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TRANSFORMING THE BUILT ENVIRONMENT: APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN THE CONSTRUCTION INDUSTRY

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Abstract

The construction industry is undergoing a significant transformation with the integration of Artificial Intelligence (AI). The growth of the construction industry is severely limited by the myriad complex challenges it faces such as cost and time overruns, health and safety, productivity and labor shortages. Also, construction industry is one the least digitized industries in the world, which has made it difficult for it to tackle the problems it currently faces. An advanced digital technology, Artificial Intelligence (AI), is currently revolutionizing industries such as manufacturing, retail, and telecommunications. The subfields of AI such as machine learning, knowledge-based systems, computer vision, robotics and optimization have successfully been applied in other industries to achieve increased profitability, efficiency, safety and security. While acknowledging the benefits of AI applications, numerous challenges which are relevant to AI still exist in the construction industry. This study aims to unravel AI applications, examine AI techniques being used and identify opportunities and challenges for AI applications in the construction industry.

Keywords:
Transforming, Built Environment, Application, Artificial Intelligence, Construction Industry.

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A critical review of available literature on AI applications in the construction industry such as activity monitoring, risk management, resource and waste optimization was conducted. Furthermore, the opportunities and challenges of AI applications in construction were identified and presented in this study. This paper explores the applications of AI in construction, highlighting its potential to improve efficiency, productivity, and safety. We discuss AI-powered technologies such as Building Information Modeling (BIM), predictive analytics, machine learning, and robotics. Case studies demonstrate the benefits of AI adoption, including reduced costs, enhanced decision-making, and improved project outcomes. This study provides insights into key AI applications as it applies to construction-specific challenges, as well as the pathway to realize the accruable benefits of AI in the construction industry.

Introduction

The construction industry is a significant contributor to global economic growth, accounting for approximately 13% of worldwide GDP [1]. However, the industry faces numerous challenges, including inefficiencies, safety concerns, and environmental impacts. Artificial Intelligence (AI) offers a promising solution to these challenges [1, 2]. AI can analyze vast amounts of data, identify patterns, and make informed decisions, revolutionizing the construction process.

Overview of artificial intelligence and its subfields

The idea of developing machines exhibiting intelligence like humans traced back to several fields, which include philosophy, fiction, imagination, computer science, electronics and engineering inventions [3]. Alan Turing's test for intelligence [4] was a turning point in the field of AI as the test exceeds the traditional theological positions and mathematical conclusions about the possibility of intelligent machines. Sixty years later, intelligent machines are outperforming humans in so many domains such as learning [5, 6] by leveraging rapid advances in other technologies such as big data and computer processing power [7]. The definition of AI as given by Ref. [8]; states that "*AI is the study of how to make machines do things, which at the moment, people do better*" captures the concept of AI perfectly.

Machine learning is a subfield of Artificial Intelligence that is concerned with creating computational models that mimic the linguistic capabilities of human beings [8, 9, 10, 11]. NLP has been applied in the fields of machine translation, natural language text processing and summarization, user interfaces, multilingual and cross language information retrieval, speech recognition and expert systems [12]. Tasks involved in NLP

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include part-of-speech tagging, chunking, named entity recognition and semantic role labelling [13].

Optimization

Optimization is concerned with making decisions or choices that provides the best outcomes given a set of constraints. According to [14, 15]; an optimization problem is a construct of the problem of making the best choice from a set of choices. Optimization is a lifelong phenomenon, originally known as a mathematical discipline concerned with finding an optimal solution to any given problem. With the birth of AI in the 1950s, a new family of metaheuristic algorithms known as evolutionary algorithms (EA) was created [16, 17, 18]. Some of the recent algorithms belonging to the EA family include evolutionary strategies (ES), evolutionary programming (EP), genetic algorithms (GA), differential evolution (DE) and particle swarm optimization (PSO) [16, 17, 18].

Trends of AI application in the construction industry

The trend of an increasing number of publications in the artificial intelligence domain from the 1960s decade onwards. In the 1960s, the use of artificial intelligence was still at its infancy with very few publications applying optimization techniques. Over time, optimization has been the foremost area of research interest in the application of AI subfields for the construction industry. This could be attributed to the age long struggle of the industry with low productivity levels [19]. Another insight from the research trends over the years is that machine learning has overtaken knowledge-based systems as a subfield of interest in the construction industry in the last decade. This can be attributed to the increased need to meet up with labor and skill shortages. Furthermore, robotics has also come to the fore of AI applications in the construction industry in the introduction of 3D printing, exoskeletons, UAV technologies for construction processes [20]. However, natural language processing has been the least researched subfield in the construction industry.

Another challenge is machine reading comprehension (MRC), which is the ability of computers to understand a given text, formulate questions against it and generate well-formed answers. MRC is a very challenging task that researchers are working on rigorously. There are several datasets specific to some domains have been made publicly available for benchmarking and training MRC models e.g. MS MARCO [21, 22, 23]. However, there are no datasets unique to the construction industry, which are essential to train construction MRC models. This presents an opportunity for further research that could improve MRC in construction and ultimately, contract management.

Voice user interfaces

The hands-busy and eyes-busy nature of construction work makes voice-enabled user interfaces (VUI) a viable alternative to the current modes of communication with devices on construction sites [24, 25, 26]. Construction workers often have to communicate with software applications e.g., BIM on the construction site, but typing on devices to retrieve information could lead to safety hazards. This has led to considerations for other means of communication with digital tools such as speech. This is further amplified by the rising popularity of speech-enabled user interfaces sometimes employed as automated assistants e.g. Alexa, Siri, Cortana [27, 28, 29]. The findings in this study reveal that speech in construction research has not garnered much attention by researchers.

Even though there has been a lot of recent improvements in VUIs, its use is still hindered by some challenges, especially those specific to the construction industry. One major challenge is that construction sites are usually very noisy [30, 31], which puts unwanted information in the speech signal. This could generate too many errors which may frustrate the users and eventually lead to discontinuity of use. Other challenges include speaker variability, voice enhancement, homophones, ambiguity, amount of data and search space. Solving these challenges could potentially lead to the seamless use of VUIs in the construction industry. To this end, development of a robust dataset of common voice commands in different situations on the construction site needs to be collected. This can be used to train construction voice application models.

AI-driven audit system for construction financials

Despite the huge economic outputs generated by the construction industry, the rate of insolvency of firms in still is very high [32]. This may be partly because most construction businesses find it hard to manage their finances due to the uniqueness and long duration of projects, which is critical for project success [33]. Construction firms often have multiple projects running simultaneously involving the movement of employees and equipment between projects [34], with thin profit margins due to competitive bidding and overhead costs that are not properly accounted for [35]. Hence, it is important to ensure projects and general overhead costs are effectively tracked [36]. The focus should not only be on delivering quality work, but proactive management of financial resources [37]. Currently, there are no AI-driven financial audit tools to effectively track project costs and predict potential financial problems before they arise [38]. Accordingly, financial managers can proactively respond when a project is overspending or underspending and measure its overall effect on other projects and the entire business in real-time. This will guide the decisions of the firm's stakeholders and save the firm from bankruptcy. So far, this study has identified the opportunities as well as emerging trends in AI application

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in construction processes. To further strengthen this area of knowledge, it is important to identify and discuss the key challenges.

Methodology

A comprehensive literature search was conducted using databases such as Scopus, Web of Science, and Google Scholar. Keywords used included "Artificial Intelligence," "Construction Industry," "Building Information Modeling," "Predictive Analytics," "Machine Learning," and "Robotics." Relevant articles published between 2015 and 2023 were selected.

Applications of AI in Construction

1. **Building Information Modeling (BIM):** AI-enhanced BIM enables real-time collaboration, automated clash detection, and optimized building design [39, 40, 41, 42].
2. **Predictive Analytics:** AI-driven predictive models forecast project timelines, budgets, and resource allocation [39, 40, 41, 42].
3. **Machine Learning:** AI-powered machine learning algorithms analyze sensor data to monitor structural integrity, detect anomalies, and predict maintenance needs [39, 40, 41, 42].
4. **Robotics and Automation:** AI-controlled robots and drones enhance site safety, improve productivity, and reduce labor costs [39, 40, 41, 42].
5. **Site Management:** AI-powered site management systems optimize resource allocation, track progress, and identify potential delays [43, 44, 45].
6. **Quality Control:** AI-driven quality control systems detect defects, monitor materials, and ensure compliance with regulations [43, 44, 45].
7. **Safety Management:** AI-powered safety management systems identify potential hazards, predict accidents, and provide real-time alerts [43, 44, 45].

Some examples of AI in construction industries includes, construction of the Dubai Mall which the AI-powered BIM reduced construction time by 30% and saved $100 million, the London's Heathrow Airport Expansion where some AI-driven predictive analytics optimized project timelines, reducing delays by 25%, automated bricklaying which AI-powered robotics increased productivity by 50% and reduced labor costs by 30% [46, 47, 48].

Applications of Artificial Intelligence (AI) in Civil Engineering and Architecture [49, 50]

Design and Planning

1. Generative Design: AI generates optimal design options based on project requirements.

2. Building Information Modeling (BIM): AI enhances BIM by automating data exchange and clash detection.
3. Structural Analysis: AI optimizes structural design and analyzes stress patterns.

Construction Management

1. Predictive Analytics: AI forecasts project timelines, budgets, and resource allocation.
2. Site Management: AI optimizes site layout, logistics, and resource allocation.
3. Quality Control: AI detects defects and monitors quality through image and sensor data analysis.

Safety and Risk Management

1. Hazard Detection: AI identifies potential hazards through site monitoring and sensor data.
2. Accident Prevention: AI predicts accident likelihood and provides real-time alerts.
3. Emergency Response: AI optimizes emergency response plans and evacuation routes.

Visualization and Communication

1. Virtual Reality (VR) and Augmented Reality (AR): AI enhances design visualization and client communication.
2. AI generates accurate 3D models from 2D designs.
3. Rendering and Animation: AI accelerates rendering and animation processes.

Construction and Operations

1. Construction Planning: AI optimizes construction schedules and resource allocation.
2. Facility Management: AI streamlines maintenance and operations through predictive analytics.
3. Smart Buildings: AI integrates building systems for improved efficiency and occupant experience.

Urban Planning and Development

1. Urban Design: AI generates optimal urban design scenarios.
2. Transportation Planning: AI optimizes transportation systems and infrastructure.
3. Land Use Analysis: AI analyzes land use patterns and recommends optimal development strategies.

Applications of Artificial Intelligence (AI) in Quantity Surveying [51, 52]

Cost Estimation and Management

1. Automated Quantity Takeoff (QTO): AI extracts quantities from drawings and specifications.
2. Cost Prediction: AI models predict construction costs based on historical data and project specifics.
3. Cost Risk Analysis: AI identifies potential cost risks and provides mitigation strategies

Tendering and Procurement

1. Automated Tender Analysis: AI evaluates tender submissions and recommends best-value bids.
2. Supplier Selection: AI optimizes supplier selection based on performance, price, and risk.
3. Contract Management: AI streamlines contract administration and compliance.

Project Management

1. Schedule Optimization: AI optimizes project schedules and resource allocation.
2. Risk Management: AI identifies potential project risks and provides mitigation strategies.
3. Progress Monitoring: AI tracks project progress and predicts completion dates.

Building Information Modeling (BIM)

1. Automated Quantity Extraction: AI extracts quantities from BIM models.
2. Clash Detection: AI detects clashes between design elements.
3. Cost Estimation: AI generates accurate cost estimates from BIM models.

Conclusion

Artificial Intelligence is transforming the construction industry, enhancing efficiency, productivity, and safety. As AI adoption increases, it is essential to address challenges and develop strategic frameworks for implementation. The future of construction will be shaped by AI-powered technologies, enabling the creation of smarter, more sustainable, and resilient built environments.

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