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Human-AI Partnership to Improve Construction Workers' Experience on Safety, Performance, and Health: A Systematic Review of The North American Construction Industry

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Abstract: Although construction is one of the oldest sectors of the global economy, the digital innovation and application of artificial intelligence (AI) in the industry are still insignificant. For the past several years, however, with rapid advancements in supporting technologies and computing power, the construction industry has made several strides in areas such as digitalization, data-driven design and planning, and automation. As the industry is in the process of adopting and customizing AI-powered tools and technologies in its daily workflows to improve safety, new opportunities are being created to enable human workers and stakeholders to seamlessly collaborate with AI in various aspects of project design, planning, construction, operation, and maintenance. The promise of human-AI collaboration in construction has, in turn, given rise to new research endeavors that focus on adaptability, usability, and expandability rather than mere algorithmic development. Prior to implementing any new AI technology in construction, users need to understand its impact on the human worker. Despite several systematic literature reviews on the applications of AI in construction, to date, there is limited investigation into the workers' experience during such transition from traditional to AI-driven work. In this study, a systematic literature review on AI in the construction industry is conducted through the lens of how such implementation might affect human workers' performance, behavior, and experience. The paper identifies common human factors involved in introducing AI and discusses the connection between those factors and potential AI applications in the industry. Finally, future directions for human-AI partnership in construction are outlined.

Keywords: Human-AI, human factors, workers' experience, construction.

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1. Introduction

With more than 8 million (Statista Research Department, 2023) employees nationwide, construction is one of the key contributors to the U.S. economy, creating nearly $7 trillion worth of built environment and infrastructure projects annually (Simonson, 2021). Despite this large footprint, unlike transportation, manufacturing, healthcare, and aviation industries, digital innovations and applications enabled by artificial intelligence (AI) in the construction sector are still in their infancy (Blanco et al., 2018b; Rao, 2022; Sands and Bakthavachalam, 2019; Walch, 2020). The experience and evidence from other domains point to the direction that AI has the potential to contribute to efficiency throughout the construction project lifecycle. However, to date, most existing AI-related research and prototypes tackle narrowly defined problems in pre-planning/scheduling, construction safety, and productivity, leaving out critical aspects of such implementations on the workers, a topic that is currently under investigation in other domains under the general theme of human-AI interaction.

Construction work consists of several physically demanding trades. About 40% of U.S. construction workers regularly engage in tasks that put their bodies under severe fatigue, gradually causing negative consequences concerning safety, performance, and general well-being (Jebelli et al., 2019b; Ng and Tang, 2010). This fatigue also increases the likelihood of accidents due to human fault, work-related musculoskeletal disorders (WMSDs), and productivity loss (Hallowell, 2010a, 2010b; Sluiter, 2006; Toole, 2005). Some of the major applications of AI involve machine learning (ML) or deep learning

(DL) based detection, prediction, and assessment solutions for construction safety powered by one or more technologies such as wearable sensors, field sensors, cameras, drones, virtual reality (VR), and computer vision (CV) (Emaminejad and Akhavian, 2022; Guo et al., 2021; Jebelli et al., 2019a, 2019b; N. Kim et al., 2021; Mostafa and Hegazy, 2021; Nath et al., 2020; Sakib et al., 2021a; Wang et al., 2019). In addition to human safety being a pivotal issue in the construction industry, previous literature has also cited a lack of work in areas related to trust in AI and robotics, particularly concerning issues such as explainability, reliability, robustness, performance, and safety of technology integration (Emaminejad and Akhavian, 2022; Simonson, 2021).

From experience in other sectors, such as manufacturing and transportation, AI is also expected to improve human work conditions and performance in construction. However, considering the dynamic and fragmented nature of the construction industry, the positive impact of AI on human workers in other industries may only be partially transferable to the construction domain. As large-scale use cases of AI are still evolving in the construction industry, now is the right time to study how AI can positively (or negatively) impact human workers and plan for future AI implementation opportunities. The existing literature contains some work on the impact of AI on different construction trades, but it still lacks a comprehensive systematic review. This paper focuses on some of the current applications of AI in construction from the perspective of work performance and usability improvement.

2. Literature Review

2.1. AI in Construction

While worker productivity has been increasing in almost all major industries in the past few decades, this vital metric has shown only a slight improvement in the construction industry (Kristensen, 2011; Schia, 2019b). Previous surveys show that construction is the second least digitalized global industry after agriculture and hunting (Agarwal et al., 2016; Schia, 2019a). While the application of AI-powered technologies in construction is currently very limited, this limitation can turn into an opportunity that leads to construction's next frontier for cost reduction, risk management, and productivity improvement (Blanco et al., 2018a; Hagras, 2018) as research shows that AI-based systems can use historical data to improve workflow and productivity on-site (Schuh et al., 2017).

Digital technologies can be critical elements for improving construction productivity (Alaloul et al., 2020; M. Wang et al., 2020). While AI has been so far used to address issues related to inefficiency, safety hazards, and workforce in healthcare, automation, and manufacturing industries, the construction industry still needs more attention (Emaminejad and Akhavian, 2022; Hallowell, 2010b; Pagliarini and Lund, 2017; Pillai et al., 2021). A recent study pointed to the lack of complete and accessible information as a significant barrier to adopting BIM and AI technologies in the construction industry (Sacks et al., 2020). Similarly, other key barriers to AI adoption include the lack of understanding of how resulting changes affect human workers. Previous systematic literature reviews in this area have discussed the application and influence of AI tools in architecture, engineering, and construction (Manzoor et al., 2021; Momade et al., 2021) particularly in fall detection (Z. Wang et al., 2020), image-based construction applications and solutions (Mostafa and Hegazy, 2021), automated activity recognition (Sherafat et al., 2020), wearable sensing (Ahn et al., 2019), and trustworthiness of AI in construction (Emaminejad and Akhavian, 2022). There is, however, a clear gap in these studies related to issues surrounding the human-AI interaction in construction.

2.2. Human-AI Interaction

Recent advancements in automation have enabled faster and more consistent responses to dangerous situations (Abbass, 2019; Schia, 2019a). While humans lack the extraordinary capability of extensive data analysis and quick access to information and knowledge, today's AI-based technologies lack creativity, ethical considerations (as a result of limited data), and visionary thinking (Carpenter et al., 2018). Therefore, a collaboration between humans and AI can leverage the strengths of both worlds and lead to technological solutions that are creative, ethical, and inclusive (McCaffrey, 2018).

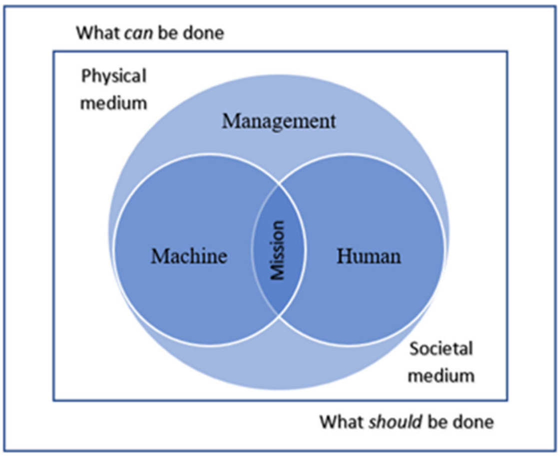

Fig. 1. The five M's framework (Harris and Harris, 2004)

In the meantime, recent developments in AI are more focused on usability, interpretability, and efficacy for the user instead of developing pure computational algorithms (Zhu et al., 2018). Fig. 1 is adopted from Harris et al. (2004) and represents how any given field operation/task is not merely a collaboration between humans and machines but is also affected by the role of organizational management. As with any successful human-human partnership, a successful human-AI collaboration also requires defined tasks and responsibilities (Schia, 2019a). Intensive interaction is needed for this kind of collaboration. A significant factor is that underlying data structures should be stable by both humans and AI (Zhu et al., 2018). Additionally, it is critical to design effective methods of establishing and calibrating trust between humans and AI by investigating how elements of AI design, such as system interface, functionality, level of automation, and explainability, can contribute to the level of user trust in technology (Hagras, 2018; Oksanen et al., 2020).

3. Systematic Review Method

This study performed a systematic literature review (Lockwood and Oh, 2017) by carefully selecting and thoroughly reviewing the most relevant publications using two different search engines, namely Engineering Village and Web of Science. The Engineering Village search internally includes four databases, Compendex, Inspec, GEOBASE, and GeoRef, while Web of Science covers the Elsevier database. Table 1 lists the Boolean search strings applied to find the relevant literature. These strings are derived from four initially selected main search domains of artificial intelligence, human workers, and human factors in the construction industry.

Table 1. Boolean search string for literature search

Search domain	Boolean search string
Artificial intelligence	“ai” OR “artificial intelligence” OR “machine learning” OR “deep learning”
Construction	“Construction*”
Human	“human*” OR “worker*” OR “labor*” OR “operator*”
Human factors	factor*” OR “performance*” OR “behavior*” OR “experience*” OR “stress*” OR “ergonomic*” OR “emotion*” OR “capability*” OR “fatigue*” OR “productivity*” OR “safety*” OR “teamwork*”

After combining the search results from two different databases and removing all duplicates, a total of 1,965 publications are selected for title and abstract screening. Title and abstract screening eliminate 1,534 publications, leaving 431 for full-text study assessment. Following the full-text study assessment, studies that do not include all aspects of the literature review outline (i.e., AI, construction, human workers, human factors) are removed, leading to a total of 34 publications for data extraction. Out of the 34 pieces of literature, three were found to be review papers. This entire selection process is administered on the systematic review platform provided by Covidence (https://www.covidence.org). Fig. 2 shows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram for the screening stage after exporting from the databases.

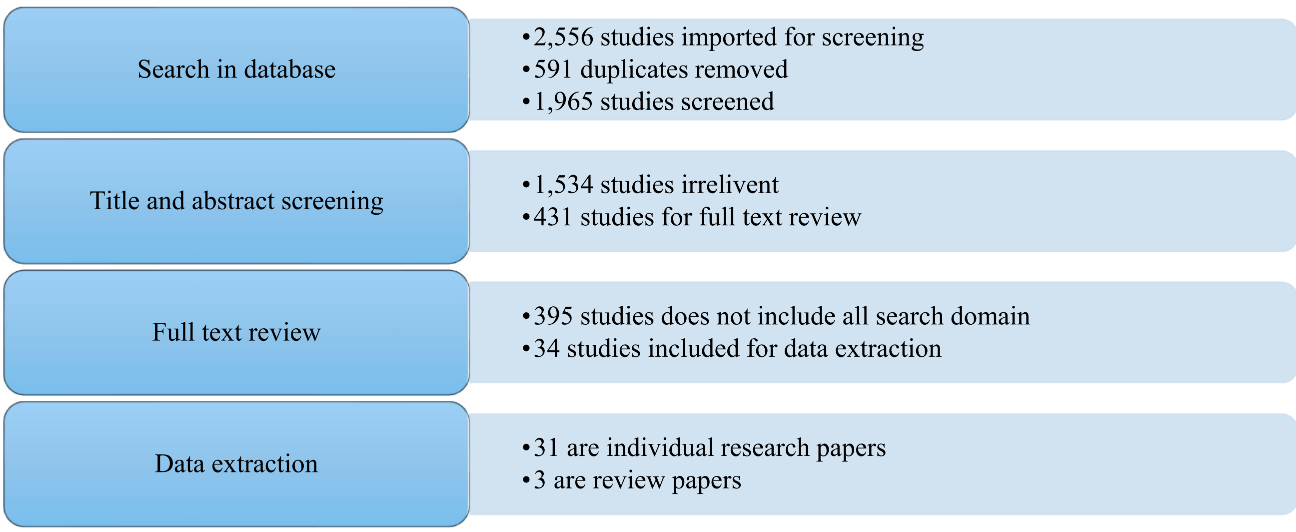

Fig. 2. PRISMA diagram for literature selection

4. Findings of the Literature Review

One of the primary motivations for implementing AI in construction is to support human workers by increasing their safety, performance, and productivity. Tables 2 and 3 summarize the full-text analysis of the reviewed literature in this chapter. From a thorough review of these papers, the main application of AI in construction, as related to human factors, can be grouped into two main categories: (1) workers' safety, performance, and productivity (Table 2) and (2) workers' health (Table 3).

Table 2. Literature related to workers' safety, performance, and productivity

References	Human Factor	Application	Artificial Intelligence	Data Collection Methods	Accuracy
(Cho et al., 2018)	Safety	Monitoring scaffolding structures	SVM	Strain sensor	97.66%
(Sakhakarmi et al., 2019)			SVM	Computer simulation	96%
(Wang et al., 2019)		Workers risk recognition	CNN and Bayesian-network	Camera	95%
(Cai et al., 2020)		Worker trajectory prediction	Context-augmented LSTM	Camera	FDE = 8.51 pixels
(Siddula et al., 2016)		Measurement of safety performance	SVM	Crowdsourcing	97.50%
(Y.-C. Lee et al., 2020)		Hazardous activity identification	KNN	Sound recorder	100%
(Nath et al., 2020)		PPE detection	CNN	Camera	mAP = 72.3%
(K. Kim et al., 2021)		Workers and equipment detection	CNN	Computer simulation	F1 score = 0.48
(Golparvar-Fard et al., 2013)	Safety, productivity	Equipment activity recognition	SVM	Camera	Average accuracy for Excavator= 86.33% and Dump truck= 98.33%
(Akhavian and Behzadan, 2015)			ANN	Mobile phone, RFID smart tags	Classification accuracy up to 98.59%
(Akhavian and Behzadan, 2016)		Worker's activity recognition	ANN, Decision Tree (DT), KNN, Linear Regression (LR), and SVM	Mobile Phone-based Sensors	Upto 97% for user-dependent and 96% for user-independent
(Kim and Cho, 2020)			LSTM	Wearables: Motion sensors	94.73%
(Ogunseiju et al., 2021)			KNN and CNN	Wearables: Wrist wearable IMU	KNN = 99.8%, CNN = 97.1%
(Roberts et al., 2020)			CNN	3rd party video data	78.5%
(Bangaru et al., 2020)	Safety, performance	Worker's activity recognition	ANN	Wearables EMG	80%
(Bangaru et al., 2021)			ANN	Wearables EMG and inertial IMU	94%
(Ebrahimi et al., 2021)	Productivity	Worker's productivity prediction	RF	Survey-based field data	RMSE = 0.137

4.1. Workers' Safety, Performance, and Productivity

Safety, performance, and productivity are significant concerns in any construction job. The literature on safety factors for human workers is generally related to either equipment activity detection or equipment-worker activity detection, which primarily supports the goal of eliminating physical collisions. Due to the risk involved in the scaffolding job, Cho et al. (2018) and Sakhakarmi et al. (2019) used support vector machine (SVM) and scaffolding structures' strain data to detect scaffolding structural failures during construction work. Wang et al. (2019), Cai et al. (2020) and Siddula et al. (2016) used construction photos to measure risk and safety performance. Wang et al. (2019) used crowdsourced labeled data to detect complex construction scenes and enable vision-based workplace safety. Cai et al. (2020) used sequence-to-sequence data along with a long short-term memory (LSTM) model and wearable to predict workers' trajectories multiple steps ahead.

Table 3. Literature related to workers' mental and physical health

References	Human Factor	Application	Artificial Intelligence	Data Collection Methods	Accuracy
(Aryal et al., 2017)	Fatigue	Fatigue detection	Boosted tree classifiers	HR monitor, EEG sensor, and temperature sensors	82.6%
(Nath et al., 2018)	Ergonomic risk	WMSDs	SVM	Smartphone-based sensors	90.2%
(Akanmu et al., 2020)			RL	Wearable IMU sensors, HTC Vive trackers	N/A
(Zhao and Obonyo, 2020)			CNN-LSTM	Wearable IMU sensors	F1 Score personalized model = 0.911
(Mudiyanselage et al., 2021)			DT, SVM, KNN	Surface EMG	99.35%
(Zhao and Obonyo, 2021)			Incremental CLN	Camera	F1 Score = 0.87 (personalized), 0.84 (generalized)
(H. Lee et al., 2020)	Stress		CNN-LSTM Network	Wearable IMU sensors	Load-carrying weight = 92.46% and Posture classifications = 96.33%
(Jebelli et al., 2018)		Occupational stress	Gaussian SVM	EEG	80.32%
(Jebelli et al., 2019a)			Gaussian SVM	Wrist wearable biosensors	84.48%
(Sakib et al., 2021b)	Stress	Performance, MWL, and stress detection	Machine Learning	Wrist and chest wearable biosensors	In 83% of cases
(Jebelli et al., 2019a)	Physical demand	Physical demands	Gaussian SVM	Wrist wearable biosensors	90%
(Tang and Golparvar-Fard, 2021)		Worker-level severity	CNN	Camera	86.6%
(N. Kim et al., 2021)	Worker's inattentiveness	Struck-by hazards	SVM	Wearable IMU sensors, HTC Vive eye tracker	Unweighted average recall (UAR) = 0.722
(Lee et al., 2021)	Workers perceived risk	Workers' safe or unsafe behaviors	Gaussian SVM	Wrist wearable biosensors	81.2%

In addition, Siddula et al. (2016) also used construction images to see rooftop work to ensure proper safety standards during the construction process. Lee et al. (2020) used a completely different data modality by working on an audio-based safety detection system to identify construction safety hazards and accidents. Both Nath et al. (2020) and Kim et al. (2021) used convolutional neural network (CNN) models to implement visual recognition of workers and equipment on the job site and consequently detect workers' personal protective equipment (PPE).

Generally, identifying safety and productivity comes as a package while using AI for equipment/worker activity recognition. Golparvar-Fard et al. (2013), and Akhavian and Behzadan (2015) detected construction equipment activities using AI. In particular, Golparvar-Fard et al. (2013) used video data with an SVM model to achieve activity recognition up to 98.33%, while Akhavian and Behzadan (2015) only used smartphone-based sensors and radio-frequency identification (RFID) smart tags along with an artificial neural network (ANN) model to achieve 98.59% accuracy. Both papers suggested a novel method to detect performance through activity detection and take corrective actions. On the other hand, to ensure workplace safety and productivity, Akhavian and Behzadan (2016), Kim and Cho (2020), and Ogunseiju et al. (2021) used wearable devices (i.e., smartphones, motion sensors, IMU) along with AI to detect workers' activities. In all three studies, researchers achieved more than 90% accuracy for activity prediction using DL algorithms (i.e., ANN, LSTM, CNN).

Bangaru et al. (2020) used electromyography (EMG) sensor data to train an ANN model in a gesture-based performance recognition experiment, which helped detect the performance of wearing earplugs with 80% accuracy. In addition, the system provided timely feedback during the training process. In another experiment, Bangaru et al. (2021) used EMG and inertial measurement unit (IMU) to train an ANN model to detect scaffold builder activity with 94% accuracy, enabling real-time monitoring of worker activity to promote safety, productivity, and project control. Roberts et al. (2020) used CNN to estimate and track workers' poses and detect workers' activities with up to 78.5% accuracy. Ebrahimi et al. (2021) used construction labor productivity (CLP) data along with random forest (RF) to predict workers' productivity in a construction project.

4.2. Workers' Mental and Physical Health

Other than safety, one of the biggest challenges faced by construction workers is long-term health issues due to physically demanding tasks often performed in dynamic and harsh environments (Abdelhamid and Everett, 2002; Aryal et al., 2017; Tixier et al., 2016). There are several studies on workers' mental as well as physical health related to construction work. For example, Aryal et al. (2017) used wearable sensors (e.g., EEG, infrared temperature) to estimate workers' fatigue using a boosted tree classifier and achieved up to 82.6% accuracy in predicting fatigue.

WMSDs are also very significant in the construction industry because workers may be tasked with physically demanding activities that require them to go past their physical body limits, often leading them to experience awkward body postures for extended times. Nath et al. (2018), Akanmu et al. (2020), Zhao and Obonyo (2020), and Mudiyanselage et al. (2021) used wearable sensors (i.e., smartphone, IMU, EMG) to detect awkward and unsafe body postures using AI that might cause WMSDs. Nath et al. (2018), Zhao and Obonyo (2020), and Mudiyanselage et al. (2021) achieved 90.2% accuracy, 0.911 F1 score, and 99.35% accuracy, respectively. All participants agreed that the virtual reality (VR) based posture training system developed by Akanmu et al. (2020) enhanced their understanding of risks associated with unsafe body posture. Using an incremental learning strategy in the CLN network, Zhou and Obonyo (2021) were able to detect awkward body postures leading to WMSDs. Jabelli et al. (2018) used EEG signals with an SVM model to detect occupational stress with an accuracy of 80.32%. Later, Jabelli et al. (2019) improved the occupational stress detection accuracy to 84.48% by using wrist wearable biosensors with the SVM model. More recently, with the goal of understanding the effectiveness of VR training for drone operators, Sakib et al. (2021) correctly predicted workers' performance, mental workload (MWL), and stress levels in 83% of cases.

Jebelli et al. (2019), and Tang and Golparvar-Fard (2021) detected physical demand using a combination of different technologies. While Tang and Golparvar-Fard (2021) used photos and video data with a relatively more complex DL model to achieve 86.6% accuracy, Jebelli et al. (2019) used data from wrist wearable biosensors and SVM model to achieve 90% accuracy. Kim et al. (2021) and Lee et al. (2021) coupled SVM with wearable sensors to detect workers' inattentiveness and perceived risk, respectively.

5. Summary and Conclusion

This study provided a comprehensive study on the application and impact of artificial intelligence (AI) in the construction industry. It explored how AI can improve worker safety, productivity, and well-being. The study included a systematic literature review, identifying key areas where AI is used in construction, such as safety performance and productivity, mental and physical health of workers, and the interaction between humans and AI. Construction is one of the most hazardous industries worldwide, which explains why most AI research has historically focused on safety-related problems. While the risk of injury in construction is undeniable, current advances and the availability of technology may not be sufficient to overcome this issue in the foreseeable future. Hypothetically, the risk of workers' accidents and injuries can be eliminated if all construction tasks are automated. However, while the complete automation of all project activities seems unrealistic and practically impossible, state-of-the-art AI technologies can be used for workers' safety through early prediction and intervention. A proper body posture and sound work methodology will also help avoid future bodily injuries and WMSDs. Beyond detection and intervention, AI can be used for appropriate workforce training.

The literature review in this paper provided evidence that the successful implementation of AI can improve health, safety, performance, and productivity in construction. However, in the current state, AI is not a replacement for the human workforce but rather a helping hand, ensuring a positive technology experience, which will, in turn, motivate more workers to adopt AI and technology spontaneously.

Finally, this systematic literature review can draw a future outline for AI applications in construction. Undoubtedly, more research on AI and automation is needed in construction. Although there are several examples from the literature in areas related to job site ergonomics, safety, and performance, there is still a clear gap with respect to the value of using AI to understand and promote workers' health due to excessive workload. Since construction jobsites are dynamic and intense workplaces, along with bodily injuries, there is an opportunity for future research to also focus on health-related issues (both physical and mental) in various construction trades and work settings and recommend operational and policy changes to eliminate and ultimately remove contributing factors to safety and health problems in construction. While AI holds significant potential for improving various aspects of the construction industry, a deeper understanding and careful implementation are necessary to fully realize its benefits and mitigate any negative impacts on workers.

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Author Contributions

Md Nazmus Sakib contributes to conceptualization, methodology, analysis, investigation, data collection, draft preparation, manuscript editing, and visualization. Amir H. Behzadan contributes to conceptualization, methodology, validation, analysis, manuscript editing, supervision, and project administration. All authors have read and agreed with the manuscript before its submission and publication.

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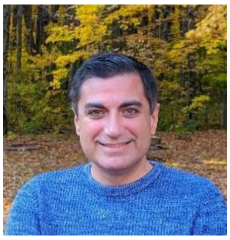

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