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HUMAN-IN-THE-LOOP DIGITAL TWIN FRAMEWORK FOR ERGONOMIC ASSESSMENT OF EXOSKELETONS IN CONSTRUCTION

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SUMMARY: *Exoskeletons are increasingly recognized as ergonomic solutions for work-related musculoskeletal disorders in the construction industry. However, users of active back-support exoskeletons are susceptible to various physical and psychological risks, which could be exoskeleton-type or task-dependent. A test bed is needed to enable deployment and assessment of risks associated with exoskeleton use for construction tasks. This study presents a human-in-the-loop digital twin framework for assessing ergonomic risks associated with using active back-support exoskeletons for construction work. Through a literature review, a digital twin system architecture for assessing risks associated with active back-support exoskeletons was developed. Semi-structured interviews were conducted to identify construction tasks that are most suitable for active back-support exoskeletons. Based on the identified tasks, a laboratory experiment was conducted to quantify the risks associated with the use of a commercially available active back-support exoskeleton for carpentry framing tasks. The efficacy of the digital twin framework is demonstrated with an example of the classification of exertion levels due to exoskeleton use using a 1D-convolutional neural network. The results show that the performance of the model improved significantly with synthetic data. The dashboard provides a visualization of exertion risk classification outcomes to aid decision-making. The study highlights the potential of digital twins for ergonomic assessment, allowing stakeholders to proactively address ergonomic risks and optimize the use of exoskeletons in the construction industry. This study sets a precedent for future research on using digital twins to monitor the performance of exoskeletons in construction. Such efforts could enhance the sustainability of exoskeleton solutions in construction workplaces.*

KEYWORDS*: Digital Twin, Ergonomics, Exoskeletons, Risk Assessment, Sensing Technologies, Work-related musculoskeletal disorders.*

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1. INTRODUCTION

The United States Bureau of Labor and Statistics (BLS, 2020) reports that the construction workforce faces a higher rate of work-related musculoskeletal disorders (WMSDs), with 40.6 per 10,000 full-time employees affected, compared to 26.9 per 10,000 full-time employees in other industry sectors. This leads to a median loss of 16 workdays in the construction industry compared to 14 days in other industries. Back-related injuries make up about 43% of all WMSDs in construction (BLS, 2023), with construction workers being 1.6 times more likely to sustain back injuries than their counterparts in other industries (22.2 per 10,000 full-time employees versus 13.6 per 10,000). This prevalence has significant consequences for construction companies and workers, including annual compensation payouts of $400 million due to WMSDs (Bhattacharya, 2014). In severe cases, back injuries can lead to permanent disability or premature exit from the industry (N. Gonsalves et al., 2023).

Exoskeletons, particularly, active back-support exoskeletons have emerged as potential solutions to WMSDs (Okunola et al., 2023). These exoskeletons can reduce the risks of overexertion, a common cause of back-related injuries. Studies have shown that exoskeletons can lower muscle activity (Theurel et al., 2018), discomfort in the body parts (Gonsalves et al., 2021; Kim et al., 2019), rate of exertion (Alemi et al., 2020; Baltrusch et al., 2021), and range of motion (Cumplido-Trasmonte et al., 2023; Okunola et al., 2023). These benefits motivate construction contractors to explore active back-support exoskeletons for construction work. However, exoskeleton use on construction sites may lead to unintended consequences such as loss of balance or fall risks (Alabdulkarim et al., 2019; Kim et al., 2019; Massardi et al., 2023), physical discomfort and pain (N. Gonsalves et al., 2023; Gonsalves et al., 2021), fatigue (Theurel et al., 2018), and movement restriction when climbing ladders (de Looze et al., 2016; Kim et al., 2019). These issues suggest that exoskeleton use may need to be task-specific, and consequences may vary depending on the type of exoskeleton used (Fox et al., 2019; Kim et al., 2019). With the growing availability of commercial exoskeleton solutions, establishing a testbed would aid in testing and evaluating these solutions for construction tasks. This could facilitate real-time monitoring of exoskeleton use during construction activities, which may lead to more effective strategies for minimizing unintended risks.

Sensing technologies offer opportunities to measure risks associated with exoskeleton use (Akanmu et al., 2020; O. Ogunseiju et al., 2021). Data from sensing technologies could be analyzed and used to inform control strategies such as deciding when and how to use exoskeletons, which types are most appropriate, and potential design modifications. This approach involves creating a digital representation, a human-in-the-loop digital twin, that can facilitate the interaction between workers, exoskeletons, and virtual models to manage and control risks (Zhang et al., 2024). This allows stakeholders to monitor the ergonomic impact of using exoskeletons, improving their ability to manage or self-regulate workers' exposures (O. Ogunseiju et al., 2021).

Thus, this paper presents a digital twin framework for assessing the risks associated with exoskeleton use in construction work. A literature review was conducted to identify risks associated with exoskeleton use, the sensing technologies for quantifying the risks, and assessment techniques. These enabled the development of a system architecture to support the development of a human-in-the-loop DT framework that can inform decisions to support the sustainable use of exoskeletons in construction. Construction practitioners were interviewed to identify tasks that would benefit from active back-support exoskeletons. The effectiveness of the framework is demonstrated through an example of predicting exertion levels resulting from the use of an active back-support exoskeleton for one of such tasks. This study encourages discussion on the application of human-in-the-loop digital twins in construction. The study shows how physiological risks related to exoskeleton use can be predicted and managed. The paper includes background information on the research gap, methodology, results, discussion, and conclusion. The study underscores the potential of digital twins for ergonomic assessment, enabling stakeholders to proactively address ergonomic risks and optimize exoskeleton use in the construction industry. This research adds to the limited body of literature on using digital twins to assess the suitability of exoskeletons for construction work. It highlights the important role of physiological sensing and machine learning techniques in implementing the digital twin framework. Additionally, the study sets the stage for future research on using digital twins to monitor exoskeleton performance in construction settings, potentially enhancing the sustainability of exoskeleton solutions in the construction industry.

2. BACKGROUND

2.1 Exoskeletons for Construction Work: Risk and Assessment Techniques

Studies have shown that exoskeletons have intended benefits and unintended consequences. Exoskeletons are prospective innovative ergonomic interventions aimed at reducing overexertion in various parts of the body (Gonsalves et al., 2021; Nussbaum et al., 2019). This may in turn reduce the occurrence of WMSDs among construction workers. There is evidence that exoskeletons can reduce back muscle activities by 23 - 35% (Abdoli-e & Stevenson, 2008), range of motion (Ogunseiju et al., 2022), and perceived exertion (Kim et al., 2021). Other benefits revealed in the literature include reduced discomfort to body parts (Alemi et al., 2020), increased productivity, financial gains, worker retention (Kim et al., 2019), increased ability to lift heavier loads and perform repetitive tasks (Mahmud et al., 2022). Despite these benefits, there are some unintended consequences associated with exoskeletons. Exoskeletons have been known to trigger risks broadly classified in Table 1 as physical and psychological risks. Physical risks include joint hyperextension, instability and fall risk, muscle fatigue, bruising, skin and soft tissue injury, and increased cardiovascular demand and metabolic cost (Howard et al., 2020; Massardi et al., 2023; Theurel et al., 2018). For example, skin irritation or chemical burns could occur if an exoskeleton battery leaks corrosive materials onto the user (Howard et al., 2020). Additionally, physical risks may arise from difficulties working in confined spaces and poor anthropometric fit (Fox et al., 2019; Schwerha et al., 2021). The added weight of an exoskeleton can also affect the user’s center of gravity, leading to balance problems and a reduced recovery rate (Alabdulkarim et al., 2019). Liu et al. (2021) reported that exoskeletons can also cause thermal discomfort.

Gonsalves et al. (2021) showed that exoskeletons result in discomfort in the chest and thigh regions. Other studies suggest that exoskeletons can redirect loading from one part of the body to another (Picchiotti et al., 2019). For example, during overhead work, exoskeletons may reduce muscle activity in the shoulder and the back regions of the arm, while increasing muscle activity in the lower back, abdomen, and legs (Theurel et al., 2018). Additionally, usability, self-efficacy, and safety could be negatively impacted because the exoskeletons could get caught around wires and may affect work postures (Baltrusch et al., 2021). Exoskeletons may also be incompatible with certain personal protective equipment such as safety harnesses (N. J. Gonsalves et al., 2023), and they could restrict movement or exert pressure on body parts (Omobolanle Ogunseiju et al., 2021). Psychological risks identified in previous studies include decreased situation awareness/distraction, cognitive overload, fear of the device, decreased vigilance, and overconfidence in the device. Various sensing technologies, such as inertial measurement units (IMU) and electromyography (EMG), have been employed to quantify these risks. Additionally, objective measures from the sensing technologies have been validated with subjective assessment instruments such as the NASA Task Load Index and Berg Balance Scale. These are highlighted in Table 1.

Table 1: Risks and assessment techniques. Part One.

Categories of risks	Risks	Objective Assessment	Subjective Assessment	Related Studies
Physical risks	Joint hyperextension	Inertial measurement units; Cameras	Local Perceived Pressure scale; Borg Rating of Perceived Exertion scale	(Theurel et al., 2018)
	Instability; Fall	Pressure insoles; Force plates	Berg Balance Scale	(Alabdulkarim et al., 2019; Kim et al., 2019; Massardi et al., 2023)
	Muscle fatigue	Electromyography	Borg Rate of Perceived Pain Scale; Borg Rate of Perceived Exertion Scale	(Theurel et al., 2018)
	Hygiene issues/Bruising; Skin and soft tissue injury	Biocompatibility tests	Usability questionnaires e.g., System Usability Scale	(Howard et al., 2020; Massardi et al., 2023)
	Cardiovascular demand	Electrocardiogram; Photoplethysmogram	Workload assessment questionnaires e.g., NASA Task Load Index (TLX)	(Moyon et al., 2018; Theurel et al., 2018)
	Metabolic cost	Indirect calorimetry	Questionnaires for workload assessment (e.g., NASA TLX), Rating perceived exertion (RPE) with the Borg Category Ratio (Borg CR-10)	(Alemi et al., 2020; Baltrusch et al., 2021)

Table 1: Risks and assessment techniques. Part two.

Categories of risks	Risks	Objective Assessment	Subjective Assessment	Related Studies
Physical risks	Usability issues (e.g., perceived discomfort, chest pain, catch and snag risks)	Eye tracker; Electromyography	Focus groups; Usability questionnaires; Borg CR 10 scale; Body part discomfort scale	(Gonsalves et al., 2021; Kim et al., 2019; Ogunseiju et al., 2022)
Psychological risks	Distraction/ reduced situation awareness	Eye tracker	NASA-TLX	(de Looze et al., 2016; Delgado et al., 2020)
	Fear; Lack of trust	Electromyography; Photoplethysmogram; Electrodermal activity (EDA) sensor	Interview; Self-developed questionnaires; subjective psychological impact test	(Omoniyi et al., 2020; Upasani et al., 2019)
	Cognitive overload	Electroencephalography; Eye tracker; Electrodermal activity sensor	NASA-TLX; MF (M-VAS) and boredom (B-VAS)	(Cumplido-Trasmonte et al., 2023)
	Overconfidence effect	Camera Videos; Optical tracking system (OTS)	Focus groups; Questionnaires (e.g., Modified Spinal Function Sort)	(Baltrusch et al., 2021; Siedl et al., 2021)

2.2 Digital Twin for Ergonomic Risk Assessment

Efforts to reduce ergonomic risks in the construction industry involve a variety of strategies, including training, modification of work layouts and tools, and the use of wearable devices (Akanmu et al., 2020; Albers et al., 2005; Yan et al., 2018). Training could take the form of conventional manual-based instruction on safe working postures and practices or could occur in virtual environments, as demonstrated by Akanmu et al. (2020). Wearable devices, such as exoskeletons, offer support to different body parts and reduce ergonomic risks (N. J. Gonsalves et al., 2023). Assessing ergonomic risks is a crucial step for effective ergonomic risk reduction. Subjective methods of assessment, such as questionnaires and observational approaches like Rapid Entire Body Assessment (REBA) and Rapid Upper Limb Assessment, often come with challenges such as being post hoc, time-consuming, prone to error and bias, and potentially interrupting construction activities (Vijayakumar & Choi, 2022). Migliaccio et al. (2013) and Tao Cheng et al. (2013) argued for real-time and remote monitoring of workers as a precursor to improving the health and safety of the construction workforce. The increasing use of wearable sensors provides objective, real-time, and continuous monitoring of ergonomic risks, which helps to address the limitations of subjective methods. For example, Nath et al. (2017) showed how a smartphone-based wearable sensor can identify ergonomic risks. Yan et al. (2018) developed an IMU-based personal protective equipment to monitor and notify construction workers of ergonomic risks. The potential of digital twin (DT) allows for the optimization of ergonomic risk assessment through real-time information on risks, providing a virtual representation of construction workers. This can enhance the control and virtual replication of construction workers, leading to a more comprehensive and accurate evaluation of ergonomic risks (Jimenez & Maire, 2024). This DT-based assessment can support self-management of ergonomic risk as shown by Ogunseiju et al. (2022) and can be used by ergonomists and safety managers to monitor and control ergonomic risks through evidence-based decisions.

Grieves and Vickers (2017) defined the digital twin as “a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level”. The concept is based on creating a digital representation of a physical system, containing the same information, and being linked to the physical counterpart. Lui et al. (2018) further defined DT as a living model that represents a physical asset or system that continually adapts to changes in operations based on online data and information collected and can predict the future of the corresponding physical counterpart. The DT can improve based on its adaptations to the environment, which is achieved through the effective simulation of data obtained using embedded sensors (T. Cheng et al., 2013; Madubuike et al., 2022). Consequently, DT consists of three parts, which include the physical product, the virtual product, and the communication platform between them (Glaessgen & Stargel, 2012). In recent years, there has been growing interest in applying DT for diverse purposes in various fields, including workforce health and safety in industries such as manufacturing, aviation, and healthcare. However, its application in construction remains limited (Omobolanle Ogunseiju et al., 2021). For example, in manufacturing, Jimenez and Maire (2024) proposed ErgoTwin using an enhanced REBA method for the virtual representation of workers. The authors showed how DT can be used for real-time postural risk assessment and predictive analytics across six body regions. Caputo et al. (2019) used DT to improve ergonomics in workplace design by reducing the cost and time required to develop new assembly lines in the automobile industry. Jia et al. (2024) emphasized the integration of DTs into ergonomics to mitigate safety hazards from human and non-human sources in the petrochemical industry. Maruyama et al. (2021) developed a human-robot collaboration system using DT, which assesses workers' movements and simulates work processes and physical strain to enhance productivity and ergonomic assessment. Sharotry et al. (2022) developed a DT to track biomechanical fatigue in operators caused by repetitive lifting activities, using a dynamic time-warping algorithm to analyze changes in joint angles. Another study (Greco et al., 2020) mapped DT workstations' ergonomic risk using a wearable motion capture system and virtual simulated environments. With the DT, the authors were able to identify risk indexes related to working postures, exerted forces, material handling, and sources of biomechanical overload. In construction, an assessment of the ergonomic performance of construction tasks was carried out by Migliaccio et al. (2012) and T. Cheng et al. (2013). Their studies focused on fusing data from Real-time Location Sensing (RTLS) technologies and Physiological Status Monitors (PSMs) to monitor multiple resources in real-time. Prior studies such as Migliaccio et al. (2013) and Tao Cheng et al. (2013) combined real-time location sensing and physiological monitoring to automatically and remotely assess unsafe behaviors of construction workers. Recently, O. Ogunseiju et al. (2021) developed a DT framework for improving self-management of ergonomic risks. However, scarce studies have explored the assessment of exoskeleton use in a DT environment. Greco et al. (2020) also noted that existing DT frameworks offer limited involvement for users or stakeholders, emphasizing the importance of designing supporting technologies to accommodate human input (Sharotry et al., 2020).

2.3 Research Gaps

Previous studies have emphasized the benefits and unintended consequences of using exoskeletons to mitigate WMSDs (Gonsalves et al., 2021; Kim et al., 2020; Mahmud et al., 2022; Okunola et al., 2023). These studies have assessed and quantified risks associated with exoskeleton use through both subjective and objective measures. However, there is limited research on aggregating physical and psychological risks related to exoskeleton use to guide decision-making. Past efforts to employ DT for workforce health and safety have primarily focused on sectors like manufacturing, military, and healthcare (O. Ogunseiju et al., 2021). In contrast, the construction industry has an opportunity to utilize sensors and other enabling technologies to develop DT frameworks for evaluating and tracking ergonomic impacts related to exoskeleton use in construction applications. Therefore, this study attempts to fill this gap by proposing a DT framework for assessing the ergonomic implication of exoskeleton use in the construction industry.

3. METHODOLOGY

The approach employed in conducting this study is shown in Figure 1.

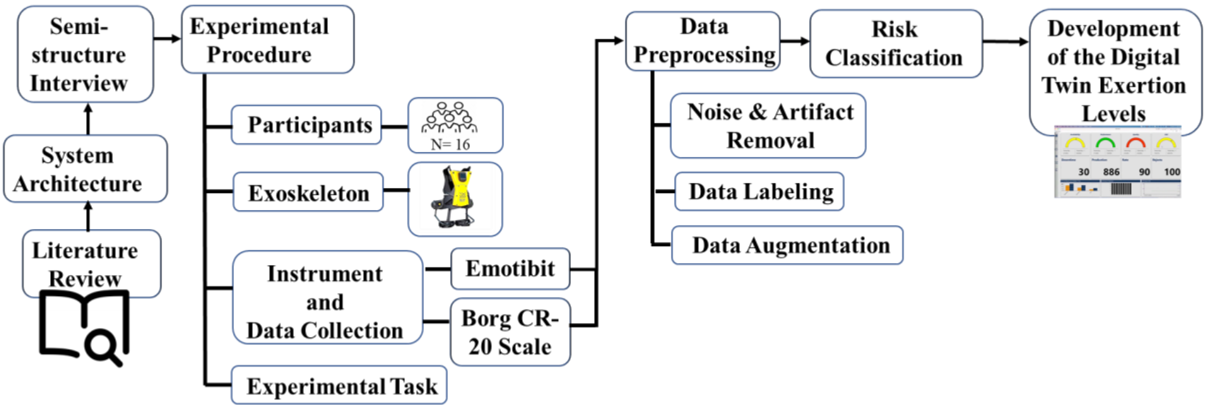

Figure 1: Overview of research methodology.

First, a review of the risks associated with exoskeletons and the metrics for measuring the impact of the risks was conducted (Section 2.1). This informed the development of an architecture of a human-in-the-loop DT system for assessing risks associated with active back-support exoskeletons. Semi-structured interviews were conducted to identify construction tasks that would benefit from the use of active back-support exoskeletons. A laboratory experiment was conducted to quantify the risks associated with using active back-support exoskeletons. This informed the development of an example of a DT-based model for assessing levels of exertion during exoskeleton use. These are described as follows:

3.1 System Architecture

The system architecture shown in Figure 2 is built to illustrate the proposed human-in-the-loop DT framework. The system architecture shows the enabling technologies and their role in supporting the assessment of ergonomic risks associated with exoskeleton use. The architecture comprises six layers including the physical layer, data layer, data transmission layer, storage layer, application layer, and access layer. These are described as follows:

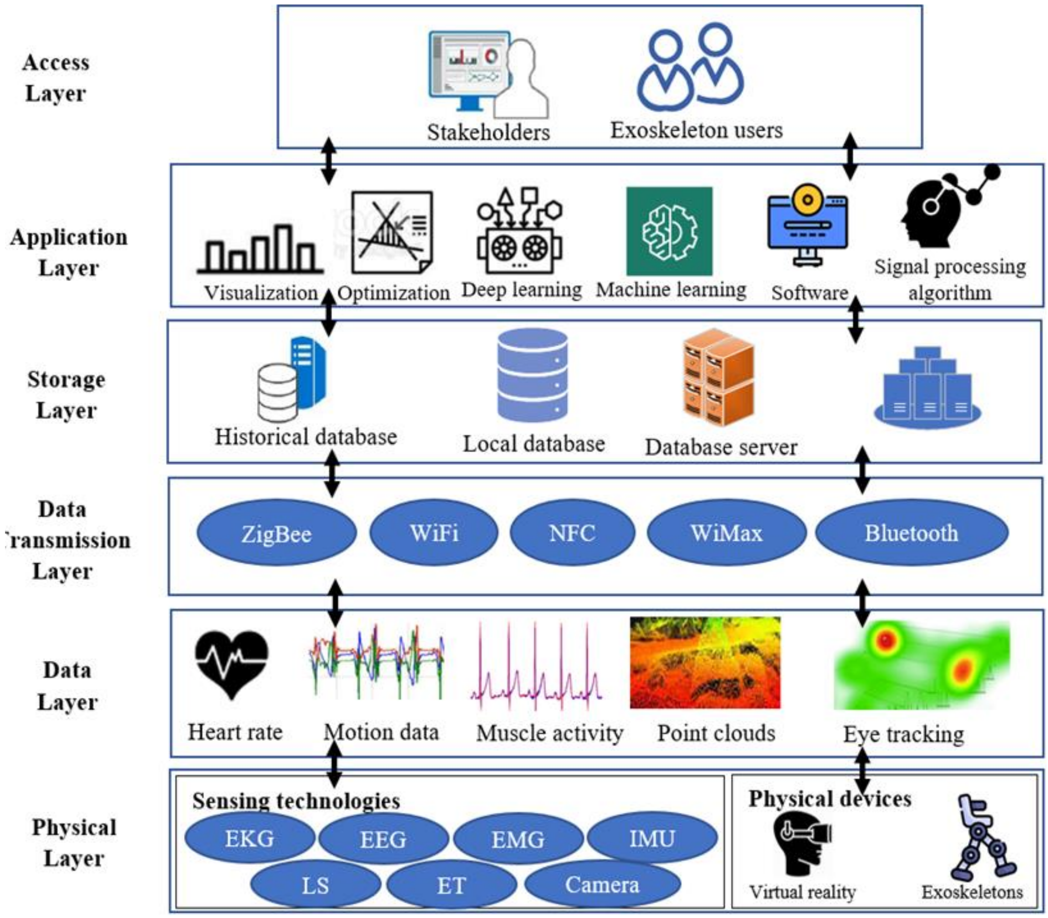

Figure 2: System architecture.

3.1.1 Physical layer

The physical layer comprises sensing technologies and physical devices. The sensing technologies support capturing of physical and psychological risks, and environmental characteristics of work areas. The physical risks include local muscle fatigue, fall risk, joint hyperextension, and metabolic risk which can be measured using electromyography (EMG), pressure insole, inertia measurement unit (e.g., comprising of accelerometers, gyroscope, and magnetometer), and calorimeter respectively. The psychological risks include cognitive overload, lack of trust, and decreased vigilance which could be measured using an electroencephalogram (EEG), electrocardiogram (ECG), photoplethysmogram, and eye tracker respectively. The workspace or site conditions can be captured using environmental sensors such as temperature and humidity sensors and image-based sensors such as cameras and laser scanners. Physical devices include reality technologies such as virtual and augmented reality devices, and other data acquisition technologies for collecting subjective data to evaluate the objective measures. Reality technologies support the development of risk-free simulated construction site environments where workers can practice work with different exoskeletons.

3.1.2 Data layer

Data from the physical layer is captured in the data layer. The data layer contains the data generated from the sensors and physical devices, such as raw acceleration and angular velocity from the IMU, brain waves from EEG, electrical conductance of the skin from EDA sensors, eye fixations from eye trackers, muscle activity from EMG, and temperature and humidity from temperature and humidity sensors. Subjective data (such as perceived cognitive load, rate of exertion, and discomfort levels) are also stored in the data layer. This layer also contains videos of construction work and general characteristics of the work area that might explain or influence risk factors of WMSDs.

3.1.3 Data transmission layer

The data transmission layer transfers data from the data layer to other layers for storing, modeling and analysis, and DT representation. Different communication technologies could be used in this layer, such as short-range transmission technologies e.g., Wi-Fi, Bluetooth, Zigbee, near-field communication (NFC), and Zwave, and long-range transmission technologies e.g., 3G, 4G long-term evolution (LTE), and low-power wide-area networks.

3.1.4 Storage layer

This layer consists of cloud services that store data received from the data transmission layer and application layer. Heterogenous data from these layers are gathered and stored in a cloud storage system for exchange or sharing with other layers. The data or information can be beneficial for extracting other insights that can help improve the health and safety of workers. Depending on the stakeholders and their information needs, multiple repositories may be included. As such, different access rights may be provided. For instance, a data analyst may need access to label subjective data obtained from the data layer to enable assessments involving risk classifications. A safety/health manager may be provided access to data that can inform impact on workers' health while a project manager may be provided access to data relating to impact on productivity.

3.1.5 Application layer

This layer includes algorithms and applications for processing and analyzing data obtained from the storage layer. The data are processed and represented in formats that can be used by decision-makers in the access layer (Section 3.1.6) for decision-making. For example, to assess workers' levels of exertion from their electrodermal activity (EDA) signals, this layer will use signal processing algorithms, feature extraction, and deep learning networks (e.g., conditional generative adversarial network, recurrent neural network, and long short-term memory), and visualization algorithms. Signal processing algorithms such as discrete wavelet transforms, and adaptive predictor filtering methods will be used to reduce artifacts from the EDA signals. An asymmetric multilayer perception model for extracting features will be used to extract informative features from the EDA signals. The extracted features will be fed into deep learning networks to classify the EDA signals into the levels of exertion. This layer can also be made to include predictive models to predict future states of workers from the data in the storage layer.

3.1.6 Access layer

In the access layer, stakeholders can visualize the impact or extent of the risks as a virtual replica of the worker and a rating meter. This layer includes the following: (1) beneficiaries of the DT platform and (2) how they access the DT platform. The beneficiaries may include safety managers, project supervisors, and product manufacturers. Safety managers may want to understand if the workers are reaping the intended health benefits of the technology. Project supervisors may want to know the impact of the technology on project performance. Both stakeholders could use the feedback to work with manufacturers to plan more suitable designs for their projects. The stakeholders can monitor the performance of the workers via interactive dashboards and web applications. The performance of the workers will be shown in the form of their virtual replica and a rating meter to interpret the risks. For example, the levels of exertion associated with an exoskeleton (e.g., no exertion, low exertion, medium exertion, and high risk) that is computed in the application layer, will be shown as different colors in a virtual replica and rating meter (e.g., green, yellow, and red human). The information and outputs provided via the access layer serve as a feedback system. The display on the dashboard could also serve as a means to alert stakeholders and exoskeleton users by showing the levels of ergonomic risk exposure. In this way, the project stakeholders can understand the type and extent of the risk, which could inform decision making such as which type of exoskeleton to use for what task, how long the exoskeleton should be used for the task, and changes that should be made to the device to better adapt it to construction work.

3.2 Semi-Structured Interview

Semi-structured interviews were conducted with industry practitioners (n=8) to understand the construction tasks that would benefit from the use of active back-support exoskeletons. A purposive sample was used to identify and select potential participants who could provide valuable insights for the study. The research team selected participants with experience in construction safety and technology implementation in the construction industry. The interviews were conducted over Zoom and recorded. The transcripts of the interview were coded, and emerging themes were identified. An inter-coder reliability test was conducted on the coded data using the Cohen-Kappa coefficient. Cohen-kappa coefficient of 0.90, indicating a strong level of agreement, resulted from the assessment.

3.3 Experimental Procedure

3.3.1 Participants

Sixteen students were recruited to participate in a carpentry task, one of the tasks identified from Section 3.2 as suitable

for active back-support exoskeletons. The participants reported no prior issues related to musculoskeletal disorders that could affect their performance in the study. The experiment was approved by the Virginia Tech Institutional Regulation Board (IRB: 19-796).

3.3.2 Exoskeleton

The study used the CrayX active back-support exoskeleton (Figure 4), manufactured by German Bionic. The exoskeleton weighs approximately 15lb and can support lifting of about 60lb load. The exoskeleton fits directly onto the back and is secured to the body with straps positioned around the waist, chest, shoulders, and thighs. The exoskeleton is powered by a 40-volt battery that controls two motors, providing the necessary torque to assist the wearer's body. The exoskeleton functions primarily in three modes: lifting, bending, and walking.

3.3.3 Instruments and data collection

Emotibit: The electrodermal activity of the participants was measured using EmotiBit, an open-source biosensor developed by the engineers and designers at Connected Future Labs (Montgomery et al., 2023). The sensor, shown in Figure 3, is designed to capture physiological data such as electrodermal activity, skin temperature, and photoplethysmogram. The sensor was attached to the thumb of each participant's non-dominant hand, to avoid interfering with their ability to carry out the task efficiently. The data was collected at 50Hz i.e., 50 data points per second.

Figure 3: Emotibit Multi-modal sensor.

Perceived rate of exertion: Borg's Rating of Perceived Exertion (RPE) scale, also known as the Borg CR-20 scale, was used to capture each participant's perceived exertion level. The scale ranges from 6 to 20, with higher numbers indicating higher levels of exertion (Albert et al., 2021; Borg, 1982). A score of 6 on the Borg CR-20 scale represents no exertion. Scores of 7 to 8 indicate extremely light exertion, while 9 to 10 suggest very light exertion. Light exertion falls within the range of 11 to 12, while 13 to 14 signify somewhat hard exertion. Very hard exertion is denoted by scores of 16 to 17. A score of 19 reflects extremely hard exertion, and a score of 20 signifies maximum exertion.

3.3.4 Experimental Task

An experiment was conducted involving a simulated carpentry framing task to collect both objective and subjective data on exertion levels while participants used an active back-support exoskeleton. Before starting the experiment, participants received training on the exoskeleton's components and operation. The carpentry framing task was also demonstrated to the participants to prevent interruptions during the experiment. Participants wore the exoskeleton (see Section 3.3.2) and Emotibit sensor (see Section 3.3.3) throughout the study. The carpentry framing task involved the following subtasks: (1) measuring timber planks (i.e., two 1"x4"x47" planks and four 1"x4"x70" planks) needed to construct a 47"x70" frame; (2) assembling the measured timber materials; (3) nailing the assembled timber frame using a nail gun; (4) lifting and moving the erected frame, which weighs approximately about 40lbs, to an upper floor via staircase for installation on the upper floor; and (5) installing the frame by aligning the frame with an existing wall. Figure 4 shows a participant involved in the nailing subtask with the active back-support exoskeleton and an Emotibit in his thumb. After performing the framing task, each participant was presented with Borg's rating of exertion scale (Borg CR-20) and asked to provide subjective ratings of their perceived exertion for the entire task. The task was video recorded.

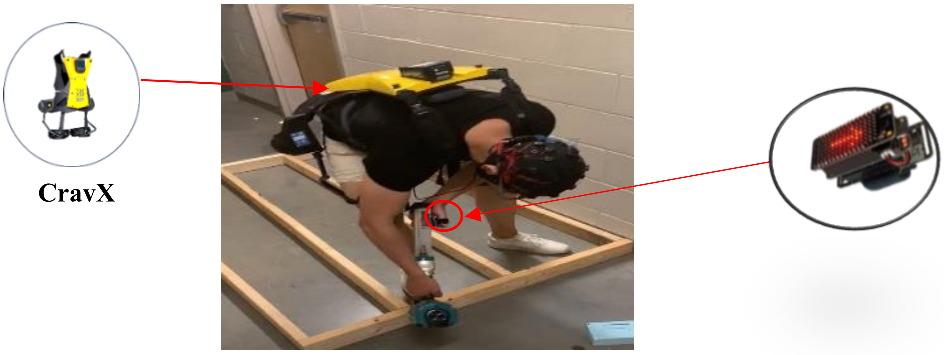

Figure 4: Participant performing framing task while wearing an exoskeleton and Emotibit sensor.

3.4 Data Preprocessing

3.4.1 Noise and Artifact Removal

The collected EDA data was processed to eliminate noise and artifacts. A high-pass filter with a cut-off frequency of 0.05 Hz was used to remove low-frequency noise caused by environmental factors. Then, a moving average filter was applied to smooth out high-frequency noise (Lee et al., 2020).

3.4.2 Data labeling

The time-stamped video recorded during the experiment allowed for the organization and structuring of the EDA data according to the tasks each participant performed. Next, the EDA data was categorized based on the participants' ratings of their exertion levels. Exertion levels from 7 to 11 were labeled as low exertion, from 12 to 14 as medium exertion, and from 15 to 20 as high exertion (Chowdhury et al., 2019). The sorted EDA data of each participant was then labeled according to their intensity class as shown in Table 2.

Table 2: Classes, labels, and data points.

Classes	Labels	Number of data points
Low Exertion	LE	76782
Medium Exertion	ME	5963
High Exertion	HE	9915

3.4.3 Data augmentation

The structuring of EDA data into the categories of Low Exertion, Medium Exertion, and High Exertion, as outlined in Section 3.4.2, uncovered an imbalance among the classes, as demonstrated in Table 2. Due to this imbalance, the EDA data for the minority classes (i.e., Medium Exertion and High Exertion) were augmented using the Synthetic Minority Oversampling Technique (SMOTE). SMOTE employs a k-nearest neighbor algorithm to generate synthetic data in minority classes to match the majority class (Sowjanya & Mrudula, 2023). The effectiveness of SMOTE in balancing class distribution in time series data has been recognized across many studies (Jeatrakul et al., 2010; Jiang et al., 2016; Pritalia et al., 2020), resulting in enhanced model performance and reliability (Chawla et al., 2002). In this study, SMOTE was employed to generate more data to balance the datasets in the minority classes (i.e., Medium Exertion and High Exertion) to align with the Low Exertion class.

Table 3: Classes, labels, and data points (raw and balanced).

Classes	Labels	Number of raw data points	Number of balanced data points
Low Exertion	LE	76782	76782
Medium Exertion	ME	5963	76782
High Exertion	HE	9915	76782

3.4.4 Risk Classification

This study used a 1-D convolutional neural network to classify the raw and augmented EDA data into the above-mentioned classes (i.e., Low Exertion, Medium Exertion, and High Exertion). 1-D CNN is suitable for 1D signals whose applications have high signal variations (Zhang et al., 2022). The network comprises an input layer, a convolution 1-D layer, a batch normalization layer, a Rectified Linear Unit (ReLU) layer, a dropout layer, a maxpooling layer, a fully connected layer, a softmax layer, and a classification layer. The input layer receives the raw or augmented EDA data. The convolution layer uses 32 filters, each with a width of 5, to process the input data from the input layer and extract unique features. The batch-normalization layer normalizes the input from the convolution layer to improve training stability and speed. The ReLU layer applies a non-linear activation function to the output of the batch-normalization layer. The dropout layer helps to prevent overfitting of the model. The maxpooling layer down-samples the output of the dropout layer. In the fully connected layer, a linear transformation is applied to the input vector through a weight matrix so that every input influences every output of the output vector. The softmax layer takes in the output from the previous layer and presents a vector that illustrates the probability of the class that the input belongs to. The classification layer presents the results of the softmax layers as classes of the assessed risks.

The network was trained using the Adam optimizer (Karim et al., 2019). Due to the size of the dataset, the model was trained for 200 epochs with a learning rate of 0.01. The balanced data was divided into 70% for training, 15% for validation, and 15% for testing the trained model. MATLAB R2023a, running on a machine equipped with NVIDIA GeForce RTX 2080 GPU and 16GB memory, was used for the classification.

$$Accuracy = \frac{Number\ of\ positively\ predicted\ classes}{Total\ number\ of\ classes} \times 100\% \tag{1}$$

$$Precision = \frac{Positive\ predictions\ of\ a\ class}{Total\ samples\ of\ a\ class} = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{Positive\ predictions\ of\ a\ class}{Total\ positive\ predictions\ as\ a\ class} = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{4}$$

Commonly used metrics for assessing the performance of machine learning models were employed in this study (See Equations 1-4). These include accuracy, precision, recall, and F1-score (Bangaru et al., 2021). The confusion matrix demonstrates the accuracy of a trained model (Hasnain et al., 2020). It provides a summary of the predicted outcomes in a classification problem, with the true classes usually represented on the y-axis and the predicted classes on the x-axis. According to Hasnain et al. (2020), the confusion matrix yields four results: True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). True Positive (TP) occurs when all observations from positive classes are correctly predicted as positive. False Negative (FN) is achieved when observations from negative classes are misclassified as positive. False Positive (FP) arises when true observations from negative classes are incorrectly predicted as positive. True Negative (TN) is when all cases from negative classes are accurately predicted as negative. While accuracy (Equation 1) provides a general percentage of model performance, recall and precision offer a more detailed look at classification outcomes. Precision, or Positive Predicted Values (Equation 2), assesses how reliable the model is at identifying positive classes. A low precision value indicates a higher occurrence of false positives compared to true positives. Recall, or True Positive Rate (Equation 3), measures the model's ability to accurately predict positive classes and the proportion of true positives. The F1-score is the harmonic mean of precision and recall. Generally, a high F1-score indicates strong recall and precision values (Equation 4). These performance measures are detailed in Equations 1-4.

3.5 Development of the Digital Twin of Exertion Levels

The dashboard was designed using the output of the classification in Section 3.4.2 and the elements of the system architecture to categorize EDA data into low, medium, and high exertion levels. It was designed to meet project stakeholders' needs by enabling visualization of risks associated with exoskeleton use. The dashboard employs methods such as avatars and clear visualization icons to present the data in an accessible way. The inclusion of human-like figures could enhance understanding and foster emotional connections with construction workers. Studies have indicated that avatars can increase user engagement and create a sense of participation by offering a sense of body ownership (Freeman et al., 2020; Seinfeld et al., 2021). The dashboard emphasizes readability and usability, using appropriate fonts and icons such as rating meters. It is conceptualized as a web platform for broad accessibility and compatibility with different systems. The main page of the dashboard features tabs that visualize the severity of each risk (e.g., cognitive load, falls, and exertion), focusing on exertion risks as a proof of concept. This includes detailed visualization of the levels of exertion due to exoskeleton use.

4. RESULTS

4.1 Construction Tasks for Active Back-Support Exoskeleton-Use

The results of the semi-structured interview were represented as a word cloud. Word clouds are graphical representations of the frequency of concepts or keywords that are significant in discourses (Adu, 2019). The word cloud in Figure 5 provides a quantitative and visualized method to illustrate the key construction tasks suggested by the participants to benefit most from active back-support exoskeletons. The most mentioned tasks include plumbing, carpentry, steel, drywall and rebar installation, and labor work. The least mentioned tasks include ceiling, electrical, scaffolding, and flooring work, mason, and ceiling work.

Figure 5: Word cloud of construction tasks that benefit from active back-support exoskeletons.

4.2 Example of Prediction of Level of Exertion from Exoskeleton-Use

This section presents the performance of the 1-D convolutional neural network in classifying the levels of exertion during exoskeleton use for a framing task.

4.2.1 Model Performance Evaluation

The accuracy of the 1D-CNN in classifying the levels of exertion due to exoskeleton use for the framing task with the raw data is 58%. The confusion matrix of the model for the raw data is illustrated in Figure 6. The matrix shows that the model performed well in detecting the LE class but could not detect the ME and HE classes properly. For example, the model detected the LE class with 99% accuracy, the ME class with 50%, and the HE class with 25% accuracy. However, the confusion matrix of the model for the augmented data shown in Figure 7, indicates that the model performed better at detecting all the classes compared with the raw data with an accuracy of 97%. The model correctly detected 98% of the LE class and 96% of the ME and HE classes.

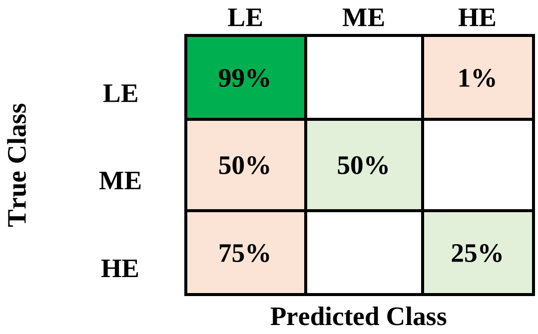

Figure 6: Confusion matrix showing classification accuracies of levels of exertion due to exoskeleton use for the raw data.

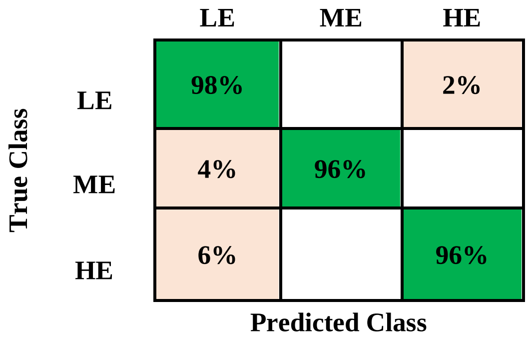

Figure 7: Confusion matrix showing classification accuracies of levels of exertion due to exoskeleton use for the augmented data.

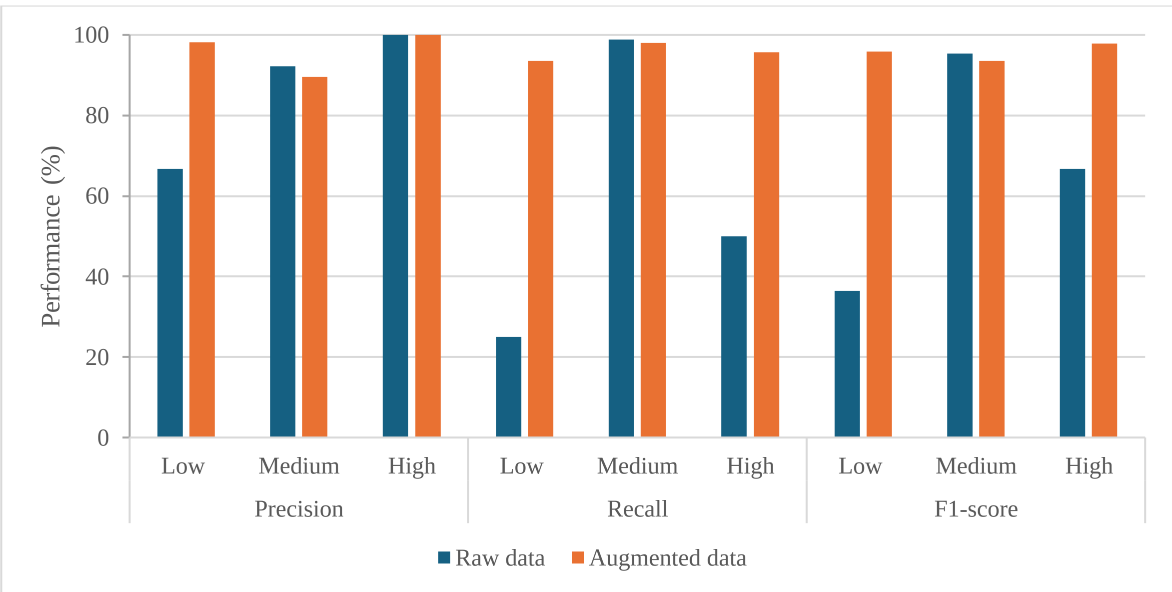

Figure 8: Performance metrics for ID-CNN for the classes (Raw and augmented data).

Figure 8 presents the comparison of the performance metrics of the model for the raw and augmented data. The results show that with the augmented data, the model performed better with all the classes. For the LE class, the precision (93%) and F1 score (98%) of the model with the augmented data were higher than those with the raw data. Only the recall (99%) of the model with the raw data is slightly higher than the recall (98%) with the augmented data. Similarly, for the ME class, the recall (96%) and F1 score (98%) of the model were higher with the augmented data. However, the precision (100%) was the same for the raw and augmented data. In the same vein, for the HE class, the precision (98%), recall (96%), and F1 score (97%) of the model were higher with the augmented data.

4.2.2 Level of Exertion and Digital Twin

The digital twin of the exoskeleton users and the rating meter (shown in Figure 9) show the level of exertion resulting from the results of the model. The digital twin shows an exoskeleton user experiencing medium exertion. The meter comprises a pointer and three different colors, red, yellow, and green indicating high, medium, and low exertion respectively. The pointer reflects the level of exertion which is currently shown as medium exertion.

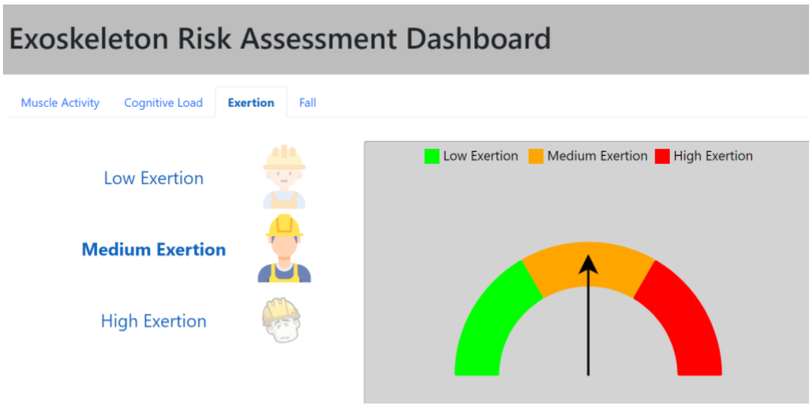

Figure 9: Dashboard showing digital twin representation of the level of exertion.

5. DISCUSSION

The findings of this study hold significant implications for the construction industry, particularly in the area of ergonomic risk assessment and the use of exoskeletons. The implications of the study's findings are described as follows:

5.1 Construction Tasks for Active Back-Support Exoskeleton-Use

Construction activities involve dynamic movements and different body kinematics, making the implementation of active back-support exoskeletons especially pertinent. Semi-structured interviews with practitioners revealed a range of construction activities, such as carpentry work, rebar installation, concrete work, and masonry, where exoskeletons could prove beneficial. This aligns with industry reports (BLS, 2023) and research studies (Antwi-Afari et al., 2023; N. Gonsalves et al., 2023) highlighting back-related injuries as a major concern in the construction industry. The practitioners identified carpentry, rebar installation, concrete work, and masonry as tasks suitable for exoskeleton use, which aligns with the findings of (Kim et al., 2019). Additionally, N. Gonsalves et al. (2023) noted that framing and plumbing tasks may benefit from back-support exoskeletons. Given this context, the carpentry framing task was chosen as a case study to assess the ergonomic impacts of using active back-support exoskeletons.

5.2 Example of Prediction of Level of Exertion from Exoskeleton-Use

Given the unintended consequences associated with exoskeletons, DT could provide an effective framework for assessing the ergonomic implications of using exoskeletons in construction tasks. DT offers comprehensive ergonomic risk representation, enabling more accurate evaluation (Jimenez & Maire, 2024) and self-management of ergonomic risk as shown by Ogunseiju et al. (2022). These affordances are critical for construction project managers, ergonomists, and safety managers in monitoring and controlling ergonomic risks. Although DT is increasingly being used in other industry sectors, the application is emerging in the construction industry (O. Ogunseiju et al., 2021). The approach developed in this study is critical as exoskeletons were originally designed for other industries such as manufacturing, automotive, military, and healthcare (Fox et al., 2019). Understanding the dynamics of exoskeleton use in construction could inform design modifications to enhance suitability, ultimately improving the health and safety of the construction workforce. The system architecture of the human-in-the-loop digital twin framework provided in this study could help construction organizations in the implementation process.

To demonstrate the system architecture's ability to aid in exoskeleton risk assessment and inform decision-making, an example of how a DT can be used for exertion risk assessment was explored. The study assessed the human-in-the-loop DT framework by explaining how the interaction from the physical layer to the access layer. An essential part of a DT is the communication (linkage) between the physical and virtual products, which involves analytics at every step (Madubuike et al., 2022). The study employed a 1-D convolutional neural network to classify the EDA data from the carpentry framing task according to three levels of exertion: low exertion, medium exertion, and high exertion. The model's performance using raw data, with an accuracy of 58%, showed reliable detection of the LE class but needed improvement in identifying ME and HE classes. When using augmented data, overall accuracy increased significantly to 97%, demonstrating the potential for data augmentation in training models for construction applications. The model could accurately detect all classes, leading to efficient monitoring and adjustment of workers' exertion levels. The findings of this study have shown the effectiveness of 1D-CNN in classifying EDA signals. Performance metrics, such as precision, recall, and F1 score, were higher with augmented data, further supporting the implementation of advanced monitoring systems on construction sites (Rao et al., 2022). The lowest F1-score obtained in this study is still high and can be compared to other construction-related studies (Xiong et al., 2022). The higher performance of the model with the augmented data also supports prior studies (Chawla et al., 2002; Meyer et al., 2021) that have underscored the effectiveness of data augmentation techniques, such as SMOTE, in balancing class distribution in time series data to enhance model performance and reliability. However, the use of augmented data should be with caution because augmented data might not always provide an actual representation of real-world scenarios (De Cristofaro, 2024).

The dashboard presents a very informative interface for construction personnel such as safety managers and project managers to obtain evidence-based information for decision-making. For instance, the dashboard showing a digital twin representation of the level of exertion showed that the exoskeleton user had medium exertion during the carpentry task. This finding emphasizes the attribute of the device in reducing the exertion of exoskeleton users. Walter et al. (2023) reported a decrease in the rate of perceived exertion with an increasing support level of the exoskeleton, resulting in a significantly lower RPE when lifting with the active exoskeleton. The visual representation of the physiological impact of using exoskeletons can improve ergonomic risk assessment and mitigation strategies. Locklin et al. (2021) showed the possibilities of creating similar interfaces for data acquisition as a human-in-the-loop digital twin. This exoskeleton risk assessment dashboard can also be extended to show the muscle activity, cognitive load, and fall rating of the exoskeleton user. This vital data, collected via sensors and visualized on the dashboard, can be useful for supervisors and managers to monitor workers using the exoskeletons.

6. CONCLUSIONS AND LIMITATIONS

This study aims to investigate a digital twin framework for assessing the risks associated with exoskeleton use for construction work. A review of the literature was conducted to identify risks related to exoskeleton-use, and objective and subjective methods for assessing the risks. A system architecture was developed to illustrate the enabling technologies and their roles in supporting the proposed framework. Results of interviews with construction workers identified carpentry framing task as one of the construction tasks that can benefit from active back-support exoskeletons. Electrodermal signals were collected during the experimental simulation of the framing task with an active back-support exoskeleton. The 1D-CNN model trained to classify electrodermal data demonstrates the potential of the DT framework to predict the exertion levels of exoskeleton users during framing tasks. This study contributes to the scarce literature regarding the use of digital twins for assessing the suitability of exoskeletons for construction work. The study demonstrates the role of physiological sensing and machine learning techniques in facilitating the implementation of the digital twin framework. Furthermore, this study sets precedence for research involving the use of digital twins for performance monitoring of exoskeletons during construction work. Such efforts could promote the sustainability of exoskeleton solutions in the construction workplace. This study had some limitations which should be acknowledged. Given the multiple risks associated with the use of exoskeletons and that only EDA was used to assess exertion in this study, future research efforts could focus on exploring other objective risk assessment metrics such as electroencephalogram for mental workload, eye tracking for vigilance, electromyography for muscle fatigue, and electrocardiogram for cardiovascular demand. Also, a similar digital twin framework could be developed for other construction trades and activities such as masonry, concrete work, painting, and floor layers. In addition, the EDA data used was generated from students engaged in a laboratory-based simulation of framing tasks. The use of experienced workers in real job scenarios using the exoskeleton for a longer duration could produce data that can help develop prediction models that are generalizable to the construction populace. This can help assess the risks associated with exoskeletons over a long duration and identify construction activities that may be unsuitable with exoskeletons. Future studies could also involve a usability assessment of the digital twin framework by intended users. Similarly, future digital twin frameworks should take cognizance of environmental factors that could influence the ergonomic implications of exoskeleton use. Despite the use effectiveness of SMOTE in balancing class distribution to enhance the model performance in this study, future studies could consider using advanced techniques like SMOTE-ENN (a combination of SMOTE and Edited Nearest Neighbors) to reduce noise and refine synthetic samples. In addition, there may be a need to validate the model on separate test data to ensure its generalization to unseen data.

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