction tasks related to AI software are still under development but are expected to provide the construction industry with seamless integration of automated equipment in a 5D BIM planning environment [104]. The major robotic companies that have already entered the market are SAM100, Ekso Bionics, and Piaggio Fast forward. These models enable an intelligent link between 3D CAD/CAM components with schedule information and costs, providing stakeholders with a means to improve project delivery times, health and safety, and financial performance [105].

*VR modeling:* DAQRI and Nyfty.AI are systems in rapid growth, which give engineering firms the means to increase safety and talk to subcontractors through scheduling programs. VR allows firms to check the accuracy of design constructability, select methods based on space and accessibility constraints, and assign resources based on availability [106–108].

## 5. Discussion

As a powerful technology, AI has become apparent in all industry sectors [109]. This paper investigated AI adoption in the construction industry to synthesize the existing knowledge and identify the key AI adoption opportunities and challenges. The systematic review highlights an emerging emphasis on technological solutions that integrate AI-driven algorithms. The AI disruption potential is low in deconstruction, medium in construction, and high in planning and operation [110,111]. In addition, the research found that four constellations will have the most significant impact on the construction industry, namely: (a) AI and analytics; (b) 3D printing modularization and robotics; (c) digital twin technology; and (d) supply chain optimization and marketplaces.

The potential disruption and growth of these constellations will determine the progress of the construction industry adopting AI technologies in the long run [112]. The accessibility of data should be transparent in the construction industry as it will improve the efficiency and accuracy of AI adoption. It may be possible that external third parties leverage engineering and construction data to train their models. This situation would improve the



results within the construction industry but limit competitive advantage for individual firms. Nevertheless, this seems improbable given the limitations on data sharing and ownership [113]. Table 8 outlines the prospective of unique AI technologies that stem from the four constellations identified in Figure 2.

**Table 8.** Prospective AI applications in the construction industry [15].

Application	AI Technology	Purpose
Automated scheduling	Machine learning	Evaluate interminable data combinations and alternatives based on comparable projects and optimize the most efficient critical construction path to meet the milestones, identify future events, project delivery alternatives, and improve the overall project preparation.
Retail supply chain	Automation	Increase predictability of materials being received on-site and reduce manufacturing downtime that may impact project-related costs, logistic burdens, and material variability. Gradient boosting trees can be directly applied as modularization and prefabrication become more prevalent in the construction industry. There is a surge in offsite construction as materials and supply chains are coordinated and become more effective to control the costs and cash flow of a project.
Digital twin	Automation	The lack of transparency and proactive problem solution has a direct negative effect on productivity gains. Digital twin technology can capture real-time data that give stakeholders a real-time comparison of the progress from initial designs.
Storing space	Pattern recognition	A digital map that is constantly updated and shows the location of stored materials and machines. The visual data can be accessed on a digital map that is up to date and reduces the time spent to find a specific item.
Robotics and modularization	Deep learning	The construction industry is beginning to transition to manufacturing-like systems that allow for mass production. Robotic technology such as bricklaying and welding robots, self-driving heavy machines make construction safer, and wearable robotics improves the mobility of workers. Furthermore, modular construction technology will include applications that turn a 2D drawing or 3D model into a prefabricated building component.
Analytical platforms	Pattern recognition	Enhanced analytical platforms that gather data from sensors to understand signals and algorithm patterns to deploy real-time solutions, reduce costs, highlight risk mitigation strategies, and avoid unplanned downtimes incidents.
Automated image recognition	Automation	Video data are collected on-site to identify unsafe working behaviors and priorities safety education by aggregating data. In addition, video imagery can detect people and find those who are not registered on a construction site.
Predictive AI algorithms	Pattern recognition	Forecast project risk, constructability, structural stability and provide insight during the decision-making stage of various technical solutions. In addition, predictive AI can improve construction profit margins by reducing uncertainties and enhancing project value by using linear/quadratic discriminant algorithms. Furthermore, it can detect dangerous situations early by using machine learning algorithms and pattern recognition.
Design optimization	Machine learning	The supervised learning algorithm that uses clustering to classify essential data is necessary for making a recommendation. These applications are beneficial to project stakeholders as they inform them based on several criteria, such as total cost of ownership, time to complete the project, and the likelihood of defective mistakes during construction.

### 5.1. Key Findings

The review revealed that how data are generated and stored is critical in adopting AI in construction. Connecting all the necessary components to introduce AI in construction will be fundamental for an easy transition from traditional methods. IoT will also significantly influence the implementation of AI in construction, as it is highly dependable on accurate sourcing data and designing new data models [114]. Data reduction techniques can ease the transition to incorporate IoT using principal components analysis. In addition, edge node computation can also help the change by sending data to a digital twin for a real-time digital counterpart [115,116].

The frequency of opportunities and challenges was measured by the number of times common discussions were mentioned in the 72 papers reviewed. In addition, keywords

from the papers were also considered when determining the frequency of major findings. The most frequently mentioned opportunities in the literature review were: (a) reduce the time spent on repetitive tasks by using big data; (b) improve current work processes; and (c) increase the accuracy of plans in the design and planning stage. Furthermore, opportunities that drive AI applications in the construction industry were: (a) produce outcomes that all stakeholders easily understand and (b) enhance consistency and reliability as AI is highly unlikely to make mistakes.

Meanwhile, the most common challenges include: (a) AI applications are highly specialized and need constant algorithm training to spot patterns; (b) fragmented nature of the construction industry may result in data acquisition problems; (c) incompatibility with existing construction processes and practices; and (d) AI platform constantly need investment to ensure data are up to date and accurate. Furthermore, the challenges that will only slightly delay the development of AI in construction are: (a) security and reliability of large amounts of data; (b) multi-point responsibility may result in non-actionable tasks; and (c) non-standardization of a construction project makes it difficult to implement AI.

To overcome these challenges, construction companies need to adjust their corporate structure to incorporate AI into their corporate network. Therefore, companies need to recognize areas where AI-powered algorithms impact most in the short run [117]. This will give businesses a return on R&D investment and motivate them to spend more on AI technologies. Without a clear business case, AI will be wasteful in time and resources [11]. Businesses need to prioritize their investment into research and development into areas that will have an influence over the firms' profit target [118].

AI will have the most significant impact in the planning stage, as it has the highest capacity to improve. Technologies that will see the most growth during this stage are predictive modeling that determines risk, prevents cost overruns by using machine learning algorithms, and increases the health and safety of on-site personnel by analyzing images simultaneously [119–121]. To efficiently use these technologies, firms need to invest in the appropriate tools and strategies for data collection and processing, cloud infrastructure, and advanced data analytics [122]. According to Bughin et al. [23], companies with a strong digitalization background are 50% more likely to make a profit by using AI and robotics.

The future trends of AI in construction are established around four central themes of better awareness and acceptance of these AI-powered technologies: (a) improvement of technologies' affordability and obtainability; (b) a substantial increase in the range and usage of AI technologies; (c) improvement in technologies that allow for more flexibility and more straightforward use; and (d) change in the construction industry that allows for better integration and more standardization of design and work processes. Along with this, we also underline the critical role of open innovation—a distributed innovation process beyond the boundaries of a company—in the construction industry, as such innovation approach will increase the collaboration between research and construction organizations and help in the increase in productivity in the industry [123–125]. It will also help innovation and construction ecosystems merge [126].

## 5.2. Research Contributions

AI is a powerful technology with increased contributions to industries [127,128]. The paper investigates AI techniques used in the construction industry and summarizes AI opportunities and challenges in planning, design, and construction stages. The opportunities and challenges were derived from the ( $n = 72$ ) literature reviews and formed to create 12 clusters. These clusters were then analyzed against AI technologies to understand the potential of AI in a project.

The technologies examined are limited to those being used in the planning, design, and construction stages only. Research in the broader construction life cycles such as maintenance and demolition are plentiful, and commercial products are already readily available. As AI is an emerging field in construction and is a relatively new concept, the contribution of this paper are as follows:

- A new body of knowledge concerning AI technologies practices in construction.
- An understanding of the potential and existing application of AI analysis in the construction industry.
- A review on the opportunities and challenges that the construction industry encounters when they implement AI.
- A groundwork for future research based on the data findings.
- An analysis of the use of new technologies on construction sites in planning, design, and construction stages.

In the light of the insights generated in this paper, our prospective research will continue exploring the adoption challenges of AI and the opportunities offered for the construction industry.

### 5.3. Research Limitations

The study has some limitations: (a) the scope of the research constrains the paper in itself; (b) it needs additional literature reviews to expand the current findings and develop a better understanding of the opportunities and challenges of AI technologies; (c) AI opportunities and challenges are constantly changing, as it is still a relatively broad concept. There is a lack of similarity between companies, which has resulted in various business structures; (d) as the paper's objective is to provide an outlook of the AI opportunities and challenges in the construction industry via studying existing research, we have not experimented with other sets of data; for example, sensitive data from professionals on sites, their viewpoints concerning the opportunities and challenges of adopting AI technologies in real applications via interviews and surveys; and (e) we may expand our scope of research and reveal the strengths, weaknesses, opportunities, and threats (SWOT) when we adopt AI on sites.

Given these limitations, we need to expand our research to technological development in areas that may not be practical due to certain constraints. We may also provide a clearer picture of what technologies are available at certain price levels via interviews and surveys. This will allow us to know more about the cost and improve the technologies acceptance.

## 6. Conclusions

This study has conducted a systematic review of the literature on AI in the construction industry by using the PRISMA protocol. The study findings highlighted that the construction industry should take advantage of AI throughout the project lifecycle, as it brings significant advantages. The increasing complexity of modern construction in pre-construction, procurement, and post-construction stages is now the main driver for developing interest in digital technologies. However, AI applications for the industry are only in the initial stage, and there remain significant research gaps that turn digital inventions for construction sites into reality [129]. The construction industry needs to close this gap by looking at how AI applications are being used in other industries.

In each instance, the construction industry would benefit from other initiatives and sectors' technological research and development efforts. Nevertheless, additional research is required for the industry to undergo the transformation and familiarization with constantly changing built environments [130]. This will give the construction industry a good starting point in adopting AI technologies. Despite the potential and availability to deploy AI technologies in a construction project, there is still a missing data link between humans and technology. This is evident as most work completed on a construction site is labor intensive. As a result, efforts are needed to utilize appropriate digital solutions in an entire lifecycle, including but not limited to sensors and smart wearable technologies [131].

The construction industry's future will depend heavily on taking a system view that combines current technologies with the new AI applications [132–135], which resembles a complex cyber-physical system. The constituent technologies will continuously improve current processes by reducing device sizes, improving communication technologies, increasing power storage volume in batteries, and higher computational power

in IoT edge devices [136]. The smart work concept also influences the design of human computer/machine interface and brings a new level of on-site sensing, monitoring, and real-time updates [87,137,138]. Development in robotics is also growing in the modular building, as it carries over much of the process that relies heavily on manual input. This is also the case when used in BIM systems and 4D CAD/CAM models as they are transitioning from manual input to digitalize processes. In addition, mixed reality will support on-site activities as it ensures that the correct procedure is undertaken. Any possible hazards are detected and made aware to everyone on the project.

The landscape of AI in construction is consistently changing, and it is speculated that the opportunities will far outweigh the challenges in the long run when AI technologies are mature. Since AI needs a considerable amount of data for algorithm training, large-scale companies are likely to be more advantageous in the short run [129]. However, these benefits will spread to medium and small-scale companies shortly when they recognize the cost and time benefits it may bring.

The exponential growth of innovation and technological advancements are offering new opportunities to the urban development and the construction industry [139]. AI is a core technology of the Fourth Industrial Revolution (a.k.a. Industry 4.0) and will continue to expand in the construction industry [140–142]. The construction industry will begin to see AI as a major driver of change to improve efficiency, productivity, work processes, accuracy, consistency, and reliability in the long run. In addition, it decreases costs, unforeseen risks, and accidents on sites [25]. The challenges and opportunities of AI applications for the construction industry will provide a new perspective for further exploration in 5–10 years.

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