

DRIVING THE MOMENTUM TOWARDS ADOPTING WEARABLE COGNITIVE ASSISTANCE IN LEAN CONSTRUCTION 4.0

Amira Eltahan¹, Lynn Shehab² and Farook Hamzeh³

ABSTRACT

Despite the transformative potential of Wearable Cognitive Assistance Devices (WCADs), their integration into the construction industry remains limited, marked by challenges such as practicality and regulatory barriers. Additionally, the increasing interest in implementing Lean principles in construction for enhanced project performance creates a potential intersection. This study aims to bridge both concepts by developing a conceptual framework for the implementation of WCADs in construction tasks within the Lean Construction 4.0 paradigm. It first explores the current state of WCAD in various industries and proposes a WCAD implementation framework for construction. The framework employs a stepwise approach, and its theoretical implementation in masonry works illustrates its adaptability to specific construction contexts. This framework's contribution lies in its potential to offer dynamic, adaptive, and personalized support, optimizing cognitive functions, and promoting safer and more productive task execution. This framework utilizes wearable sensors as one of its data collection methods; thereafter, the integration of the data collected will then provide users with near real-time feedback to mitigate risks and enhance workers performance. As a theoretical foundation, this research paves the way for practical validation and future enhancements, aiming to enhance the construction industry's approach to worker well-being and performance.

KEYWORDS

Lean Construction, Design Science, Continuous Improvement, Wearable Cognitive Assistance.

INTRODUCTION

In the dynamic nature of construction, where innovation meets the rigors of the job site, Wearable Cognitive Assistance Devices (WCADs) emerge as transformative tools to redefine how tasks are executed and managed. These devices, equipped with advanced sensing technologies and real-time cognitive support capabilities, hold the potential to improve the construction industry's approach to worker well-being, safety, and overall productivity.

WCADs can be envisioned as intelligent companions for construction professionals and practitioners, seamlessly integrating into their work environment to provide not only physical assistance but also cognitive support. These devices comprise of a combination of wearable sensor devices (WSDs), including but not limited to Electrocardiogram (ECG) sensors, Skin conductance sensors, Temperature sensors, Electrodermal Activity Sensors (EDA), Electroencephalogram (EEG) Sensors, and more (Shehab & Hamzeh, 2023). By collecting physiological data from WSDs, such as heart rate, skin conductivity, and brainwave patterns,

¹ Ph.D. Student, Haskayne School of Construction Engineering, University of Alberta, AB, Canada

² Ph.D. Candidate, Haskayne School of Construction Engineering, University of Alberta, AB, Canada

³ Professor, Haskayne School of Construction Engineering, University of Alberta, AB, Canada

WCADs gain holistic insights into the wearer's cognitive state and physical well-being. These devices transcend traditional wearables by not only tracking physical activities but also offering real-time feedback and assistance based on the wearer's cognitive state and the specific tasks at hand (Belletier et al., 2021). Imagine a construction professional receiving instant alerts about potential safety hazards, personalized guidance on optimal work postures, or timely reminders to mitigate fatigue—all delivered through a compact, unobtrusive wearable device.

Despite their transformative potential, the integration of WCADs into the construction industry has not been fulfilled yet. Therefore, this study seeks to explore the merging of WCADs with Lean Construction 4.0 (LC 4.0)—a paradigm that converges traditional Lean principles with the transformative capabilities of Industry 4.0 technologies (Sanders et al., 2016). Through the lens of this merging, the aim of this study is to develop a conceptual framework for the effective implementation of WCADs in construction tasks. LC 4.0, a strategic merging of methodologies, emphasizes efficiency, waste reduction, and continuous improvement while leveraging advanced digital tools.

The principles of LC 4.0 prioritize the well-being of the construction team and are complemented by cutting-edge technologies (Hamzeh et al., 2021), including sensor network devices that are suggested in this study. These technologies not only monitor the site but provide real-time insights that enhance safety and allow immediate responses to challenges, aligning with the objective of improving workers' well-being, safety, and productivity through WCADs.

The synergy between LC 4.0 principles and WCADs offers a dynamic and adaptive system, connecting the transformative potential of both methodologies to drive sustainable improvements in construction project management. The proposed framework offers near-real-time feedback based on the collected cognitive data from construction workers. To achieve this, a stepwise approach is developed where it includes three major stages with a total of five steps.

Whereas the major objective is to gain a refined understanding of the worker's cognitive and physical state during task execution and thereby provide near-real time feedback. This paper begins with a literature review on LC 4.0 and WSDs. Afterwards, WCADs are introduced, and the conceptual framework is proposed. A theoretical implementation of the framework is presented, followed by final conclusions.

LITERATURE REVIEW

LEAN CONSTRUCTION 4.0 PRINCIPLES AND TOOLS

Lean Construction 4.0 (LC 4.0) represents a convergence of traditional Lean Construction principles with the transformative capabilities offered by Industry 4.0 technologies. Industry 4.0, characterized by the integration of digital technologies, automation, and data-driven processes, has ushered in a new era of efficiency and innovation across various industries (Lasi et al., 2014). In construction, the integration of Industry 4.0 into Lean Construction practices has the potential to enhance productivity, improve workers' safety and wellbeing, and optimize resource utilization (Noueihed & Hamzeh, 2022).

Several researchers have explored the relationship between Industry 4.0 and Lean Construction, recognizing the similar nature of both approaches. Studies such as that conducted by Sanders et al., (2016) have explored the impact of Industry 4.0 technologies on traditional Lean principles, shedding light on how advancements like Internet of Things (IoT), big data analytics, and automation can reshape lean methodologies.

Other studies (Hines et al., 2023; Karmaoui et al., 2023) have also provided perspectives on the interplay between Industry 4.0 and Lean Construction through the analysis of existing practices, applications, and technologies. They collectively emphasize the transformative potential of integrating digital technologies and lean principles in construction. LC 4.0, therefore, is not merely an integration of terms, but a strategic merging of methodologies aimed at creating

a holistic and technologically advanced approach to construction project management. The utilization of Industry 4.0 technologies within Lean Construction practices presents opportunities for real-time monitoring, predictive analytics, and improved decision-making throughout the project lifecycle (González et al., 2022). As the construction industry continues to evolve, LC 4.0 emerges as a pivotal paradigm that not only embraces the advancements of the Fourth Industrial Revolution but also harnesses them to drive sustainable improvements in the construction industry's overall efficiency and effectiveness.

At its core, LC 4.0 emphasizes the relentless pursuit of efficiency, waste reduction, and continuous improvement, all while leveraging advanced digital tools to enhance these objectives (González et al., 2022). However, the principles and tools are not just about cutting-edge technologies; they are centered around enhancing the human experience within construction projects. The principles prioritize the well-being of the construction team, focusing on minimizing risks and overburden and ensuring that every effort contributes meaningfully to the project.

Some of the main technologies for Construction 4.0 were discussed by (McHugh et al., 2022), such as Building Information Modeling (BIM), which acts like a shared visual language that brings everyone together, fostering collaboration and understanding. Moreover, Artificial Intelligence (AI) enables analyzing data to predict potential obstacles or threats and offers valuable insights for informed decision-making. Reality capture is another technology that captures construction sites as point cloud models for depicting real site conditions, providing significant aid in building spatial awareness within the production team, producing realistic and systematic construction logistics and site planning, and more (McHugh et al., 2022).

From a human-centric perspective, these technologies can be used to train construction teams for safety and hazard prevention and recovery drills, all while avoiding real injuries or risks. Finally, Internet of Things (IoT) and sensor network devices act as essential enablers, not just monitoring the site, but providing real-time insights that enhance safety and allow immediate responses to challenges. Safety and hazard indicators are described as sensors that detect potential safety hazards and notify the production team by providing safety alerts and warnings (McHugh et al., 2022). They also aim at capturing worker health and safety conditions with the ultimate goal of maintaining productive and healthy workspaces.

WEARABLE SENSOR DEVICES (WSDs)

The advancement of wearable sensing technology in recent years has expanded the potential for monitoring workers' behaviour on construction sites. Researchers have explored the potential of using wearable sensors for worker behaviour monitoring. Such sensors collect data including physiological responses (W. Lee et al., 2017; Shehab & Hamzeh, 2023), gaze movement (Cheng et al., 2022), musculoskeletal engagement (tendons, bones, etc.) (Alwasel et al. 2011), gait (Inertial measurement unit IMU sensors) (Ren et al., 2022), and posture (Nath et al., 2018; Ren et al., 2022). These studies have demonstrated the effectiveness of using sensing-based approaches to study the factors affecting workers' safety behaviour, such as emotion and stress levels. Physiological response data can be collected through various WSDs, such as Electrocardiogram (ECG or EKG) sensors, Skin conductance sensors (Galvanic Skin Response), Temperature sensors, Electrodermal Activity Sensors (EDA), blood pressure sensors, Electroencephalogram (EEG) Sensors, Electromyography (EMG) Sensors, Camera sensors, microphones and audio sensors, moisture and sweat sensors, chemical sensors, etc.

Regarding musculoskeletal involvement, gait, and posture, numerous studies have explored the movement patterns of physical activity, with a specific focus on the lower body movements of workers. These studies propose that the sensory data derived from lower body movements can offer valuable insights into workers' safety behaviours, particularly their responses to slip, trip, and fall hazards (Ren et al., 2022). This is attributed to the cyclical nature of lower body

movements, where monitoring these movements can unveil individuals' responses to various environments or objects through alterations in leg movement patterns. For instance, research in construction safety has utilized gait data obtained from inertial measurement unit (IMU) sensors to examine how workers modify their walking patterns in high-risk conditions (Ren et al., 2022) or in proximity to slip/trip/fall hazards at construction sites (Yang et al., 2016). These studies indicate that employees alter their walking style upon identifying a nearby hazard or sensing a potential risk. Different sensory signals, including visual, auditory, and somatosensory inputs, influence the intentional regulation of human walking, impacting factors such as locomotion direction, speed, and the adjustment of stride to environmental limitations.

THE CURRENT STATE OF WSDS IN CONSTRUCTION

WSDs are becoming increasingly prevalent in the construction industry due to their potential to enhance safety, productivity, and overall efficiency on job sites. These sensors can provide real-time data and insights to both workers and management, helping to prevent accidents, optimize workflows, and improve decision-making. WSDs in the construction industry are gaining traction, but their adoption is not yet universal. They have witnessed a tremendous advancement over the course of the past 10 years. Yet the challenges that come with implementing it on construction sites have hindered the industrial use of these devices.

The emergence of wearables started in early 2010s with the first generation of smartwatches and fitness trackers (Mukhopadhyay, 2015). Thereafter, in mid 2010s the introduction of safety helmets and safety wearables were explored (Park et al., 2015). These helmets were designed to monitor workers' movements to improve safety on construction sites. In late 2010s the augmented reality (AR) technology led to more advancement in the field of wearable technology including the development of eye tracking and AR glasses (Cheng et al., 2022).

The common objective in implementing WSDs in construction has been occupational safety and hazard assessment (G. Lee et al., 2021). Ahn et al. (2019) have divided the applications for implementing WSDs in construction health and safety as reported in literature into: preventing musculoskeletal disorders, preventing falls, assessing physical workload and fatigue, evaluating hazard recognition abilities, and monitoring workers' mental status. Shehab & Hamzeh (2023) have summarized the use of physiological sensors in construction. They have identified 20 studies that measured physiological markers using wearable sensors and correlated it with performance (safety behaviours and productivity). Anwer et al. (2021) used textile wearable sensors measuring heart rate, breathing rate, and skin temperature to monitor physical fatigue. This study was conducted on bar bending and fixing construction tasks and a moderate to excellent correlations was concluded between physical fatigue and the measured physiological markers.

Ke et al., 2021 have attempted to detect distraction in workers using wearable electrocochleography (EEG). This study has established a link between attention (cognitive ability) and the measured signals of EEG. Exoskeletons (Nnaji et al., 2023) are used to reduce strain on workers body when strenuous activities are executed where WSDs are used to collect data related to fatigue and musculoskeletal engagement to reduce the risk of musculoskeletal injuries. Also, Kinematic sensors, including accelerometers and gyroscopes, were employed to record instances of workers narrowly avoiding falls and uncomfortable postures during their work (Nath et al., 2018).

Research on WSDs aimed to establish a link between using wearable sensors and individualized performance (safety behaviours, and self-reported productivity). However, no study has no study has systematically investigated the integration of Wearable Cognitive Assistance Devices (WCADs) within the context of LC 4.0 to enhance both the physical and cognitive aspects of worker performance. Existing studies often focus on the physiological aspects, neglecting the potential of cognitive support through real-time feedback. Therefore,

this study aims to explore the application of these technologies as a tool to enhance workers' cognitive abilities and decision-making process through real-time feedback to proactively introduce remedial measures. By addressing this gap, our research aims to contribute valuable insights to the effective implementation of WCADs in construction, aligning with LC 4.0 principles and advancing the holistic well-being, safety, and productivity of workers.

METHODOLOGY

This paper aims to develop a conceptual framework for the implementation of WCADs in construction from an LC 4.0 perspective. To achieve this goal, this paper follows a Design Science Research (DSR) methodology. DSR is a scientific method for developing a new artifact that addresses an identified problem, followed by the evaluation of this artifact (Rocha et al., 2012).

In this study, the problem is identified as the unsafe conditions that prevail on construction sites and the lack of a real-time feedback system that provides workers with cognitive support to enhance their safety and well-being. Therefore, and in order to contextualize the study within LC 4.0, the paper begins with a comprehensive review of Lean Construction (LC) 4.0 principles and tools, followed by a review of WSDs in general and their current state in construction. Afterwards, the study proceeds to identify the gap: the absence of a real-time feedback system supporting workers' cognitive functions. This identification sets the stage for the introduction of WCADs and their applications, followed by the development of a conceptual framework for adopting WCADs in LC 4.0.

This framework aligns with LC 4.0 principles, which include continuous improvement, real-time monitoring, data-driven decision-making, worker-centric focus, and utilizing advanced digital tools. The framework is divided into three major phases which include model design, model development and cognitive assistance feedback as explained in section 5. To validate the theoretical implementation of the framework, it is tested theoretically on a masonry construction example.

WEARABLE COGNITIVE ASSISTANCE DEVICES

Wearable Cognitive Assistance Devices (WCAD) are wearable devices that offer real-time cognitive assistance. These devices can provide support and guidance through sending warnings or alerts based on the wearer's cognitive state and the tasks at hand (Belletier et al., 2021). They integrate the data collected using WSDs to offer a real time feedback using the collected data. There are various applications of WCADs, including healthcare, manufacturing industry, education and training, sports and fitness, and military and defence. In healthcare, they are used to monitor the patients' cognitive states to provide real time updates to healthcare professionals to ease timely interventions. In the manufacturing industry, they can be used to enhance safety by providing safety alerts to workers once it detects unsafe conditions. In sports and fitness, these devices are used extensively by various competing companies to provide users with personalized feedback and fitness programs based on the collected psychological data using wearable sensors. Regarding military and defence, WCADs can be used to track the vital signs of soldiers as well as enhancing their situational awareness. Table 1 lists some of the examples where WCAD are used in different industries and the objective of each of those applications.

Table 1. Examples of WCAD Applications in different Industries

Industry	Study	Objectives
Healthcare	Zhao et al., 2020	An automatic external defibrillator
	Wu et al., 2018	Wearable watch for monitoring patients with chronic compulsory pulmonary disease
Manufacturing	Oyekan et al., 2021	Tracking assembly tasks and ergonomic indicators
Sport and fitness	Hajj-Boutros et al., 2023	Tracking stress levels by monitoring heart rate, EDA, ECG, and skin temperature using wearable watch
	H. Jung et al., 2022	Provide a holistic view of wellbeing through sleep tracking, heart rate monitoring, and stress levels using a wearable watch
Military and Defence	Admile & Barguje, 2023	Situational awareness and monitoring vital signs

DEVELOPMENT OF CONCEPTUAL FRAMEWORK FOR USING WCADS IN LEAN CONSTRUCTION 4.0

The developed conceptual framework offers a way to implement WCADs in construction within the context of LC 4.0 by using the established work by various researchers, confirming the correlation between various physiological markers and various indicators on the performance of construction workers. Thereafter, such indicators could be used to offer near real-time feedback to workers to enhance their performance.

To achieve this, the conceptual framework presented in Figure 1 was developed. This framework is generic and could be tailored to any construction task of interest. Construction tasks requires physical strength for various activities such as lifting heavy materials, digging, carrying, welding, operating machinery, and performing tasks that require physical endurance. Therefore, enhancing individual performance is a key contributor to the overall project success. In this study, the definition of individual performance as introduced by Hurrell & McLaney, 1988 was adopted. It includes self-reported productivity and safety behaviours.

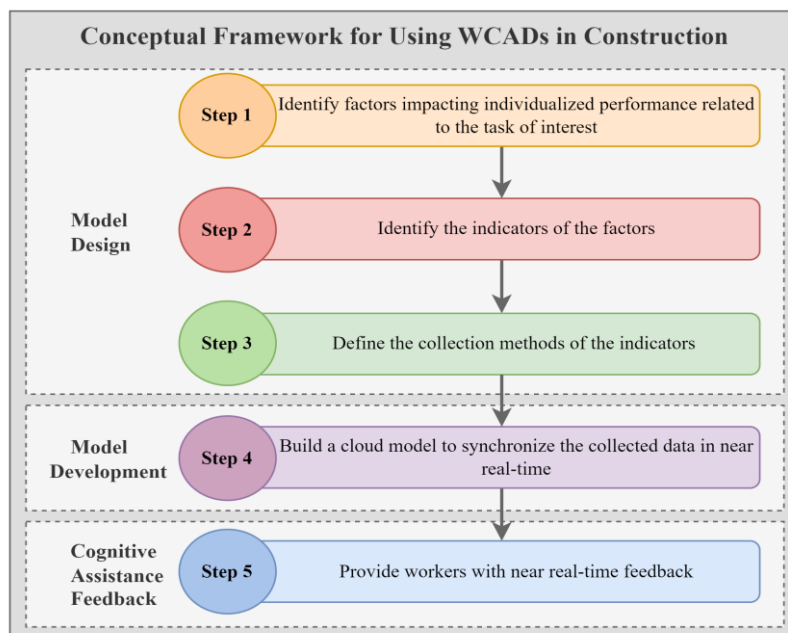


Figure 1. Framework for implementing WCADs in Construction

The first step in the framework is identifying the factors that could impact the individualized performance in the task of interest (Step 1). The purpose of this step is shortlisting the contributors to poor safety behaviours and loss of productivity. The nature of the task of interest is an important factor to consider, as construction tasks vary in terms of the required physical and mental workloads. For example, the demands and risks associated with masonry works are different than those of concrete works. Drawing from LC 4.0 principles, which prioritize efficiency and continuous improvement, the critical role of individual performance in overall project success is recognized.

After identifying the factors influencing performance, Step 2 involves determining the means to detect the existence of these factors. These detection methods, referred to as indicators, encompass various measures such as physiological markers, site conditions (e.g., environmental factors), and worker-based data (e.g., sleep patterns, stress levels, fitness levels). This step focuses on recognizing and quantifying the elements impacting individualized performance in construction tasks. It aligns with the LC 4.0 emphasis on real-time monitoring and data-driven decision-making.

Afterwards, the collection methods of these indicators need to be defined (Step 3). This step describes how these indicators are to be converted into quantifiable data to be able to perform further analysis. Such data could either be quantitative (physiological data from WSDs) or qualitative (questionnaires). Inspired by LC 4.0, where principles emphasize the relentless pursuit of efficiency and waste reduction, this framework ensures a harmonious integration of quantitative measures, such as physiological qualitative inputs. This holistic approach aligns with LC 4.0's emphasis on utilizing advanced digital tools for enhancing project objectives.

This framework aims to enhance the cognitive abilities through merging various forms of data collection methods to provide users with a proactive near real-time support during tasks execution. Since humans are not commodities, and since individual performance varies from one individual to another, it is important to capture these individual differences to be able to tailor the expected performance from one user to another. Therefore, step 4 involves the integration of diverse data collection methods, such as the aforementioned WSDs capturing physiological responses and qualitative inputs from questionnaires. These data then undergo a comprehensive sorting process. This sorting is executed in a secure cloud-based infrastructure that serves as the central repository for data integration and analysis. Within this cloud environment, data analytics are performed. These analytics examine the attributes of the collected data, recognizing patterns, correlations, and individual characteristics. The objective is to gain a refined understanding of the worker's cognitive and physical state during task execution. Individual differences are thoroughly calibrated during this analytical phase. External factors, including environmental conditions, and internal factors, including physiological responses, are factored into the calibration process. This ensures that the feedback provided is not only constructive but also highly personalized, acknowledging the unique characteristics of each worker. The aim of this step is to harness the power of data analytics within a cloud-based framework, offering a dynamic and adaptive system that goes beyond generic support. By tailoring feedback based on individual characteristics, the model optimizes its effectiveness in enhancing cognitive functions and promoting safer and more productive task execution. In alignment with LC 4.0 principles, this step emphasizes the individualized calibration of feedback considering external and internal factors.

Finally, in Step 5, users receive proactive near real-time support during task execution, aligning with the LC 4.0 principles of continuous improvement and worker-centric focus. Recognizing the inherent variability in individual performance among workers, this step underlines the significance of capturing these differences to customize expected performance tailored to each user. By integrating the LC 4.0 principles of optimizing human experience within construction projects, this model not only seeks to boost cognitive functions but also to

contribute to LC's overarching goal of creating a safer, more productive, and efficient construction environment. Ultimately, this integration ensures that advancements in technology are employed not just for technological sake but with a profound commitment to improving the well-being and performance of the construction workforce, echoing the human-centric principles inherent in LC 4.0.

THEORETICAL IMPLEMENTATION OF THE FRAMEWORK IN MASONRY WORKS

In this section, a theoretical implementation of the developed framework in masonry construction is presented. Various factors impact the performance of construction workers and can lead to loss in reported productivity and poor safety behaviours, as listed in Table 2. Regarding the first factor, physical fatigue and posture are significant considerations in the occupational health and safety of masonry workers. The nature of masonry work, which often involves repetitive tasks, heavy lifting, and prolonged periods of standing or kneeling, can contribute to musculoskeletal issues and fatigue. Various researchers correlated between physical exertion/ fatigue and labour productivity using WSDs (Umer et al., 2020). In this study we adopted the technique used by Umer et al., 2020 by using the EQ02 LifeMonitor (Akintola et al., 2016) with embedded ECG electrodes, skin temperature sensor and respiration sensor interwoven invest to monitor masonry workers' physical exertion on construction sites. The selection of this method takes into consideration the comfort of the workers and the nature of movement during task execution. The state of personal well-being is another factor, which varies among individuals and can also fluctuate within the same individual from day to day. Therefore, it is suggested to demonstrate some questions to workers at the beginning of every day as a daily check in for their mental status, including their number of sleeping hours, perceived health status on a scale of 1-5, and a ranking of personal stressors (if any) on a scale of 1-5 (Alhola & Polo-Kantola, 2007). It has been reported that the average sleep length to maintain adequate cognition is between 7 and 8.5 hours per day (Carskadon & Dement, 2005).

Biomechanical stress, along with considerations of posture and body mechanics, plays a significant role in influencing musculoskeletal health and the potential for injuries among construction masonry workers. Therefore, it is one of the crucial factors to include for masonry works. Various researchers have linked gait and ergonomics with safety behaviours and enhancing occupational health and safety of workers (Ren et al., 2022) to prevent musculoskeletal injuries and fall hazards. The suggested collection methods are wearable electromyography (EMG), Inertial measurement units (IMUS) which includes accelerometers and gyroscopes.

Situational awareness for construction masonry workers is crucial for ensuring safety, productivity, and the successful completion of projects. Situational awareness involves being aware of one's surroundings, understanding the current situation, and anticipating potential hazards or challenges (Lappalainen et al., 2021). Therefore, time is of essence when it comes to notifying workers with surrounding hazards, which could include chemical exposure, temperature extremes, fall hazards, electricity hazards, moving equipment as well as oxygen levels in confined spaces.

External factors including time of day and noise have been reported to affect productivity and postural control (Weizenbaum et al., 2020). Therefore, including the time of day could reduce the potential errors of the system and help calibrate the system in a realistic way to mimic expected human behaviour. Also, excess noise level should be detected and mitigated to support performance.

The level of stress and emotional responses can have a substantial impact on the performance of individuals working in construction. Research in construction has established a link between performance and emotional states through using WSDs including

electrocochleography (EEG) and wearable tracking glasses that monitor gaze and eye movement to detect the individual's emotional state (Arpaia et al., 2020).

Table 2. Factors, Indicators, and Collection Methods for WCADs in Masonry Works

Factors Affecting Individualized Performance in Masonry works	Indicators	Collection method
Fatigue/Physical Strain (Umer et al., 2020)	Electrical Activity in the heart	ECG
	Skin Temperature	Infrared Skin Temperature Sensor
	Respiration Rate	Respiration Sensor
Personal well-being (Alhola & Polo-Kantola 2007)	Sleeping hours, perceived health status, personal stressors	Questionnaire
Biomechanical Stress/ Posture and Body Mechanics (musculoskeletal injuries) (Ren et al., 2022)	Gait Analysis, Posture and Ergonomics	Wearable EMG Wearable Strain Sensors IMUs
	Fall detection	Wearable fall detection devices
	Material handling Excess weight	Wearable EMG
	Medical History of musculoskeletal injuries history	Questionnaire
Surrounding Hazards - Situational awareness (Lappalainen et al., 2021)	Chemical Exposure	Gas Sensors on site
	Temperature Extremes (heat stress or cold stress)	Thermal Sensors, EDA sensor
	Electricity Hazards	Voltage Detectors
	Moving Equipment	Proximity sensors
	Confined Spaces	Oxygen Sensors
External Factors (Weizenbaum et al., 2020)	Time of day	Sensor Networks
	Noise	Sound level metrics
Stress level and emotional responses (Arpaia et al., 2020)	Gaze, Eye movement, Facial expressions	Wearable Eye Trackers
	Electrical activity in the brain	EEG
Attention levels (Ke et al., 2021)	Electrical activity in the brain	EEG
Perceived Risk (G. Lee et al., 2021)	Heart volumetric change	PPG
	skin electric properties	EDA
	skin temperature	Thermopile
Demographics of worker (Murman, 2015)	Years of Experience, age, fitness level	Questionnaire

Additionally, attention level could also be detected using wearable EEG (Ke et al., 2021), which contributes to safety behaviour and individual productivity. Moreover, perceived risk is one of the influences of safety behaviours demonstrated by workers on construction sites and it was

quantified by G. Lee et al., 2021 by measuring the heart volumetric change, skin electric properties, and skin temperature.

Finally, demographics of the workers will aid the calibrations and personalization of the model according to the individual's years of experience, age, and fitness level.

This section establishes how the factors - that are expected to impact the performance of masonry construction workers - can be collected on site. Future steps could include uploading collected data to the cloud-based model that can be developed to mimic the expected cognitive performance tailored to the individual's input data. Once the analysis is complete, proactive near real-time support is offered to masonry construction workers during task execution.

CONCLUSION

This paper presents a comprehensive conceptual framework for the implementation of WCADs in construction, with a LC 4.0 perspective. The primary aim is to enhance workers' well-being, safety, and productivity by leveraging WCADs to provide near real-time feedback. The developed framework, presented in five sequential steps, offers a generic yet adaptable approach applicable to various construction tasks.

The framework begins with the identification of factors impacting individualized performance, acknowledging the diverse demands and risks associated with distinct construction activities. Following steps involve determining detection methods (indicators), defining collection methods, and integrating diverse data collection methods, including WSDs and qualitative inputs. The cloud-based analytical phase plays a pivotal role in calibrating individual differences, considering external and internal factors.

The theoretical implementation of the framework in masonry works exemplifies its practical application. Factors influencing masonry workers' performance, such as physical fatigue, personal well-being, biomechanical stress, situational awareness, external factors, and emotional responses, are considered. The proposed collection methods offer a holistic approach to understanding and enhancing workers' cognitive and physical states. Moreover, the inclusion of worker demographics facilitates the calibration and personalization of the model, reflecting individual variations in experience, age, and fitness level. The result of the model, housed within a cloud-based system, provides users with proactive near real-time support during task execution, accommodating the inherent variability in individual performance.

This research contributes to the evolving environment of LC 4.0 by bridging the gap between theoretical advancements and practical implementation in the construction industry. The proposed framework, centred on WCADs, not only addresses safety and productivity concerns but also prioritizes the well-being of construction workers. As the construction industry continues to embrace technological innovations, this framework stands as a progressive step towards fostering a safer, more efficient, and worker-centric construction environment.

While this conceptual framework provides a foundation for integrating WCADs into construction tasks, certain limitations are acknowledged. First, the effectiveness of the framework heavily relies on the current state of WCADs and their technological capabilities. Rapid advancements in wearable technology are expected, and the framework may need adjustments to accommodate future innovations. The integration of cloud-based systems for data analytics could also raise concerns about data privacy and security. Adequate measures must be in place to ensure the protection of sensitive information collected from workers.

Recommendations for future work include evaluating the proposed framework practically through a longer-term study that should include surveys questionnaires with an expert panel focused on the use of WSDs and WCADs in construction.

ACKNOWLEDGMENTS

This study is partially funded by the NSERC Alliance Grant ALLRP 567205-21.

REFERENCES

- Admile, A., & Barguje, S. (2023). *The Future of Warfare: A Smart AR/VR AI-Driven Helmet for Real-Time Data Analysis and Tactical Advantage* (SSRN Scholarly Paper 4674792). <https://doi.org/10.2139/ssrn.4674792>
- Ahn, C. R., Lee, S., Sun, C., Jebelli, H., Yang, K., & Choi, B. (2019). Wearable Sensing Technology Applications in Construction Safety and Health. *Journal of Construction Engineering and Management*, 145(11), 03119007. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001708](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001708)
- Akintola, A. A., Van De Pol, V., Bimmel, D., Maan, A. C., & Van Heemst, D. (2016). Comparative Analysis of the Equivital EQ02 Lifemonitor with Holter Ambulatory ECG Device for Continuous Measurement of ECG, Heart Rate, and Heart Rate Variability: A Validation Study for Precision and Accuracy. *Frontiers in Physiology*, 7. <https://doi.org/10.3389/fphys.2016.00391>
- Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. *Neuropsychiatric Disease and Treatment*.
- Anwer, S., Li, H., Antwi-Afari, M. F., Umer, W., Mehmood, I., Al-Hussein, M., & Wong, A. Y. L. (2021). Test-retest reliability, validity, and responsiveness of a textile-based wearable sensor for real-time assessment of physical fatigue in construction bar-benders. *Journal of Building Engineering*, 44, 103348. <https://doi.org/10.1016/j.jobe.2021.103348>
- Arpaia, P., Moccaldi, N., Prevede, R., Sannino, I., & Tedesco, A. (2020). A Wearable EEG Instrument for Real-Time Frontal Asymmetry Monitoring in Worker Stress Analysis. *IEEE Transactions on Instrumentation and Measurement*, 69(10), 8335–8343. <https://doi.org/10.1109/TIM.2020.2988744>
- Belletier, C., Charkhabi, M., Pires de Andrade Silva, G., Ametepe, K., Lutz, M., & Izaute, M. (2021). Wearable cognitive assistants in a factory setting: A critical review of a promising way of enhancing cognitive performance and well-being. *Cognition, Technology & Work*, 23(1), 103–116. <https://doi.org/10.1007/s10111-019-00610-2>
- Carskadon, M. A., & Dement, W. C. (2005). *Chapter 2 – Normal Human Sleep: An Overview*.
- Cheng, B., Luo, X., Mei, X., Chen, H., & Huang, J. (2022). A Systematic Review of Eye-Tracking Studies of Construction Safety. *Frontiers in Neuroscience*, 16, 891725. <https://doi.org/10.3389/fnins.2022.891725>
- González, V. A., Farook, H., Alarcón, Luis Fernando, & Khalife, Salam. (2022). Lean Construction 4.0: Beyond the New Production Management Philosophy. In *Lean Construction 4.0: Driving a Digital Revolution of Production Management in the AEC Industry* (pp. 3–14).
- Hajj-Boutros, G., Landry-Duval, M.-A., Comtois, A. S., Gouspillou, G., & Karelis, A. D. (2023). Wrist-worn devices for the measurement of heart rate and energy expenditure: A validation study for the Apple Watch 6, Polar Vantage V and Fitbit Sense. *European Journal of Sport Science*, 23(2), 165–177. <https://doi.org/10.1080/17461391.2021.2023656>
- Hamzeh, F., González, V. A., Alarcon, L. F., & Khalife, S. (2021). *Lean Construction 4.0: Exploring the Challenges of Development in the AEC Industry*. 207–216. <https://doi.org/10.24928/2021/0181>
- Hines, P., Tortorella, G. L., Antony, J., & Romero, D. (2023). Lean Industry 4.0: Past, present, and future. *Quality Management Journal*, 30(1), 64–88. <https://doi.org/10.1080/10686967.2022.2144786>

- Hurrell, J. J., & McLaney, M. A. (1988). *Exposure to job stress—A new psychometric instrument*.
- Jung, H., Kim, D., Lee, W., Seo, H., Seo, J., Choi, J., & Joo, E. Y. (2022). Performance evaluation of a wrist-worn reflectance pulse oximeter during sleep. *Sleep Health*, 8(5), 420–428. <https://doi.org/10.1016/j.sleh.2022.04.003>
- Karmaoui, D., AlBalkhy, W., Lafhaj, Z., & Chapiseau, C. (2023). *Lean and Industry 4.0 in Brick Manufacturing: A Digital Twin-Based Value Stream Mapping Proposed Framework*. 230–241. <https://doi.org/10.24928/2023/0259>
- Ke, J., Zhang, M., Luo, X., & Chen, J. (2021). Monitoring distraction of construction workers caused by noise using a wearable Electroencephalography (EEG) device. *Automation in Construction*, 125, 103598. <https://doi.org/10.1016/j.autcon.2021.103598>
- Lappalainen, E. M., Seppänen, O., Peltokorpi, A., & Singh, V. (2021). Transformation of construction project management toward situational awareness. *Engineering, Construction and Architectural Management*, 28(8), 2199–2221. <https://doi.org/10.1108/ECAM-12-2020-1053>
- Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, 6(4), 239–242. <https://doi.org/10.1007/s12599-014-0334-4>
- Lee, G., Choi, B., Jebelli, H., & Lee, S. (2021). Assessment of construction workers' perceived risk using physiological data from wearable sensors: A machine learning approach. *Journal of Building Engineering*, 42, 102824. <https://doi.org/10.1016/j.jobe.2021.102824>
- Lee, W., Lin, K.-Y., Seto, E., & Migliaccio, G. C. (2017). Wearable sensors for monitoring on-duty and off-duty worker physiological status and activities in construction. *Automation in Construction*, 83, 341–353. <https://doi.org/10.1016/j.autcon.2017.06.012>
- McHugh, K., Dave, Bhargav, Tezel, Algan, Koskela, Lauri, & Patel, Viranj. (2022). Towards Lean Construction Site 4.0. In *Lean Construction 4.0: Driving a Digital Revolution of Production Management in the AEC Industry* (pp. 17–34).
- Mukhopadhyay, S. C. (2015). Wearable Sensors for Human Activity Monitoring: A Review. *IEEE Sensors Journal*, 15(3), 1321–1330. <https://doi.org/10.1109/JSEN.2014.2370945>
- Murman, D. (2015). The Impact of Age on Cognition. *Seminars in Hearing*, 36(03), 111–121. <https://doi.org/10.1055/s-0035-1555115>
- Nath, N. D., Chaspari, T., & Behzadan, A. H. (2018). Automated ergonomic risk monitoring using body-mounted sensors and machine learning. *Advanced Engineering Informatics*, 38, 514–526. <https://doi.org/10.1016/j.aei.2018.08.020>
- Nnaji, C., Okpala, I., Gambatese, J., & Jin, Z. (2023). Controlling safety and health challenges intrinsic in exoskeleton use in construction. *Safety Science*, 157, 105943. <https://doi.org/10.1016/j.ssci.2022.105943>
- Noueihed, K., & Hamzeh, F. (2022). Envisioning a Human Centric Approach to C4.0 Technologies. *Lean Construction Journal*. *Lean Construction Journal (LCJ)*, 2022–2156.
- Oyekan, J., Chen, Y., Turner, C., & Tiwari, A. (2021). Applying a fusion of wearable sensors and a cognitive inspired architecture to real-time ergonomics analysis of manual assembly tasks. *Journal of Manufacturing Systems*, 61, 391–405. <https://doi.org/10.1016/j.jmsy.2021.09.015>
- Park, M.-W., Elsafty, N., & Zhu, Z. (2015). Hardhat-Wearing Detection for Enhancing On-Site Safety of Construction Workers. *Journal of Construction Engineering and Management*, 141(9), 04015024. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0000974](https://doi.org/10.1061/(ASCE)CO.1943-7862.0000974)

- Ren, B., Luo, X., Li, H., Chen, J., & Wang, Y. (2022). Gait trajectory-based interactive controller for lower limb exoskeletons for construction workers. *Computer-Aided Civil and Infrastructure Engineering*, 37(5), 558–572. <https://doi.org/10.1111/mice.12756>
- Rocha, C. G., Carlos T. Formoso, & Patricia Tzortzopoulos-fazenda. (2012). Design Science Research in Lean construction: Process and Outcomes. *Proceedings of the 20th Annual Conference of the International Group for Lean Construction*.
- Sanders, A., Elangeswaran, C., & Wulfsberg, J. (2016). Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management*, 9(3), 811. <https://doi.org/10.3926/jiem.1940>
- Shehab, L., & Hamzeh, F. (2023). *Zooming Into Workers' Psychology and Physiology Through a Lean Construction Lens*. 92–103. <https://doi.org/10.24928/2023/0162>
- Umer, W., Li, H., Yantao, Y., Antwi-Afari, M. F., Anwer, S., & Luo, X. (2020). Physical exertion modeling for construction tasks using combined cardiorespiratory and thermoregulatory measures. *Automation in Construction*, 112, 103079. <https://doi.org/10.1016/j.autcon.2020.103079>
- Weizenbaum, E., Torous, J., & Fulford, D. (2020). Cognition in Context: Understanding the Everyday Predictors of Cognitive Performance in a New Era of Measurement. *JMIR mHealth and uHealth*, 8(7), e14328. <https://doi.org/10.2196/14328>
- Wu, R., Liaqat, D., Lara, E. de, Son, T., Rudzicz, F., Alshaer, H., Abed-Esfahani, P., & Gershon, A. S. (2018). Feasibility of Using a Smartwatch to Intensively Monitor Patients With Chronic Obstructive Pulmonary Disease: Prospective Cohort Study. *JMIR mHealth and uHealth*, 6(6), e10046. <https://doi.org/10.2196/10046>
- Zhao, S., Wang, J., Leng, H., Liu, Y., Liu, H., Siewiorek, D. P., Satyanarayanan, M., & Klatzky, R. L. (2020). *Edge-Based Wearable Systems for Cognitive Assistance: Design Challenges, Solution Framework, and Application to Emergency Healthcare*.