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Review

Artificial Intelligence in the Construction Industry: A Systematic Review of the Entire Construction Value Chain Lifecycle

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Abstract: In recent years, there has been a surge in the global digitization of corporate processes and concepts such as digital technology development which is growing at such a quick pace that the construction industry is struggling to catch up with latest developments. A formidable digital technology, artificial intelligence (AI), is recognized as an essential element within the paradigm of digital transformation, having been widely adopted across different industries. Also, AI is anticipated to open a slew of new possibilities for how construction projects are designed and built. To obtain a better knowledge of the trend and trajectory of research concerning AI technology application in the construction industry, this research presents an exhaustive systematic review of seventy articles toward AI applicability to the entire lifecycle of the construction value chain identified via the guidelines outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The review's findings show foremostly that AI technologies are mostly used in facility management, creating a huge opportunity for the industry to profit by allowing facility managers to take proactive action. Secondly, it shows the potential for design expansion as a key benefit according to most of the selected literature. Finally, it found data augmentation as one of the quickest prospects for technical improvement. This knowledge will assist construction companies across the world in recognizing the efficiency and productivity advantages that AI technologies can provide while helping them make smarter technology investment decisions.

Keywords: artificial intelligence; AI technologies; AI adoption; AI benefits; AI challenges; construction industry

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1. Introduction

On a regional, national, and global scale, construction is considered a large sector with strategic importance [1]. It is also an industry that has been plagued by a slew of issues for decades, including low production, slim profit margins, waste, and safety concerns. Its projects are extremely complex, and the danger of inefficiency and risk, which eventually contribute to project costs and delays, grows geometrically with the project's scale [2,3]. In the past, to mitigate these issues, the construction industry traditionally concentrated on generating operational benefits by employing technology to streamline processes and procedures, but the data gathered as a result of this digitization trial is often overlooked [4,5]. Surprisingly, this industry is still on the edge of digitization, which is said to disrupt existing traditional procedures while also opening up a slew of new prospects [6].

In recent years, there has been a surge in the global digitization of corporate processes and paradigms, including industry 4.0, and digital twins and digital technology development is growing at such a quick pace that the construction industry is struggling to catch up with the latest developments. A formidable digital technology, artificial intelligence (AI), is now a vital component of the digital shift (partly due to big data revolution), having gained broad acceptance in diverse sectors, including healthcare, where it assists in patient diagnosis through genetic data [7,8]; manufacturing, where it is utilized for workforce management, production process optimization, and predictive maintenance [9]; education, where it facilitates virtual lectures [10,11]; finance, particularly in fraud detection [12,13], and transportation, exemplified by the development of self-driving autonomous cars [14,15], among many others.

The definition of AI has evolved throughout time, but its foundation has always been the goal of creating machines that are capable of thinking like humans. It does this by trying to imitate human intelligence through hardware and software solutions [16]. With more data being generated every second, AI technologies encompassing robotics, machine learning, natural language processing, speech recognition, expert systems, and computer vision, among others, have aided the scientific community in harnessing the growth of big data [17]. On these massive datasets, scientists can extract information that human eyes cannot interpret quickly enough using AI.

As a result, it is clear that AI can help the construction industry improve decision-making, drive project success, and deliver projects on time and on budget by proactively unlocking new predictive insights from its ever-growing volume of project data, which was previously only archived for future reference. For instance, data collected from smart devices, sensors within the Internet of Things (IoT), Building Information Modeling (BIM), and various other data sources can be analyzed by AI technologies to find patterns in the performance and usage of current infrastructure assets and determine what sort of infrastructure is needed in the future and how it should be supplied [5].

Furthermore, the number of incremental stages necessary to bring infrastructure designs to operational status will most likely be reduced by AI. This will save time and money in the manufacturing of construction materials, alongside the development and maintenance of our infrastructure networks. In this regard, a vast body of international literature have investigated the use of AI technologies to tackle concerns related to construction projects. For example, machine learning has been applied to mitigate construction project delay risks [1,18,19], occupational health and safety concerns within the construction sector [20–22], and construction and demolition waste generation [23–25].

It is the viewpoint of Gamba, Balaguer, and Chu [26–28] that robotics can be used to automate the assembly of building elements (e.g., masonry walls, steel structures etc.). Also, Bruckmann and Wu [29–31] made an important point by adding that a robotic system, comprising a gripper connected to a frame via cables, demonstrates applicability in the domain of bricklaying. Furthermore, an expert system has been devised for the computation of fault rates in incidents related to falls in the construction domain [32–34] and natural language processing has been applied to extract and exchange information, as well as a variety of downstream applications to aid management and decision-making in smart construction projects [17,35,36].

More recently, some studies have conducted traditional narrative critical/literature reviews for a specific AI technology in the construction industry (e.g., computer vision by Xu [37], natural language processing by Wu [17], robotic system by Davila [38], etc.), while a few other studies have conducted traditional narrative critical/literature reviews for adopting generic AI technologies in the construction industry with a specific goal (e.g., Parveen [39] focused on AI's legal issues and regulatory challenges, Schia [40] focused on AI's impact on human behavior, and Abioye [41] focused on the current state, prospects, and forthcoming challenges in the field of artificial intelligence).

However, to the best of the authors' knowledge, there has been no exhaustive examination of the application of AI technologies in the construction industry. Thus, this study is motivated by the absence of a systematic review in this domain. In conducting a systematic review, independent researcher(s) design a system, based on specific guidelines (protocol), and the system then makes the decisions to determine the outcome of the research thus producing a research outcome that is explicit, reproducible, and without prior assumptions [42]. Meanwhile, in a typical traditional narrative literature review, the identification, selection, inclusion, and extraction of research articles solely (all) depends on the judgement of the author(s) in order to support their model, hypothesis, and to identify the research gaps. This poses a great concern of subjectivity, repeatability, and reproducibility of results from such research [43].

Secondly, and as a final rationale of this research, no study, to the best of our knowledge, has conducted any kind of AI review toward its applicability to the entire lifecycle of the construction value chain. In addressing this void, the aim of this study is to provide a thorough systematic review of artificial intelligence and its implementation throughout the entire construction value chain lifecycle—from building material manufacturing to design, planning, and construction, as well as facilities management. The systematic review is structured around the ensuing research questions:

1. What AI technologies have been documented in the literature so far?
2. What are the different stages of the construction project lifecycle wherein these AI technologies are applied?
3. What potential benefits arise from the implementation of the identified AI technologies, and what are the existing challenges and deficiencies in their industry adoption?

This research makes a significant contribution to the body of knowledge by addressing the knowledge gap in the field of AI in the construction industry, specifically by addressing several imaginable application cases for AI across diverse phases of the construction project lifecycle and the potential benefits of implementing AI technologies, as well as the present roadblocks and gaps in their industrial adoption. This will immensely contribute to the advancement of the Architecture, Engineering, and Construction (AEC) industry and the holistic built environment ecosystem in identifying opportunities for technological advancement.

2. Methodology

This study adopts a philosophical paradigm rooted in pragmatism, emphasizing practical applied research that employs multiple perspectives for data interpretation. Depending on the research question, the study considers both observable occurrences and subjective meanings as viable sources of knowledge [44]. This study employed a systematic review methodology. A systematic review, distinct from a conventional literature review, utilizes a precise, comprehensive, replicable, and auditable methodology to evaluate and interpret all pertinent research associated with a particular research question, subject, or domain [42]. Moreover, by scrutinizing the holistic perspective and amalgamating discrete elements to synthesize results in a structured manner, a systematic review can address the limitations inherent in a traditional narrative literature review, which is commonly used in the vast body of literature.

To develop its systematic review protocol, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were applied. PRISMA serves as a protocol for executing systematic reviews and meta-analyses, comprising a twenty-seven-item checklist and a four-phase flow diagram. Conceived by a consortium of twenty-nine scholars in the medical domain, PRISMA aims to enhance the lucidity and uniformity of literature reviews. Consequently, our examination's focal theme, exploration strategy, criteria for inclusion and exclusion, eligibility standards, data extraction, and synthesis methodologies were all delineated in adherence to this protocol which was chosen because of its comprehensiveness, wide acceptance, and applicability in different fields of study, despite the fact that it was originally established for the medical and health domain [43]. For a start, the review process was broken down into four steps: article identification, article screening, critical assessment, and data extraction and synthesis.

During the article identification process (step 1), a comprehensive exploration of the literature was conducted to identify articles for this research. Specifically, articles available in the Scopus electronic database up until 21 January 2022 were utilized as the principal source of information for the search. This database was chosen over others like ScienceDirect and Web of Science because it is the "largest abstract and citation database of peer-reviewed literature" [45]. Furthermore, Scopus indexes practically the whole ScienceDirect database, and Scopus offers a greater choice of journals than Web of Science, as well as quicker citation analysis and coverage of more articles [46]. The abstract, title, and keywords of publications in this database were searched using the following search terms: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "automation" OR "robotics" OR "expert system" OR "natural language processing" OR "optimization" AND ("construction industry" OR "building industry" OR "built environment" OR "Architecture Construction and Engineering")) with no date, language, or article type restrictions. The search terms were divided into two major parts separated by the "AND" operator, namely, AI technologies and the construction industry. The search terms also contained several interesting synonyms, word variations, and exact phrase searching symbols, such as the usage of double quotation marks in "machine learning"and "building industry", among many others.

At the article screening process (step 2), the abstracts of 2716 articles were reviewed to see whether they were related to the research questions and to make sure there were no duplicates. As such, this led to the removal of 2306 items, leaving 410. At the critical assessment (step 3), three distinct inclusion and exclusion criteria were implemented. Articles were deemed eligible if their primary emphasis centered on the utilization of artificial intelligence technologies in construction projects and excluded otherwise. Additionally, only articles presenting original research data were included, while review articles were excluded. Finally, each article's relevance was determined using a previously developed rating scale by [42,43,47]. The scale was adapted based on practical results of how artificial intelligence technology is used in a construction project, with "1" indicating low relevance, "2" medium relevance, and "3" indicating high relevance.

Consequently, the full text of all articles having information relating to genuine case studies of AI technology implementation in construction projects or AI technology application proven in a laboratory environment were extracted, exported to a file in Comma-Separated Values (CSV) format, given a "3" rating, and included in the evaluation during the data extraction and synthesis process (step 4). Finally, a comprehensive examination of the selected articles was conducted for the purpose of data extraction, encompassing elements such as research aim, project type, country/region, research method(s), and AI technology, among others. Figure 1 elucidates this process, presenting a flow diagram delineating the research article selection procedure. The diagram outlines the total count of articles identified through the database search, articles screened in accordance with eligibility criteria, articles fully accessed, and the eventual count of articles utilized for analysis in this study.

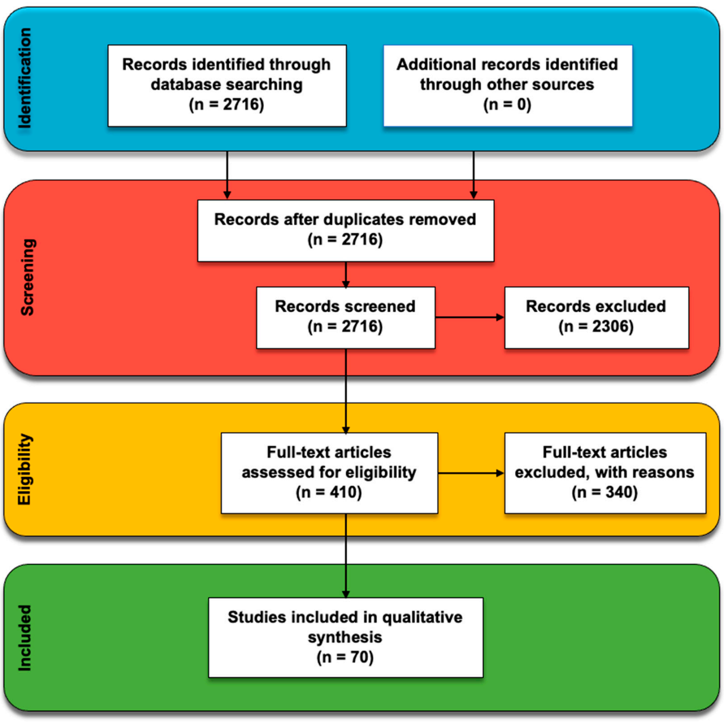

Figure 1. Flow diagram of the systematic review process.

3. Results

3.1. Summary of Selected Articles

A summary of the selected articles organized by their respective publication source is provided. It was discovered that the journals *Automation in Construction* and *Journal Construction Engineering and Management*, as well as conference proceedings from the *Conference on Computer-Aided Architectural Design Research, CAADRIA*, possessed the preeminent quantity of articles, constituting 20% of the overall selected papers. In general, 75.71% of the total papers (53 out of 70) were disseminated through peer-reviewed scholarly journals, whereas 16 articles (22.86%) were presented at conferences, and just 1 paper was part of a book series.

For two decades between 1993 and 2013, there were eight articles, each with a different year of publication (see Figure 2). There is a notable constant increase in the quantity of research publications throughout the AI in construction research community. More specifically, between 2017 and 2021, there was a constant increase in the number of research publications published in the research community, with a total of 56 articles, indicating a rising interest in the application of artificial intelligence technology to the construction industry. Figure 3 shows the number of publications according to the first author's institute's location. Predominantly, researchers from China (12 articles), the United States of America (USA) (8 papers), Republic of Korea (6 papers), Italy, the United Kingdom of Great Britain (GBR), and Australia (4 papers each) published most of the papers relevant to the research topic.

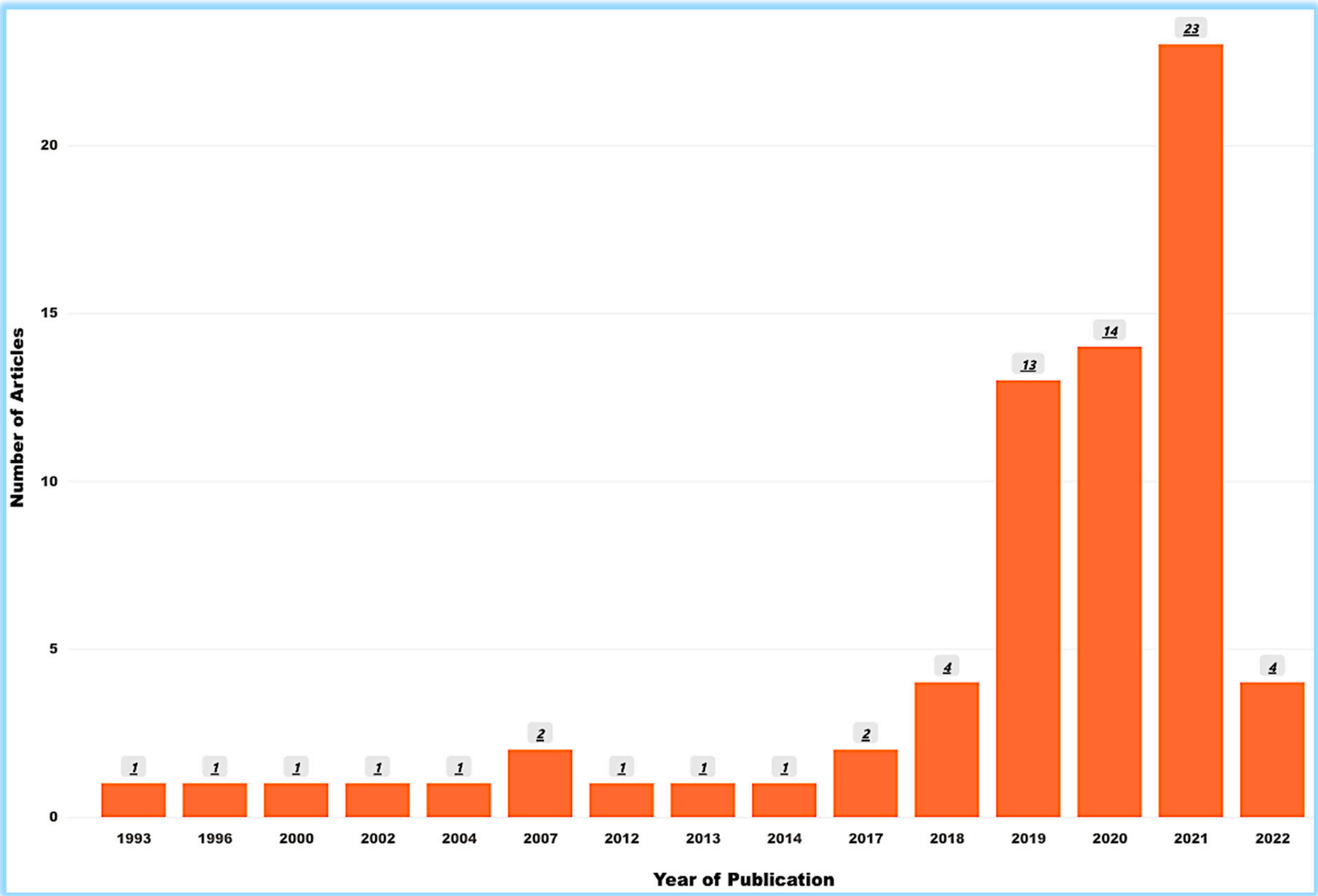

Figure 2. Sequential distribution of articles (total number of articles is 70).

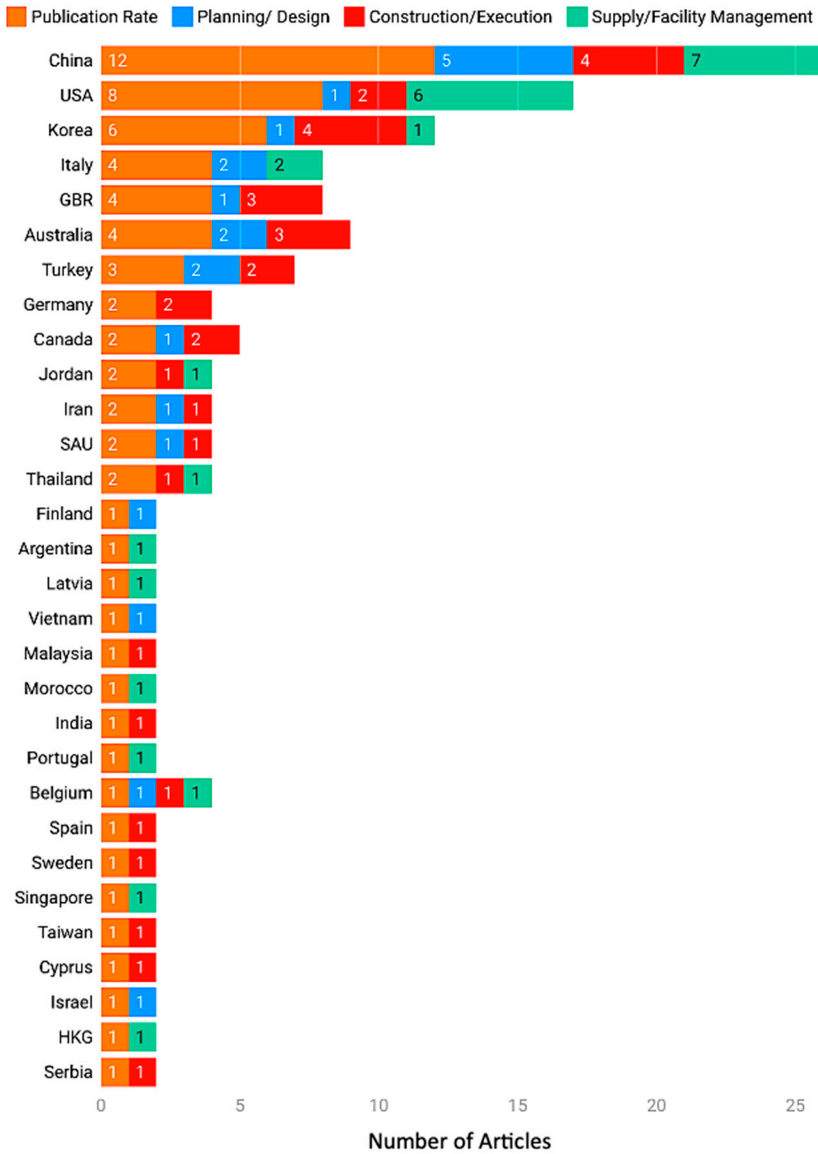

Figure 3. Geographical distribution of articles based on project lifecycle.

Upon scrutinizing the geographic dispersion of academic papers related to artificial intelligence research applied in the construction/execution lifecycle of the construction value chain, it was discovered that researchers in the Republic of Korea and China emerge as primary contributors to scholarly inquiry within this domain (4 articles each), followed by researchers in GBR and Australia (3 articles each). Interestingly, researchers in China tend to have devoted the most attention to AI applications in the supply/facility management lifecycle of the construction value chain, with seven publications dedicated to it, and five articles dedicated to the planning/design lifecycle of the construction value chain as well.

3.2. Types of AI Technologies and Categorization

Table 1 shows the different types of AI technology and their distribution across different application areas. In general, the seventy reviewed studies referenced seven AI technologies for use in the construction industry, with supervised learning, deep learning, knowledge-based systems, robotics, and natural language processing being the most often mentioned. On the other hand, AI technologies such as optimization and reinforcement learning garnered less attention. In terms of the distribution of AI technologies to their application areas in health and safety management, supervised learning was the most researched (4 articles), followed by deep learning and knowledge-based systems (3 articles each). Deep learning and supervised learning have shown to be effective time and cost management technologies (2 articles each). Also, robotics was the most often mentioned technology for prefabrication (2 articles). Furthermore, the most promising AI technologies for heating, ventilation, and air conditioning (HVAC) optimum control were identified to be optimization and deep learning technologies (2 articles each), while most papers highlighted the application of natural language processing in relation to sustainable concrete and regenerative sustainability (1 article).

Table 1. Types of AI technology and their area of application.

AI Technology	Description	Subtype	Application Area	Reference
Supervised Learning (SL)	A type of machine learning in which a computer algorithm is trained on labeled input data for a certain output.	Support vector machine (6), artificial neural network (6), bckpropagation (3), decision tree (5), random forest (4), k-nearest neighbors (3), gradient boost machine (2), adaptive boosting (2), naïve Bayes (2), extreme gradient boosting (2), logistic regression (2), ensemble method (2), light gradient boosting machine (1), extra trees (1)	Health and safety management (4), time and cost management (2), building structures (2), structural reliability (1), sustainable concrete (1), demolition waste management (1), constructability analysis (1), construction monitoring (1), construction equipment (1), occupant behavior (1), site layout (1), cementitious composite (1), energy savings and demand response (1), project selection (1), construction negotiation and conflict resolution (1)	[19,24,25,48–70]
Deep Learning	A type of machine learning that trains computers to accomplish things that humans do instinctively.	Convolutional neural network (6), deep neural network (4), autoencoder (1), long short-term memory (1)	Health and safety management (3), time and cost management (2), HVAC optimal control (1), construction monitoring (1), intelligent building design (1), 3D datasets (1), building information modeling (1), monument recognition (1), surface defect detection (1), building recognition (1), filing architectural drawings (1) parametric design (1)	[66,71–88]
Knowledge-Based System	A computerized system designed to capture and imitate human intellect in symbolic form, often through a series of if–then rules.	Expert system (5), Case-based reasoning (2), Fuzzy logic (1)	Health and safety management (3), building automation (1), productivity estimation (1), site layout (1), building diagnosis and repairs (1), performance evaluation (1), construction negotiation and conflict resolution (1), occupant behavior (1) architectural innovation (1)	[51,57,89–97]
Robotics	A technology that deals with the creation, design, construction, and operation of programmable machines.	Additive manufacturing (4), robotic beam assembly (1), soft robotics (1), robotic bricklaying (1), mobile robot (1)	Robotic prefabrication (2), digital fabrication (1), collaborative robotics (1), block assembly (1), intelligent hoisting (1), health and safety management (1), environmental impact analysis (1)	[26,71,98–104]
Natural Language Processing	An artificial intelligence technology that utilizes computers to comprehend, generate, and analyze human languages known as natural language processing.	Text clustering (1), word segmentation (1), information retrieval and extraction (1), text analysis (1)	Health and safety management (2), HVAC optimal control (1), sustainable concrete (1), regenerative sustainability (1)	[56,105–109]
Optimization	A technique that seeks to alter an existing process to enhance the occurrence of good results and decrease the occurrence of bad outcomes.	Genetic algorithm (2), gray wolf optimization algorithm (1), genetic algorithm, stochastic gradient descent (1), genetic programming (1)	HVAC optimal control (2), health and safety management (2), sustainable concrete (1), building structures (1)	[60,68,85,110]
Reinforcement Learning	A form of machine learning that enables an agent to acquire knowledge through iterative experimentation and experience while receiving feedback from its actions.	Q-learning (4)	Energy savings and demand response (1), HVAC optimal control (1), health and safety management (1), look-ahead schedule (1)	[110–113]

Quite notably (see Table 1), the articles included in this study highlighted the emergence of diverse subtypes within each AI technology. For instance, the most cited subtypes of supervised learning AI technology were support vector machine and artificial neural network (6 articles each), followed by the convolutional neural network subtype of deep learning (6 articles), and the expert system subtype of knowledge-based systems (5 articles). As Table 1 shows, most of the papers included cited adaptive manufacturing (4 articles) and Q-learning (4 articles) as the most widely used subtype of robotics and reinforcement learning AI technology, respectively. In addition, genetic algorithm appeared to be the most favorable subtype of optimization technique for the researchers (2 articles).

3.3. Construction Project Types and Their Lifecycle Application Area

In terms of the types of construction projects in which AI technologies were used, Figure 4 suggests that the majority of the scholarly articles included (58.60%) were related to built environment and residential building (28 articles in built environment and 13 articles in residential building). Following that were papers regarding high-rise and commercial buildings, which made for 18.60% of the articles chosen (7 articles in high-rise building and 6 articles in commercial building). Bridge/highway project and office building project were discovered in 7.10% and 4.30% of the total of 70 articles, respectively. Moreover, power plant, timber construction, and architectural heritage projects all had the same number of articles (2 each), with only one article (1.40%) proposing the use of AI technology in retrofit building and water treatment plants.

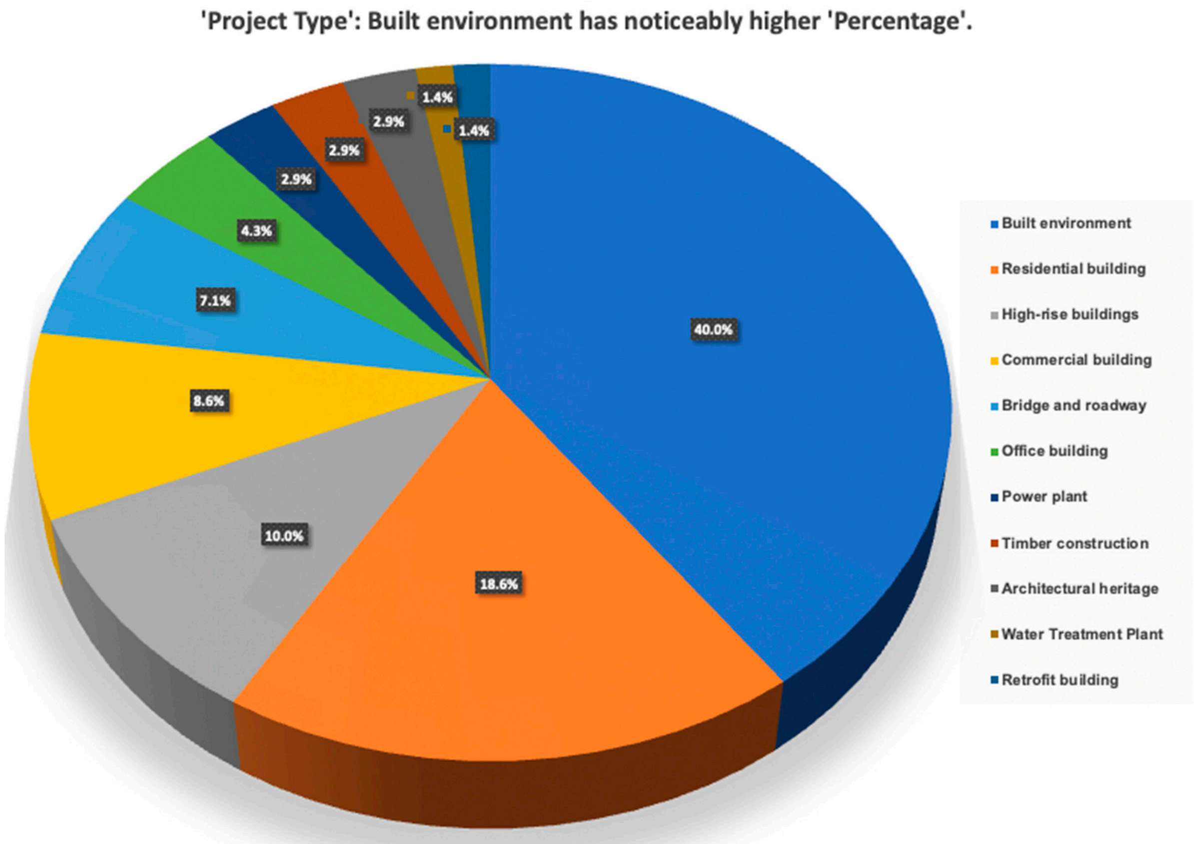

Figure 4. Distribution of articles based on project type.

Furthermore, Figure 5 depicts the distribution of articles by construction project type and lifecycle stage. The majority of articles on built environment were focused on the construction/execution stage (15 articles). However, there were only a few articles that focused on the planning/design stage of the built environment (3 article). Likewise, the planning/design and supply/facility management stages of the construction lifecycle for residential buildings received the greatest attention (6 articles each), with a smaller number of articles devoted to the construction/execution stage (1 article). Papers related to high-rise buildings had a focus toward the construction/execution stage (3 articles). All the included papers on commercial buildings (6 articles) and bridge/roadway projects (5 articles) focused on the three stages of the construction lifecycle in near equal measure. Interestingly, articles pertaining to power plant projects (2 articles) and retrofit building (1 article) exhibit a distinct emphasis solely on the construction/execution stage within the construction value chain lifecycle. Conversely, water treatment projects predominantly concentrated on the planning/design stage of the construction value chain lifecycle. Additionally, projects involving timber construction and architectural heritage shared an equal number of articles across their respective stages in the construction value chain lifecycle.

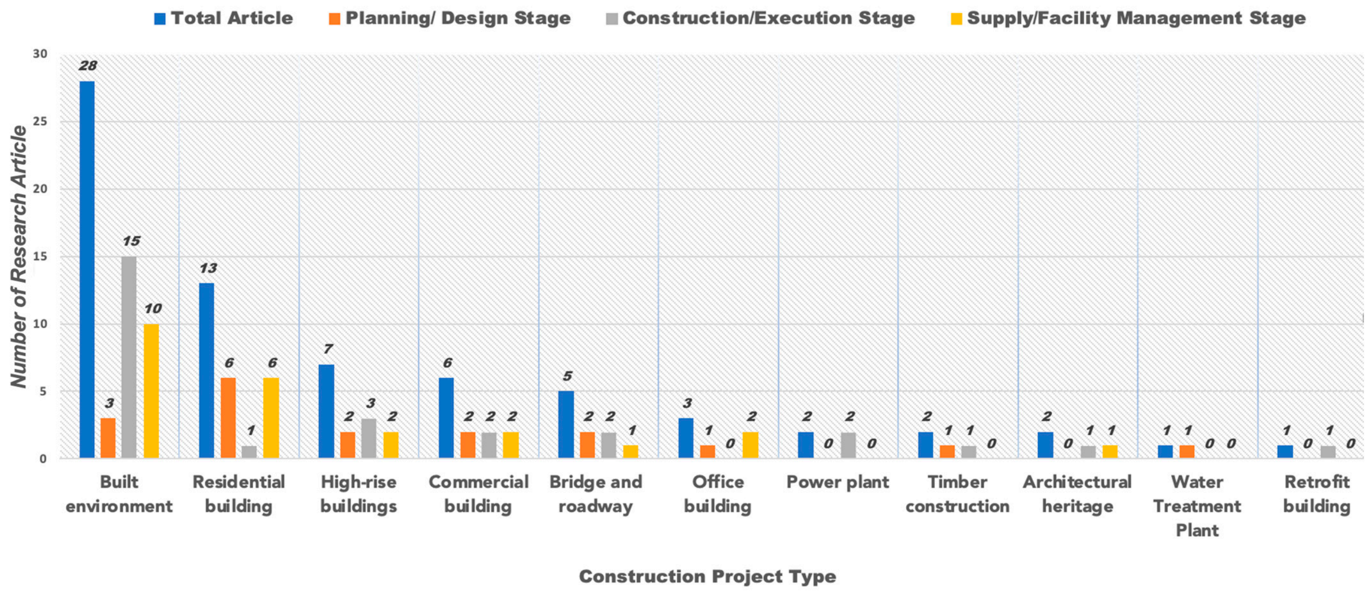

Figure 5. Distribution of articles based on project type and lifecycle.

3.4. Benefits, Challenges, and Opportunities for Technological Advancement

3.4.1. Benefits

This subsection comprehensively addresses the manifold benefits derived from the escalating prominence of artificial intelligence technologies in the construction industry. The principal benefits attributed to the integration of AI technology within the construction sector, as delineated in twenty-six out of the seventy curated articles, are succinctly outlined.

Potential for Design Expansion

Intelligent room layouts for better natural ventilation are one example of how AI technologies can lead to novel design aspects. As mentioned by Sonetti [107], who developed AI solutions for human-centered regenerative design, AI technologies are strong supporters of human-centric regenerative design when it comes to developing technologies that improve interactions between buildings and their occupants. It is the viewpoint of Lamio [82] that the application of AI technologies to automate building design processes demonstrates that an image taken from a virtual model can accurately distinguish the building type. They developed an AI tool using classical and modern machine learning techniques to categorize images of building designs into three classes. This is especially important considering the large number of BIM structures with missing information or incorrect labeling.

Possibility for Big Data Analytics

AI technologies are exposed to an unending quantity of data to learn from and improve on every day at a time when vast amounts of data are being produced in the industry [114,115]. For instance, the research led by Palma [81] explored the integration of convolutional neural networks (CNNs), a subset of deep learning methods, into the realm of architectural heritage by developing a mobile app aimed at monument recognition, pioneering the use of AI in this domain. Palma's [81] argument is compelling, especially in terms of his pointing out that the output of their adoption of AI technology resulted in the creation of open datasets for testing and evaluating AI applications in the field of architecture and architectural heritage. In addition, Keshavarzi [86], who developed a generative system that addresses the challenge of limited 3D datasets for deep learning methodologies in the built environment stated that their AI technology has the potential to facilitate data augmentation of parametric 3D scan datasets by taking an extant 3D scan as input and generating alternative iterations of the architectural configuration, encompassing walls, doors, and furnishings, accompanied by corresponding textures. This process extends the prevailing 3D geometry datasets, which are conventionally constrained in their scope.

Workplace Health and Safety

AI technology can provide a project with precise job site safety best practices based on learned knowledge. As one of the most hazardous industries to work for, this surveillance keeps people safe and accidents to a limit. In the pursuit of minimizing accident occurrences within construction sites, Zhang [56] employed a diverse set of AI technologies. Specifically, an ensemble model was devised, integrating text mining, natural language processing (NLP), and machine learning methodologies for the comprehensive analysis of construction accident records. The objective was to discern and extract salient elements associated with accidents, ultimately mitigating potential hazards. With reference to Yu [73], AI technologies can be used as non-invasive tools for workload monitoring and thorough ergonomic assessment for various construction tasks, such as assessing risk factors for work-related musculoskeletal disorders by developing an AI tool that employs a smartphone camera with advanced deep learning algorithms to extract construction workers' skeleton data, complemented by smart insoles to quantify plantar pressures during various construction activities. More so, Su [76] adopted an AI technology to predict the smoke motion and the available safe egress time in a typical atrium.

Increase in Productivity

Some AI technologies can complete repetitive tasks swiftly and precisely while being fatigue-free. For instance, Li [103] detailed the creation of a vision-based intelligent mobile robot hoisting system to improve the hoisting process, including the process of hooks identifying the hoist points and autonomously releasing the components without the need of on-site construction employees. According to García de Soto [100], by offering a process for evaluating productivity based on total cost and time per unit installed, it is conceivable to obtain considerable economic advantage from the use of additive digital fabrication to create complicated structures through the development of an AI-driven robotic construction method as part of digital fabrication in the construction industry. Furthermore, investigations by several researchers [71,98,99,101–103] have shown the possibility of replacing risky and difficult manual construction work with automated robots.

Enhanced Risk Mitigation

All construction projects have a few risks, which can take numerous forms, including quality, timeliness, and cost. A particular strength of Hong's [105] argument is that AI technologies can assist in assigning time and cost contingency to completing a construction project through the development of natural language-related AI technologies including clustering methods, including latent semantic analysis (LSA), latent Dirichlet allocation (LDA), and word2vec, amongst many others for quantitative analysis in construction scheduling. Varouqa [55] concurred and went on to say that AI technologies can be employed as optimization strategies in prefabricated construction projects to save time and money. Furthermore, Lee [108] adopted AI technology to perform a pre-emptive contract-risk evaluation, which can offer stakeholders with contractual positions and rights based on contract facts, minimizing the number of claims and conflict cases between participating parties during construction.

3.4.2. Challenges

There are several challenges described in the seventy selected articles about the implementation of AI technology in the construction industry (see Table 2). In general, a low accuracy level due to scarcity of available data was found to be the most frequently cited challenge (41.43%) during the adoption of supervised learning AI technology (15 occurrences), followed by data transformation techniques not transferable to data from other regions (12.86%) during the implementation of the same AI technology (5 occurrences), lack of real-world applicability (11.43%) when using deep reinforcement learning AI technology (3 occurrences), and incorrect image classification of structures (4.29%) during deep learning AI technology adoption (2 occurrences). However, 2.86% of the articles considered the combination of industrial robot size and weight limits and high demand for sophisticated algorithms and computing power owing to massive volumes of data being equally troublesome when adopting deep learning and supervised learning AI technology in the construction industry. Other notable challenges include difficulty in model calibration and excessive modeling errors for heating demand prediction, long installation time for robots, difficulties in developing inference rules for expert systems, and misclustering of some project milestones into building works for natural language processing, among many others.

3.4.3. Opportunities for Technological Advancement

More so, Table 2 emphasizes how AI technologies open a slew of opportunities for technological advancement in the construction industry, giving it a competitive edge by improving efficiency across the whole value chain from building materials manufacturing to design/planning, construction/execution, and supply/facility management.

Data Augmentation

In concrete, it shows that 41.43% of the selected papers who experienced a low accuracy level due to scarcity of available data suggested the need for future studies to augment datasets for the development of more robust AI technologies in the industry. For instance, Hu's [71] automatic robotic disinfection framework was unable to investigate the relationship between adequate UV light exposure and the effects of pathogen eradication due to low accuracy in segmenting the areas of potential contamination on small objects such as doorknobs and cabinet handles in adverse conditions. Furthermore, Davila Delgado [74] successfully demonstrated the application of undercomplete, sparse, deep, and variational autoencoders as novel techniques for data augmentation and generation of synthetic data in construction management, which can provide useful insights regarding the underlying non-linear relationships among variables in the datasets amongst many other selected studies.

Model Generalizability/Transferability

The opportunity for AI model generalizability and transferability became eminent as the unique data transformation employed in 12.86% of the selected articles was not transferable to the data from other regions as typical of any data-driven model. Zhang's [110] argument is persuasive in this aspect, particularly when they pointed out that their building energy AI model has better generalizability because it is based on fundamental scientific laws. A building energy model, for example, can properly estimate the energy performance of a new unseen control technique while a data-driven model may not. This is the case since the data-driven model is built using a training dataset that contains no information about the unseen control technique. In addition, Koc [60] raised awareness for future studies to take advantage of model generalizability, since he encountered the difficulty of an unbalanced dataset while using AI technology to assess construction workers' post-accident impairment status.

Table 2. Cited challenges for integrating AI technologies and opportunities for technological advancement in the construction industry.

Challenges	Opportunities	AI Technology	No. of Articles	Reference	%
Low accuracy level due to scarcity of available data	Data augmentation	Robotics, DL, expert system, optimization, SL (15), NLP	29	[24,25,48,52–55,57,59–63,66,69,71–73,75,80,84,88,89,91,94,96,97,104,108]	41.43
Data transformation not universally applicable	Model generalizability and transferability	NLP, SL, optimization, expert system, DL	9	[19,50,51,58,70,74,92,95,109]	12.86
Only experimental with lack of real-world applicability	Real-world applicability	SL, optimization, DL, RL	8	[49,68,76,78,79,85,112,113]	11.43
Incorrect image classification of structures	Computer vision and AR	DL, SL	3	[77,81,87]	4.29
Size and weight restrictions of industrial robots	Design optimization	Robot	2	[99,101],	2.86
High data demands, require advanced algorithms	Cloud computing infrastructure	DL, SL	2	[64,83]	2.86
Limited computing sSpeed	Compiling Keras/TensorFlow	RL	1	[111]	1.43
Model calibration challenges, errors in predictions	Multi-objective RL	RL, optimization	1	[110]	1.43
Long installation time	Programming safety and recalibration of peripherals	Robotics	1	[98]	1.43
Saturated neural network accuracy, optimization challenges	Enhanced random neural network structure generation.	SL, DL	1	[82]	1.43
Difficulties in developing inference rules	High optimization techniques	Expert system	1	[90]	1.43
Misclustering of some project milestones into building works	Construction schedules analysis	NLP	1	[105]	1.43
Inadequate network architecture	Large (big) datasets	SL, optimization	1	[65]	1.43
Omission of planning in robotic design	Design optimization	Robot	1	[100]	1.43
Limited scope in classification of building structures	Computer vision and AR	SL	1	[67]	1.43
Threshold limitations on Elasticsearch queried data	Load balancing	NLP	1	[106]	1.43
Limited customization of textures for walls	3D modeling and AR	DL	1	[86]	1.43
Control approach for large hydraulic robots	New control methods	Robot	1	[26]	1.43
Robot response hindered by image quality	Hgh-definition camera	Robot	1	[103]	1.43
Natural language exhibits diverse expressions	Advanced optimization	NLP, SL	1	[56]	1.43
Inability to repair walls and columns	Data-driven machine learning	Expert system	1	[93]	1.43
Heterogeneous hardware and software integration	AI knowledge experts	SL	1	[64]	1.43
Social barriers to the adoption of AI	AI education and trainings	NLP, SL, DL	1	[107]	1.43

Real-World Applicability

About 11.43% of the selected articles only tend to have simulated the adoption of AI technologies in a controlled environment thus lacking the confidence to validate their methods in a real-world setting.

According to Vázquez-Canteli [111], a useful graphical user interface (GUI) that allows users to write machine learning code or set hyper-parameters of the algorithms after the simulation environment is compiled is required for their fast AI-based building energy simulator implemented in an integrated simulation environment to be tested in a physical setting. Furthermore, as illustrated in Hong's [105] AI framework for clustering construction schedules in UK-based construction projects, Gondia's [19] AI-based model lacks the use of real construction project schedule information for their construction project delay risk prediction implementation in Egypt.

Computer Vision and Augmented Reality

The application of the most recent computer vision techniques and augmented reality functions followed suit, with 4.29% of selected articles recommending them as a means of advancing technology in the construction industry. More precisely, in the implementation of automatic image recognition of architectural heritage sites by Palma [81], for example, items in the same cultural site appeared to be extremely similar, or could appear together in the same view, making it impossible to distinguish one part from another. However, these circumstances emphasize the practical value of AI rather than the recognition of landmarks that are far apart. Thus, this implies the most up-to-date computer vision algorithms will be key to obtaining more detailed information than previously or the use of augmented reality functions to enhance their interaction.

Other notable opportunities for technological advancement that received less attention from the selected papers include design optimization and cloud computing infrastructure with 2.86%, followed by multi-objective reinforcement learning, safety programming and re-calibration of peripheral modules enterprise AI knowledge experts, and AI education and trainings, among many others (1.43% each).

4. Discussion

The findings of this systematic review primarily elucidate the dissemination pattern of research articles based on their publication sources, underscoring a pronounced prevalence of coverage within academic journals on the subject. This trend aligns cohesively with the research conducted by [41,116] affirming the transformative surge in the integration of artificial intelligence within the construction industry, largely attributed to the availability of substantial funding in this domain. Additionally, a discernible and consistent upward trajectory is observed in the quantity of scholarly research publications addressing the application of AI technology in the construction industry across the broader research community ecosystem. This arguably shows a significant improvement in the promotion of research and development of trustworthy AI solutions by funding bodies and agencies across the globe. Interestingly, this is in line with the findings of Rahkovsky [117], who argued that artificial intelligence research clusters are experiencing extreme growth due to great support from research funding organizations that are currently been led by the National Natural Science Foundation of China (NNSFC). It is no surprise from the results of this systematic review that researchers from China are dominating the research space of the application on AI technologies in the construction industry since NNSFC is the largest funder of AI technology research over other large funding bodies such as the National Institutes of Health and National Science Foundation from the USA, European Commission and European Research Council from Europe, and Japan Society for the Promotion of Science from Japan, among others.

Secondly, the analysis of this study further provided answers to all the research questions stated in the first section. More specifically, although seven major AI technology types were found in the literature, supervised learning emerged as the most influential

AI technology of choice for most researchers, especially toward its applicability in health and safety management. Supervised learning is a branch of machine learning in which computer algorithms are trained on a labeled input dataset for a certain output. From a labeled training dataset (i.e., a dataset that already has a known value for each record's output variable), supervised machine learning algorithms can find insights, patterns, and correlations. When proper answers for a given task during training are provided, the machine learning algorithm can learn how the rest of the characteristics relate to the output, allowing you to unlock insights and make predictions based on past data. This is extremely crucial for the industry and consistent with the findings of [5], which argued that the industry can derive key benefits from AI to drive further profitability only when it leverages the amount of data produced from a backlog of project schedules, as-built drawings and models, computer-aided designs, costs, and invoices, among many other sources.

Furthermore, the results showed that although AI technologies can be applied in three major stages of the construction project lifecycle, more attention is drawn towards the supply/facility management stage (see Section 3). It can be argued that this is owing to the massive quantity of data collected over time (from the design stage all the way through), making it ideal for the adoption of the most significant AI technology (supervised learning). Thus, this creates a great opportunity for the industry to capitalize by allowing, for example, facility managers to take proactive action. For instance, as argued by [110], AI can recognize portions of buildings that are not being utilized and automatically turn off the heating, ventilation, and air conditioning, substantially decreasing energy use. Moreover, AI technologies in the construction industry were found to hold promise for applications in many types of construction projects and their respective lifecycle application area with about 20% of the literature reporting their implementation in any structures and systems that are part of the built environment (urban area, pedestrian walkways, parks, etc.) projects. Kılkış's [118] argument about this is compelling, especially when they mentioned that the built environment impacts all parts of our life, including the buildings we live in, the distribution systems that provide us with water and energy, and the roads, bridges, and transportation systems we use to move about.

Additionally, most articles acknowledged that artificial intelligence technologies' growing popularity in the construction industry would offer a wide range of benefits with potential for design expansion as a key benefit according to most of the selected literature. As such, this study argues that given the substantial time investment by engineers and architects in the architectural design process and their access to an extensive database housing numerous pre-existing building plans, an artificial intelligence (AI) technology system holds the capacity to generate diverse design alternatives based on the collective information derived from the repository of designs. Consequently, designers can input design objectives and parameters into the system, allowing it to systematically explore all conceivable permutations of a solution. This process results in the creation of design alternatives that satisfy the predefined requirements, with the system progressively refining its understanding of optimal design choices through iterative learning. This iterative learning, in turn, enhances the system's efficacy with each subsequent project. Beyond the potential design benefits, the application of generative design holds promises in augmenting creativity. For instance, it can empower architects to unveil hitherto unimagined approaches to designing forms and curves or guide them toward innovative design solutions that may remain unexplored through conventional means.

However, most of the articles reported that it is challenging to apply AI technologies in the construction industry because of a low accuracy level due to the scarcity of available data. Data scarcity arises when there is a paucity of labeled training data or when there is none at all. It might be a shortage of data for a particular label as compared to the other labels (known as data imbalance). It was discovered from some of the selected literature [52–55,80], which is also in line with research [1], that mega infrastructure projects often have access to a lot of data; however, they may have data imbalances, whereas small-sized projects typically have a limited amount of labeled training data. As a result, resolving this issue cannot be overstated, as reported articles (41.43%) universally agreed, citing "data augmentation" as one of the quickest prospects for technical improvement in this area. For instance, the research [74] successfully demonstrated the application of undercomplete, sparse, deep, and variational autoencoders as novel techniques for data augmentation and generation of synthetic data in construction management which can provide useful insights regarding the underlying non-linear relationships among variables in the datasets amongst many other selected studies.

Notwithstanding, practical obstacles beyond just data accuracy persist around cultural readiness, ethical risks, skill shortages, and flaws in security posture for many construction projects exploring AI solutions. As the research [119,120] assessed, construction has often lagged significantly in digital transformation and technology assimilation compared to other industries. Coupled with an aging workforce leaning on legacy methods, this exacerbates reluctance and barriers to AI change management. For instance, PwC [121] notes generational shifts may gradually improve receptiveness, like modeling shows younger workers are 67% more open to retraining on AI tools relative to senior staff. But broad culture change inevitably remains for the long term. Customized change management programs fitting construction realties are hence vital to align teams behind AI via strategic internal communications campaigns and leadership vision as exemplified by firms such as Bechtel. Additionally, the opaque decision-making of AI systems poses ethical dilemmas around accountability as flagged by Parveen [39]. Lack of explainable outcomes or audit trails can impede transparency and responsible oversight of automated systems. There is also a dearth of standardized governance principles as highlighted in Egwim's [1] delay risk assessment.

The specialist expertise needed is another capacity challenge evidenced by widening talent gaps globally per Johnson's [122] labor market analysis. Most construction firms are not staffed with multidisciplinary data scientists or algorithm auditors. As such, the shortage of such AI and analytics roles may worsen for small- and mid-size construction companies lacking resources to reskill staff or attract experts. Additionally, many construction industry jobs also require on-site client coordination, hence diminishing flexibility that technology candidates expect. Therefore, targeted training programs are crucial to developing well-rounded internal capabilities. Finally, the vulnerability of connected tools or data handling processes to malicious threats leaves unprepared adopters exposed to crippling breaches as studied across industries [123,124]. Also, lack of transparency around data rights or algorithmic decision-making processes also introduces major ethical risks. Furthermore, antiquated security postures coupled with failures to implement robust and resilient protections can negate any assumed productivity gains. Thus, addressing these open socio-technical problems demands coordinated efforts across construction stakeholders to formulate frameworks, standards, and cultural shifts guided by construction-specific nuances.

5. Conclusions

The systematic review study covers 70 studies that were judged to be rigorous, credible, and relevant in their application of AI technology in the construction sector. The research content of these 70 publications demonstrated that artificial intelligence research in the construction sector has taken a quantum leap, with increased interest in academic journals, particularly in the last few years, owing to the availability of funding in that area. Most articles pertinent to the research topic in general were published by Chinese researchers. More precisely, scholars from the Republic of Korea and China contributed the most publications to the construction/execution lifecycle stage of the construction value chain. Furthermore, China also published most of the related articles concerning AI applications in the planning and facility management lifecycle stages of the construction value chain.

Construction AI technology was discovered to be a growing application field, with supervised learning, deep learning, knowledge-based systems, robotics, natural language processing, optimization, and reinforcement learning AI technologies all appearing to have more potential to influence the development of AI research for increased efficiency and productivity. Regarding the construction AI technology categories given above, the bulk of the featured publications used the supervised learning approach. A substantial number of the articles were connected to the built environment and residential building in terms of the construction project types in which such AI technologies are used. The papers on high-rise and commercial buildings came after that. A few studies advocated the application of AI in building retrofits and water treatment plants. Most publications on the built environment concentrated on the construction/execution stage. Similarly, the planning and facility management lifecycle stages of the residential building garnered the most attention.

According to the findings, the most significant number of studies across all building construction disciplines focused on the possibility for regenerative design expansion. However, there are various obstacles to implementing AI technology in the construction industry, with low accuracy owing to a lack of relevant data being the most commonly mentioned issue. It is also worth noting that, despite being the most prevalent AI construction method, supervised learning has been the technology of choice for the most difficult challenge to be solved in the industry. And as sparse, deep, and variational autoencoder approaches show promise in providing meaningful insights into the underlying non-linear correlations among variables in datasets, data augmentation was identified as one of the most promising areas for technical advancement.

This study presents an all-inclusive systematic review of a vast body of knowledge on artificial intelligence in the construction industry. The findings of this study present a comprehensive assessment of the many types and categories of AI technologies, as well as their application areas and the advantages of using them at the three lifecycle stages of the construction value chain. This knowledge will assist construction organizations across the world in recognizing the efficiency and productivity advantages that AI technologies can provide while helping them make smarter technology investment decisions. It will point construction organizations in the right direction in terms of imagining the construction problems that AI technology could solve. In addition, it is possible to integrate evidence from the sorts of construction projects where AI technologies were used to address technological difficulties and see what new AI technologies can accomplish in the future.

Evidently, the findings of this study are based on a systematic review methodology. Given that the research article keywords were domain-specific, the principal drawback of this study approach might be bias in publication selection. As a result, it is possible that some important papers were overlooked throughout the search. Additionally, the PRISMA protocol mandated the use of predetermined inclusion and exclusion criteria for article selection, implying that important publications that did not meet these criteria may have been overlooked as well. Furthermore, any breakthroughs in the field of AI technology in construction are pushed by experts who are unable to publish in book series, conference proceedings, or academic journals. Consequently, there is a chance that any important research from the experts or somewhere else were overlooked throughout the search.

Although the study explored a variety of AI technologies for various construction projects, further research is needed to figure out how to simplify these complicated systems and processes to establish an integrated AI system for the construction sector. Therefore, an implementation framework is crucial to soften the introduction of a system and bridge the adoption gap by addressing low accuracy due to a scarcity of available data, model generalizability, incorrect image classification of structures, high requirements for sophisticated algorithms, and limited computing speed across the existing construction value chain.

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