HUMAN-IN-THE-LOOP DIGITAL TWIN FRAMEWORK FOR ASSESSING ERGONOMIC IMPLICATIONS OF EXOSKELETONS

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ABSTRACT: *Exoskeletons are increasingly being 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 aims to develop a human-in-the-loop digital twin framework for assessing ergonomic risks associated with the use of active back-support exoskeletons for construction work. A literature review was conducted to identify risks associated with exoskeletons and the technologies for quantifying the risks. This informed the development of a system architecture describing the enabling technologies and their roles in assessing risks associated with active back-support exoskeletons. 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 study showcases the potential of digital twins for comprehensive ergonomic assessment, enabling stakeholders to proactively address ergonomic risks and optimize the use of exoskeletons in the construction industry. The framework demonstrates the significance of evidence-based decision-making in enhancing workforce health and safety.*

KEYWORDS: *Digital twin, ergonomics, exertion, exoskeletons, risk assessment, sensing technologies, work-related musculoskeletal disorders.*

1. INTRODUCTION

The United States Bureau of Labor and Statistics reports that the construction workforce continues to experience a higher rate of work-related musculoskeletal disorders compared with workers in other industry sectors combined. The back is one of the most affected body parts. Back-related injuries account for about 43% of all work-related musculoskeletal disorders (BLS, 2023). Exoskeletons are emerging as potential solutions to WMSDs. Specifically, active back-support exoskeletons, a class of exoskeletons, have been shown to reduce the risks of overexertion which is one of the triggers of back-related injuries. For example, studies have revealed a reduction in 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) due to exoskeleton-use. These benefits are motivating construction contractors to explore active back-support exoskeletons for construction work. However, studies have also mentioned that exoskeleton-use on construction sites could trigger 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 (Gonsalves et al., 2023; Gonsalves et al., 2021), fatigue (Theurel et al., 2018), and restricting movement when climbing ladders (de Looze et al., 2016; Kim et al., 2019). These highlight the likely task-specificity of exoskeletons. In addition, the unintended consequences could also be specific to exoskeleton types (Fox et al., 2020; Kim et al., 2019). With the increase in commercially available exoskeleton solutions, a testbed would be beneficial to support the testing and assessment of the solutions for construction tasks. This has downstream implications for enabling real-time monitoring of exoskeleton-use during construction, which could inform strategies for reducing unintended risks.

Sensing technologies provide opportunities to measure risks associated with exoskeleton-use (Akanmu et al., 2020; Ogunseiju et al., 2021). Data from sensing technologies could be modeled and analyzed to extract insights that can be mapped to workers' virtual replicas and controls (e.g., rating meters). This digital representation could be used by stakeholders (e.g., project and safety managers, and manufacturers) to develop control strategies such as deciding on the contextual use of exoskeletons (i.e., most suitable application tasks and duration of use), suitable exoskeleton types, and modifications to exoskeleton design. This digital representation is referred to as the human-in-the-loop digital twin which is a two-way symbiotic relationship between physical entities (e.g., workers and exoskeleton) and their virtual representative in which humans initiate the control (N. Zhang et al., 2022). The implication is that the ergonomic consequences of workers' postures while using exoskeletons can be obtained in real-time which can enhance their ability to control or self-manage their exposures (Ogunseiju et al., 2021). Thus, this paper presents 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 associated with exoskeleton-use and

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the sensing technologies for quantifying the risks. The risks 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 workers are interviewed to identify tasks that would benefit from active back-support exoskeletons. The efficacy of the DT framework is demonstrated with an example of predicting risk of exertion due to the use of an active back-support exoskeleton for one of the tasks. This study motivates discourse on human-in-the-loop Digital Twins for construction applications. The study highlights the extent to which physiological risks associated with exoskeleton-use can be predicted.

2. BACKGROUND

2.1 Exoskeletons for Construction Work: Risk and Assessment Techniques

Studies have shown that exoskeletons have intended benefits and unintended consequences. For instance, exoskeletons are prospective innovative ergonomic interventions aimed at reducing overexertion in various parts of the body (Gonsalves et al., 2021). This may in turn reduce the occurrence of WMSDs among construction workers (Akanmu et al., 2020). There is evidence that exoskeletons can reduce back muscle activities by 23 - 35% (Abdoli-e and Stevenson, 2008). Other benefits revealed in the literature include reduced discomfort to the body parts (Alemi et al., 2020), increased productivity, financial gains, and work retention (Kim et al., 2019), and 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. The 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 to the user (Howard et al., 2020). In addition, due to the added weight of the exoskeleton, the user’s center of gravity may be significantly impacted causing balance problems and a diminished recovery rate (Alabdulkarim et al., 2019). Gonsalves et al. (2021) showed that exoskeletons result in discomfort in the chest and thigh regions. Previous research has indicated that exoskeletons can redirect loading from one part of the body to another (Picchiotti et al., 2019). For example, during overhead work, exoskeletons reduce the muscle activity in the shoulder and the back of the arm but increase muscle activity in the lower back, abdomen, and legs (Theurel et al., 2018). Besides, 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 are sometimes incompatible with some personal protective equipment such as safety harnesses (Gonsalves et al., 2023). Previous studies (Omoniyi et al., 2020; Siedl et al., 2021) have also identified psychological risks such as decreased situation awareness/distraction, cognitive overload, fear of the device, and overconfidence in the device. Various sensing technologies, such as inertial measurement units and electromyographs, have been employed to quantify these risks. Similarly, 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 of exoskeletons.

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 and Fall risk	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 risk	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)

	Usability of the device (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	Decreased situation awareness/ Distraction	Eye tracker	NASA-TLX	(de Looze et al., 2016; Delgado et al., 2020)
	Exertion	Electrodermal activity sensor	Rating perceived exertion (RPE) with the Borg Category Ratio (Borg CR-10)	(Man et al., 2022; Theurel et al., 2018)
	Fear; Lack of trust	Electromyography; Photoplethysmogram; Electrodermal activity 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

In recent years, there have been increasing explorations of DT for diverse applications including workforce health and safety. Sharotry et al. (2022) developed a DT to track the biomechanical fatigue in operators caused by repetitive action in lifting activities. The study analysed changes in the joint angles in workers' body joints using a dynamic time-warping algorithm. Another study (Greco et al., 2020) presented an ergonomic risk mapping of DT workstations using a wearable motion capture system and inputting in virtual simulated environments. With the DT, the authors were able to identify risk indexes related to working postures, exerted forces, material manual handling and repetitive actions, and sources of biomechanical overload. In construction, 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 using a DT environment. Furthermore, Greco et al. (2020) opined that existing DT frameworks have limited roles for users or stakeholders. Humans play vital roles in workplace systems; therefore, supporting technologies should be designed to facilitate their input (Sharotry et al., 2020).

3. METHODOLOGY

The approach employed in conducting this study is shown in Figure 1. First, a review of the risks associated with exoskeletons and the technologies 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 BSEs. Semi-structured interviews were conducted to identify construction tasks that would benefit from the use of active BSEs. A laboratory experiment was conducted to quantify the risks associated with using active BSEs. This informed the development of an example of a DT-based model for assessing the risk levels of exertion during exoskeleton-use. These are described as follows:

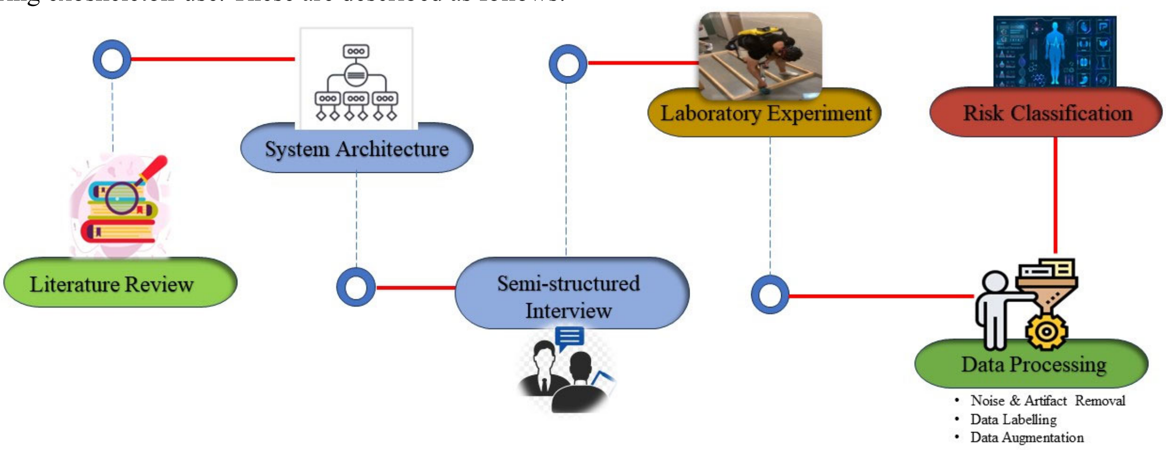

Fig. 1: Overview of research methodology.

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 include physical layer, data layer, data transmission layer, storage layer, application layer, and access layer. These are described as follows:

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 are measured using an electroencephalogram, electrocardiogram, 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 aforementioned 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 are 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 impacts 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. A symmetric 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 (e.g., conditional generative adversarial network, recurrent neural network, and long short-term memory) to classify the EDA signals into the levels of exertion. Finally, visualization algorithms will be used to augment the levels of exertion on a virtual replica of the worker and a rating meter.

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). 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.

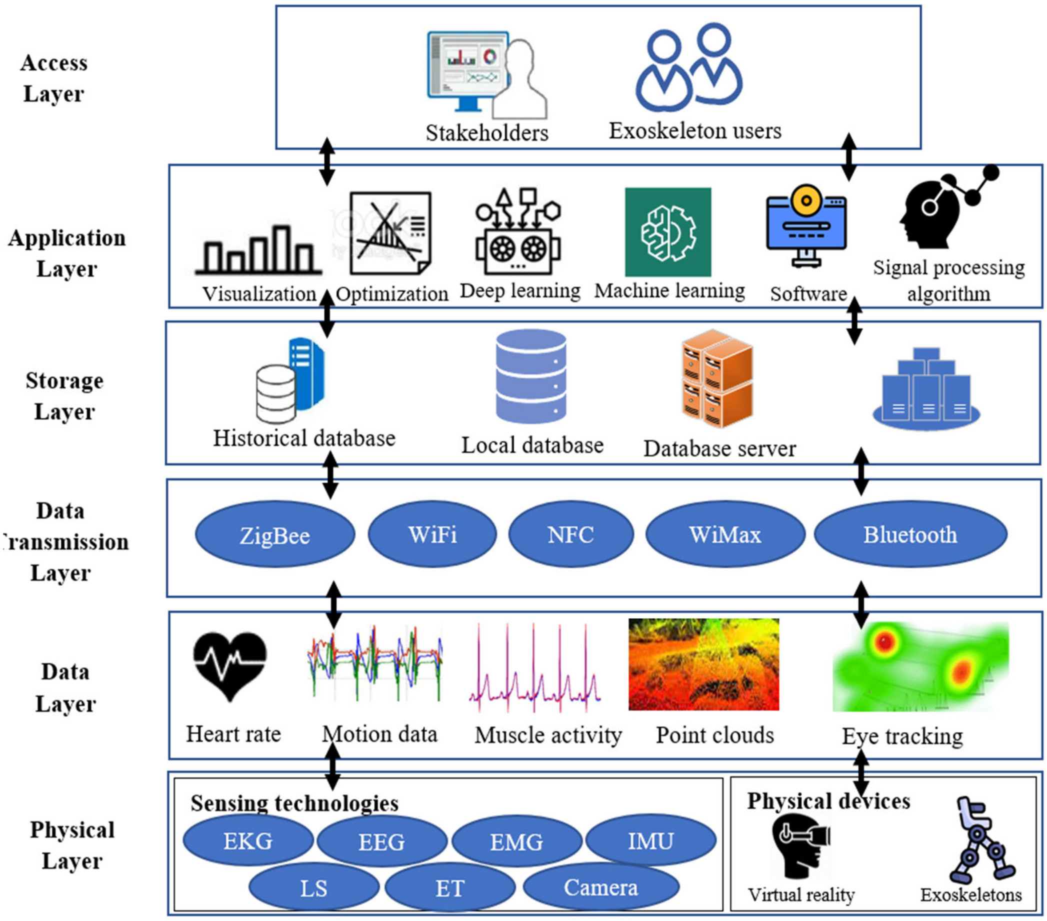

Fig. 2: System architecture.

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 to 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, Participants, and Data Collection

Sixteen students were recruited to participate in a carpentry framing activity; one of the activities identified from Section 3.2 as beneficiaries of 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). The task involved the following: (1) measuring timber planks (i.e., four 1"x4"x47" planks and two 1"x4"x70" planks) needed to construct a 47"x70" frame; (2) assembling the measured timber materials as shown in Figure 3; (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. The participants completed these tasks while wearing CrayX, an active back-support exoskeleton from German Bionics. Their electrodermal activity was measured using Emotibit, an open-source biosensor. The data was collected at 50Hz i.e., 50 data points per second. 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 Borg scale ranges from 6 (not exhausting) to 20 (extremely exhausting) (Albert et al., 2021; Borg, 1982). The participants' ratings of perceived exertion were measured using the Borg's exertion rating scale (Borg CR-20) which ranges from 6 to 20, where 6 represents no exertion and 20 represents maximum exertion. Figure 3 shows participants performing framing tasks with the exoskeleton and the biosensor. The task was video recorded.

Fig. 3: Participant performing framing task while wearing an exoskeleton and EEG cap.

3.4 Data Preprocessing

3.4.1 Noise and artifact removal

The collected EDA signals were filtered to remove the noise and artifacts. A low pass filter with a cut-off frequency of 4 Hz was employed to remove the noise. A Gaussian filter was used to smoothen and attenuate the artifacts. MATLAB was used for this purpose.

3.4.2 Data labeling

Using the time-stamped video, EDA data corresponding to each participant's tasks were sorted and structured. The ratings of 7– 11, 12 – 14, and 15 – 20 were represented as low exertion, medium exertion, and high exertion, respectively (Chowdhury et al., 2019). The sorted EDA data of each participant was labeled based on their intensity class as shown in Table 2.

Table 2: Classes, labels, and data points.

Classes	Labels	Percentages of participants (%)	Number of data points
Low Exertion	LE	70	50759
Medium Exertion	ME	12	6823
High Exertion	HE	18	14072

3.4.3 Data augmentation

The EDA data of the minority classes were augmented due to the imbalanced nature of the datasets. Studies have shown that balanced datasets result in the Synthetic Minority Oversampling Technique (SMOTE) being employed to balance the EEG data of the minority classes with the majority classes (Sowjanya & Mrudula, 2023). For example, from Table 2, the ratio of the datasets in the LE, ME, and HE classes (i.e., Low Exertion, Medium

Exertion and High Exertion respectively) is 7:1:4. As shown in Table 3, more datasets were generated with SMOTE to balance the datasets of the minority classes (i.e., Medium Exertion and High Exertion) with the class with the most datasets (i.e., Low Exertion).

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	50759	50759
Medium Exertion	ME	6823	50759
High Exertion	HE	14072	50759

3.5 Risk Classification

This study employs a 1-D convolutional neural network to classify the EDA data into the above-mentioned classes (i.e., LE, ME, and HE). 1-D CNN is suitable for 1D signals whose applications have high signal variations (Y. 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 convolution layer applies filters to the input data obtained from the input layer and extracts distinctive features using 10 filters of width 10. The batch-normalization layer improves the stability and speed of training the network by normalizing the input to each layer. 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, 300 epochs were used. The learning rate was set to 0.01.

The balanced data was split as follows: 70% of the data was set aside for training, 15% of the data was also set aside for validation and 15% was intended for testing the trained model. MATLAB R2023a, installed on a machine with NVIDIA GeForce RTX 2080 GPU and 16GB memory, was employed for the classification. Commonly used metrics for assessing the performance of machine learning models were employed in this study. These include accuracy, precision, recall, and F1-score (Bangaru et al., 2021).

4. RESULTS AND DISCUSSION

4.1 Construction Tasks for Active Back-Support Exoskeleton-Use

The results of the semi-structured interview were represented in the form of 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 4 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. The suggested tasks support reporting of industry databases (BLS, 2023) and research studies (Antwi-Afari et al., 2023; Gonsalves et al., 2023) that identified back-related injury as a concern in the construction industry. Some of the tasks suggested by the practitioners (e.g., carpentry work, rebar installation, concrete work, and masonry) were also identified by (Kim et al., 2019) as being suitable for exoskeletons. Similarly, Gonsalves et al. (2023) identified framing and plumbing as being more suitable for back-support exoskeletons.

Fig. 4: Word cloud of construction tasks that would benefit from active back-support exoskeletons.

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

This study presents an example of predicting the levels of exertion due to 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 is 82%. The confusion matrix for the model is illustrated in Figure 5. The matrix shows that the model performed better in detecting the ME and HE classes than the LE class. For example, the model detected classes ME and HE with 100% accuracy and LE class with 67%. Furthermore, 37% of the LE class is mostly confused with the HE class.

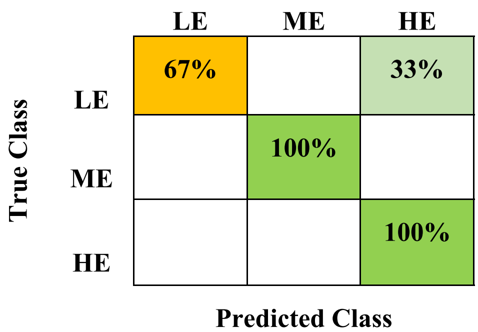

Fig. 5: Confusion matrix showing classification accuracies of levels of exertion due to exoskeleton-use.

From the precision (see Table 4), it can be observed that out of the times ME and HE classes were predicted, the model was correct 100% of the time. However, out of the times HE class was predicted, the model was correct 67% of the time. For the recall, out of all the times the HE class was predicted, only 75% of the class was correctly predicted.

F1-score explains a model's ability to both capture classes (recall) and accurately capture the classes (precision). The F1-score of the ME class is 100%, meaning that the model has a balanced ability to accurately capture all the ME classes from the data. However, in the case of the F1-scores of the LE and HE classes which are 80% and 75% respectively, the model will have a mixed reaction. For the LE class, while the model may be correct 67% of the time, all the LE class predicted will be correct. The findings of this study have shown the effectiveness of 1D-CNN in classifying EEG signals (Alzahab et al., 2021). The lowest F1-score obtained in this study is still high and can be compared to other construction-related studies (Xiong et al., 2022).

Table 4: Performance metrics for ID-CNN for the classes.

Classes	Precision	Recall	F1-score
LE	67%	100%	80%
ME	100%	100%	100%
HE	100%	60%	75%

4.2.2 Level of Exertion and Digital twin

The digital twin of the exoskeleton-users and the rating meter (shown in Figure 6) shows 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. Related studies have shown the possibilities of creating similar interfaces for data acquisition as a human-in-the-loop digital twin (Locklin et al., 2021). 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 can be useful for supervisors and managers to monitor workers while using the exoskeletons.

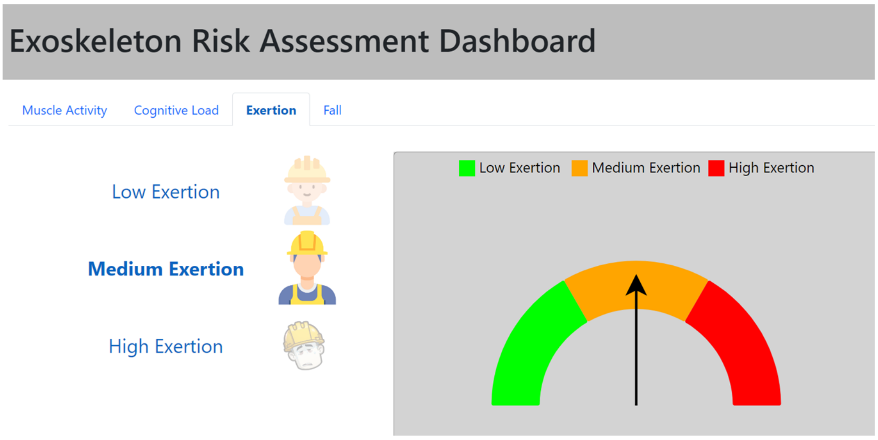

Fig. 6: Dashboard showing digital twin representation of the level of exertion.

5. CONCLUSIONS, LIMITATIONS AND FUTURE WORK

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 associated with 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. 1D-CNN 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 are currently being addressed in an ongoing study. Firstly, EDA data was generated from students engaged in a laboratory-based simulation of framing tasks. The use of experienced construction workers could produce data that can help develop prediction models that are generalizable for the construction population. Secondly, only the exertion levels using the EDA data was modeled to demonstrate the digital twin framework. Further work will involve other sensing technologies and the prediction of other physical and psychological risks. Future studies will also involve a user assessment of the digital twin framework with intended users.

REFERENCES

Adu, P. (2019). *A step-by-step guide to qualitative data coding*. Routledge.

Akanmu, A. A., Olayiwola, J., Ogunseiju, O., & McFeeters, D. (2020). Cyber-physical postural training system for construction workers. *Automation in Construction*, *117*. https://doi.org/10.1016/j.autcon.2020.103272.

Alabdulkarim, S., Kim, S., & Nussbaum, M. A. (2019). Effects of exoskeleton design and precision requirements on physical demands and quality in a simulated overhead drilling task. *Applied Ergonomics*, *80*, 136-145. https://doi.org/10.1016/j.apergo.2019.05.014.

Albert, J. A., Herdick, A., Brahms, C. M., Granacher, U., & Arnrich, B. (2021). Using Machine Learning to Predict Perceived Exertion During Resistance Training With Wearable Heart Rate and Movement Sensors. *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. https://doi.org/10.1109/BIBM52615.2021.9669577.

Alemi, M. M., Madinei, S., Kim, S., Srinivasan, D., & Nussbaum, M. A. (2020). Effects of Two Passive Back-Support Exoskeletons on Muscle Activity, Energy Expenditure, and Subjective Assessments During Repetitive Lifting. *Hum Factors*, *62*(3), 458-474. https://doi.org/10.1177/0018720819897669.

Alzahab, N. A., Apollonio, L., Di Iorio, A., Alshalak, M., Iarlori, S., Ferracuti, F., Monteriu, A., & Porcaro, C. (2021). Hybrid Deep Learning (hDL)-Based Brain-Computer Interface (BCI) Systems: A Systematic Review. *Brain Sciences*, *11*(1), 75. https://doi.org/10.3390/brainsci11010075.

Antwi-Afari, M. F., Anwer, S., Umer, W., Mi, H. Y., Yu, Y. T., Moon, S., & Hossain, U. (2023). Machine learning-based identification and classification of physical fatigue levels: A novel method based on a wearable insole device. *International Journal of Industrial Ergonomics*, *93*. https://doi.org/10.1016/j.ergon.2022.103404.

Baltrusch, S. J., Houdijk, H., van Dieen, J. H., & de Kruif, J. T. C. M. (2021). Passive Trunk Exoskeleton Acceptability and Effects on Self-efficacy in Employees with Low-Back Pain: A Mixed Method Approach. *Journal of Occupational Rehabilitation*, *31*(1), 129-141. https://doi.org/10.1007/s10926-020-09891-1.

Bangaru, S. S., Wang, C., Busam, S. A., & Aghazadeh, F. (2021). ANN-based automated scaffold builder activity recognition through wearable EMG and IMU sensors. *Automation in Construction*, *126*, 103653. https://doi.org/10.1016/j.autcon.2021.103653.

BLS. (2023). IIF Databases : U.S. Bureau of Labor Statistics. https://www.bls.gov/iif/data.htm.

Borg, G. A. (1982). Psychophysical bases of perceived exertion. *Medicine and science in sports and exercise*, *14*(5), 377-381. https://doi.org/10.1249/00005768-198205000-00012.

Chowdhury, A. K., Tjondronegoro, D., Chandran, V., Zhang, J., & Trost, S. G. (2019). Prediction of relative physical activity intensity using multimodal sensing of physiological data. *Sensors*, *19*(20), 4509. https://doi.org/10.3390/s19204509.

Cumplido-Trasmonte, C., Barquin-Santos, E., Garces-Castellote, E., Gor-Garcia-Fogeda, M. D., Plaza-Flores, A., Hernandez-Melero, M., Gutierrez-Ayala, A., Cano-de-la-Cuerda, R., Lopez-Moron, A. L., & Garcia-Armada, E. (2023). Safety and usability of the MAK exoskeleton in patients with stroke. *Physiotherapy Research International*. https://doi.org/10.1002/pri.2038.

de Looze, M. P., Bosch, T., Krause, F., Stadler, K. S., & O'Sullivan, L. W. (2016). Exoskeletons for industrial application and their potential effects on physical work load. *Ergonomics*, *59*(5), 671-681. https://doi.org/10.1080/00140139.2015.1081988.

Delgado, A. D., Escalon, M. X., Bryce, T. N., Weinrauch, W., Suarez, S. J., & Kozlowski, A. J. (2020). Safety and feasibility of exoskeleton-assisted walking during acute/sub-acute SCI in an inpatient rehabilitation facility: A single-group preliminary study. *J Spinal Cord Med*, *43*(5), 657-666. https://doi.org/10.1080/10790268.2019.1671076.

Fox, S., Aranko, O., Heilala, J., & Vahala, P. (2020). Exoskeletons Comprehensive, comparative and critical analyses of their potential to improve manufacturing performance. *Journal of Manufacturing Technology Management*, *31*(6), 1261-1280. https://doi.org/10.1108/Jmtm-01-2019-0023.

Gonsalves, N., Akanmu, A., Gao, X. H., Agee, P., & Shojaei, A. (2023). Industry Perception of the Suitability of Wearable Robot for Construction Work. *Journal of Construction Engineering and Management*, *149*(5). https://doi.org/10.1061/JCEMD4.COENG-12762.

Gonsalves, N. J., Ogunseiju, O. R., Akanmu, A. A., & Nnaji, C. A. (2021). Assessment of a Passive Wearable Robot for Reducing Low Back Disorders during Rebar Work. *Journal of Information Technology in Construction*, *26*, 936-952. https://doi.org/10.36680/j.itcon.2021.050.

Greco, A., Caterino, M., Fera, M., & Gerbino, S. (2020). Digital Twin for Monitoring Ergonomics during Manufacturing Production. *Applied Sciences-Basel*, *10*(21). https://doi.org/10.3390/app10217758.

Howard, J., Murashov, V. V., Lowe, B. D., & Lu, M. L. (2020). Industrial exoskeletons: Need for intervention effectiveness research. *American Journal of Industrial Medicine*, *63*(3), 201-208. https://doi.org/10.1002/ajim.23080.

Karim, F., Majumdar, S., & Darabi, H. (2019). Insights into LSTM fully convolutional networks for time series classification. *Ieee Access*, *7*, 67718-67725. https://doi.org/10.1109/ACCESS.2019.2916828.

Kim, S., Moore, A., Srinivasan, D., Akanmu, A., Barr, A., Harris-Adamson, C., Rempel, D. M., & Nussbaum, M. A. (2019). Potential of Exoskeleton Technologies to Enhance Safety, Health, and Performance in Construction: Industry Perspectives and Future Research Directions. *Iise Transactions on Occupational Ergonomics & Human Factors*, *7*(3-4), 185-191. https://doi.org/10.1080/24725838.2018.1561557.

Locklin, A., Jung, T., Jazdi, N., Ruppert, T., & Weyrich, M. (2021). Architecture of a Human-Digital Twin as Common Interface for Operator 4.0 Applications. *Procedia CIRP*, *104*, 458–463. https://doi.org/10.1016/j.procir.2021.11.077.

Mahmud, D., Bennett, S. T., Zhu, Z. H., Adamczyk, P. G., Wehner, M., Veeramani, D., & Dai, F. (2022). Identifying Facilitators, Barriers, and Potential Solutions of Adopting Exoskeletons and Exosuits in Construction Workplaces. *Sensors*, *22*(24). https://doi.org/10.3390/s22249987.

Man, S. S., Nordin, M., Cheng, M. C., Fan, S. M., Lee, S. Y., Wong, W. S., & So, B. C. L. (2022). Effects of passive exoskeleton on trunk and gluteal muscle activity, spinal and hip kinematics and perceived exertion for physiotherapists in a simulated chair transfer task: A feasibility study. *International Journal of Industrial Ergonomics*, *90*, 103323. https://doi.org/10.1016/j.ergon.2022.10332.

Massardi, S., Pinto-Fernandez, D., Babic, J., Dezman, M., Trost, A., Grosu, V., Lefeber, D., Rodriguez, C., Bessler, J., Schaake, L., Prange-Lasonder, G., Veneman, J. F., & Torricelli, D. (2023). Relevance of hazards in exoskeleton applications: a survey-based enquiry. *J Neuroeng Rehabil*, *20*(1), 68. https://doi.org/10.1186/s12984-023-01191-y.

Moyon, A., Poirson, E., & Petiot, J. F. (2018). Experimental study of the physical impact of a passive exoskeleton on manual sanding operations. *28th Cirp Design Conference 2018*, *70*, 284-289. https://doi.org/10.1016/j.procir.2018.04.028.

Ogunseiju, O., Olayiwola, J., Akanmu, A., & Olatunji, O. A. (2022). Evaluation of postural-assist exoskeleton for manual material handling. *Engineering Construction and Architectural Management*, *29*(3), 1358-1375. https://doi.org/10.1108/Ecam-07-2020-0491.

Ogunseiju, O., Olayiwola, J., Akanmu, A. A., & Nnaji, C. (2021). Digital twin-driven framework for improving self-management of ergonomic risks. *Smart and Sustainable Built Environment*, *10*(3), 403-419. https://doi.org/10.1108/Sasbe-03-2021-0035.

Omoniyi, A., Trask, C., Milosavljevic, S., & Thamsuwan, O. (2020). Farmers' perceptions of exoskeleton use on farms: Finding the right tool for the work(er). *International Journal of Industrial Ergonomics*, *80*. https://doi.org/10.1016/j.ergon.2020.103036.

Picchiotti, M. T., Weston, E. B., Knapik, G. G., Dufour, J. S., & Marras, W. S. (2019). Impact of two postural assist exoskeletons on biomechanical loading of the lumbar spine. *Applied Ergonomics*, *75*, 1-7. https://doi.org/10.1016/j.apergo.2018.09.006.

Sharotry, A., Jimenez, J. A., Mediavilla, F. A. M., Wierschem, D., Koldenhoven, R. M., & Valles, D. (2022). Manufacturing Operator Ergonomics: A Conceptual Digital Twin Approach to Detect Biomechanical Fatigue. *Ieee Access*, *10*, 12774-12791. https://doi.org/10.1109/Access.2022.3145984.

Sharotry, A., Jimenez, J. A., Wierschem, D., Mediavilla, F. A. M., Koldenhoven, R. M., Valles, D., Koutitas, G., & Aslan, S. (2020). A Digital Twin Framework for Real-Time Analysis and Feedback of Repetitive Work in the Manual Material Handling Industry. *2020 Winter Simulation Conference (Wsc)*, 2637-2648. https://doi.org/10.1109/Wsc48552.2020.9384043.

Siedl, S. M., Wolf, M., & Mara, M. (2021). Exoskeletons in the Supermarket: Influences of Comfort, Strain Relief and Task-Technology Fit on Retail Workers' Post-Trial Intention to Use. *Hri '21: Companion of the 2021 Acm/Ieee International Conference on Human-Robot Interaction*, 397-401. https://doi.org/10.1145/3434074.3447200.

Sowjanya, A. M., & Mrudula, O. (2023). Effective treatment of imbalanced datasets in health care using modified SMOTE coupled with stacked deep learning algorithms. *Applied Nanoscience*, *13*(3), 1829-1840. https://doi.org/10.1007/s13204-021-02063-4.

Theurel, J., Desbrosses, K., Roux, T., & Savescu, A. (2018). Physiological consequences of using an upper limb exoskeleton during manual handling tasks. *Applied Ergonomics*, *67*, 211-217.

https://doi.org/10.1016/j.apergo.2017.10.008.

Upasani, S., Franco, R., Niewolny, K., & Srinivasan, D. (2019). The Potential for Exoskeletons to Improve Health and Safety in Agriculture-Perspectives from Service Providers. *Iise Transactions on Occupational Ergonomics & Human Factors*, *7*(3-4), 222-229. https://doi.org/10.1080/24725838.2019.1575930.

Xiong, W. Y., Xu, X. A., Chen, L., & Yang, J. (2022). Sound-Based Construction Activity Monitoring with Deep Learning. *Buildings*, *12*(11). https://doi.org/10.3390/buildings12111947.

Zhang, N., Bahsoon, R., Tziritas, N., & Theodoropoulos, G. (2022). Explainable Human-in-the-loop Dynamic Data-Driven Digital Twins. *ArXiv*. https://doi.org/10.48550/arXiv.2207.09106.

Zhang, Y., Xie, X., Li, H., Zhou, B., Wang, Q., & Shahrour, I. (2022). Subway tunnel damage detection based on in-service train dynamic response, variational mode decomposition, convolutional neural networks and long short-term memory. *Automation in Construction*, *139*, 104293. https://doi.org/10.1016/j.autcon.2022.104293.