

Psychophysiological Impacts of Working with Powered Exoskeletons on Construction Sites

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Abstract

Powered exoskeletons are aimed at enhancing user strength and minimizing physical strain to prevent work-related musculoskeletal injuries. However, their widespread adoption within the construction sector remains limited, primarily due to uncertainties about their psychophysiological impacts, such as potential cognitive overload, trust issues, and changes in attention levels. To tackle these concerns, this paper sets out to empirically assess the psychophysiological risks associated with using powered exoskeletons during construction tasks. An immersive virtual reality environment was created to simulate typical construction activities, aiming to gather large amounts of high-quality physiological data. Subsequently, psychological sensing frameworks were developed to quantify workers' cognitive load, trust, and vigilance. The findings indicated that powered exoskeletons induced cognitive burden, fostering distrust among the workers without affecting vigilance levels. These findings offer a robust empirical basis for the broader implementation of powered exoskeletons in construction settings.

Keywords: Wearable assistive device; Exoskeleton; Work-Related Musculoskeletal Disorders (WMSDs); Ergonomics; Construction Worker Safety

1. Introduction

The physically demanding, unpredictable, and complex nature of construction work exposes workers to considerable safety risks, particularly related to musculoskeletal strain. Workers frequently engage in physically demanding activities while maintaining uncomfortable positions for extended durations, resulting in biomechanical stress on their musculoskeletal system [1,2]. Recent advancements in mechatronics and sensing techniques have led to the emergence of exoskeletons, as a promising solution for reducing the risk of work-related musculoskeletal disorders (WMSDs) [3,4]. Exoskeletons can be classified as powered (active) or unpowered (passive): a powered exoskeleton uses actuators, such as electric motors and hydraulics, to provide active force assistance to the human body [5]. In contrast, unpowered exoskeleton utilizes materials, springs, or dampers to store energy from human movements and provide physical support and assistance as needed, without the use of actuators. While unpowered exoskeletons are generally more cost-effective and easier to implement, the construction industry leans toward powered exoskeletons because they offer active support in addressing the physical challenges

42 faced by workers on construction site [6].

43 Powered exoskeletons offer promising opportunities to prevent work-related injuries by
44 providing active support [5]. Powered exoskeletons are equipped with power sources, such as
45 electric motors, hydraulic actuators, and pneumatic muscles [7]. Powered exoskeletons utilize
46 motors or actuators to provide extra support to workers' muscles and joints, reducing the risk of
47 fatigue and injuries. These exoskeletons actively boost workers' physical abilities, leading to
48 enhanced safety and greater productivity. As a result, powered exoskeletons are rapidly entering
49 the market as commercial products, presenting promising opportunities for preventing WMSDs in
50 the construction industry. During physically demanding construction tasks, powered exoskeletons
51 can help prevent WMSDs by optimally distributing the load exerted on the worker's body,
52 correcting workers' awkward postures, and providing lift support [8].

53 Although powered exoskeletons hold promise in mitigating the risks of WMSDs in the
54 construction industry, their widespread adoption is hindered by a limited understanding of
55 sociotechnical challenges as well as potential physiological and psychophysiological risks
56 associated with their implementation. While previous studies have explored sociotechnical
57 challenges [9] and potential physiological risks of potential powered exoskeleton [10], there
58 remains a significant gap in comprehensively understanding the psychophysiological impacts of
59 powered exoskeletons. In this paper, psychophysiological risks refer specifically to the cognitive
60 overload [11], reduced trust [12], and diminished vigilance [12]. These dimensions have been
61 selected as independent constructs, each representing a distinct facet of human performance that
62 is essential for safe and effective operation in complex environments. The theoretical foundations
63 of this paper draw from well-established frameworks in psychology and human factors. Cognitive
64 Load Theory [13] highlights the limitations of working memory and suggests that the introduction
65 of novel or cognitively demanding interfaces, such as powered exoskeletons can overload mental
66 resources during complex task execution [14]. Such increased cognitive load may result in human
67 errors at work and, in the long run, may adversely affect the mental health of workers [15]. Trust
68 Calibration Model [16] conceptualizes trust as a dynamic process that adjusts with user experience
69 and perceived system reliability. Without sufficient trust, workers may misuse or underutilize the
70 powered exoskeleton, forfeiting the intended benefits of reduced physical strain and enhanced
71 productivity [3]. Vigilance Decrement Theory [17] describes the decline in attentional focus over
72 prolonged task durations, especially in the presence of monotonous or highly assisted systems. The
73 deployment of a powered exoskeleton on a job site may cause additional distractions, negatively
74 impacting their vigilance (situational awareness) [18–20]. To facilitate the integration of powered
75 exoskeletons into work environments, it is essential to understand how their use affects users'
76 cognitive workload, trust, and vigilance within their workplace. Although these constructs may
77 appear independently in literature, they are assessed concurrently in this paper to reflect the reality
78 of human performance in construction environments.

79 Researchers have mostly relied on self-report measures to assess the psychophysiological
80 impact of exoskeletons [21–23], which are prone to biases inherent in subjective scales.
81 Additionally, these subjective methods depend entirely on the worker's ability to understand their
82 psychophysiological state, which is not consistently reproducible. However, physiological
83 reactions to workplace stimuli can provide important insights into a worker's health, mental
84 condition, and reactions to work-related stress [24–26]. Recent developments in wearable

technology provide a unique chance for non-invasive, objective, and continuous real-time monitoring of psychological status [27–29]. Although researchers have leveraged functional Near-Infrared Spectroscopy (fNIRS)-based brain connectivity analyses to assess the psychophysiological impacts of an exoskeleton [30,31], these studies were conducted in controlled lab environments using simulated tasks of lifting. Such setting contrasts sharply with the dynamic and often hazardous conditions of the construction industry, where workers utilize exoskeletons in challenging locations such as elevated heights and adopt various postures like squatting, walking, lifting, or stooping. Also, most of the research has focused on the impact of unpowered exoskeletons. Current research has yet to offer a thorough understanding of the potential psychophysiological risks associated with the use of powered exoskeletons in construction settings. As the construction industry increasingly adopts these technologies, it is crucial to objectively assess their psychophysiological effects on users during active work.

This paper aims to investigate the potential psychophysiological risks linked to the use of powered exoskeletons in construction tasks. To accomplish this, a virtual reality (VR) environment was designed to replicate typical construction activities. Specifically, a VR-based system with a tangible user interface was developed to provide realistic, yet safe, experiential simulations. These advanced VR environments accurately mirrored the physical and sensory characteristics of real-world workplaces, ensuring that workers' psychophysiological reactions in the virtual environment closely resembled those in actual work conditions [32]. This virtual testbed facilitated the collection of extensive physiological data, which includes electrodermal activity (EDA), photoplethysmography (PPG), electroencephalogram (EEG), and eye-tracking data. The physiological responses were subsequently analyzed to evaluate the impact of powered exoskeleton on cognitive load, trust, and vigilance in users carrying out common construction tasks. The results provide valuable insights into the possible psychological effects of incorporating powered exoskeleton on construction sites.

2 Research Background

While powered exoskeletons offer potential benefits in reducing physical strain and enhancing productivity [10,33–36], they can impose psychophysiological demands on workers [11,18–20]. The subsections below provide a comprehensive overview of the critical constructs such as cognitive load, trust, and vigilance, which are essential for psychophysiological well-being in technology-integrated construction environments. Further, the subsections also highlight the challenges powered exoskeletons may pose to these constructs and emphasize the need for a clear understanding of the associated risks to ensure safe and effective human-exoskeleton interaction.

2.1 Psychophysiological Well-being in Technology-driven Construction Sector: Cognitive load, Trust, and Vigilance for Worker Safety

In the construction industry, the integration of emerging technologies such as robotics heightens the need for psychophysiological well-being. Such technologies bring new complexities and learning curves, which can impact workers' psychophysiological well-being [37]. Ensuring psychophysiological well-being is essential for the construction workers in adapting to technology-driven workplaces, embracing innovation, and maintaining safe, productive work environment. The introduction of advanced technologies in construction can significantly alter cognitive demands on workers. The concept of cognitive load generally refers to mental demand experienced

for a particular task [38]. As the construction workspace continues to be laden with emerging technologies, understanding, and managing cognitive load becomes crucial to prevent overload and ensure workers can effectively interact with new systems. Performing complex tasks necessitates the use of multiple mental resources, including task-specific knowledge, working memory, and decision-making abilities [39]. However, the human brain has a finite capacity for processing and integrating information [40]. Balanced cognitive loads are key to optimizing performance and safety in a technology-driven construction setting. Likewise, trust plays a pivotal role in the successful adoption of emerging technologies in construction. As workers increasingly engage with intelligent systems in workplaces, trust emerges as a crucial component for success in technology-driven environments [41]. However, trust in technological systems largely hinges on human expectations of how these systems perform [42]. Therefore, trust can be seen as an attribute of the human user in relation to the system. As a result, workers' trust in the reliability and effectiveness of new systems is fundamental for their seamless integration into construction sites. Users must establish an appropriate level of trust that is neither blindly optimistic (excessive) nor overly cautious (insufficient). Excessive trust can lead to complacency, where workers might overlook safety standards or fail to verify the proper functionality of the system, causing possible failures in critical solutions. On the other hand, insufficient trust might result in workers hesitating to use these technologies to their full capabilities, which can reduce efficiency. In this regard, having a balanced trust with emerging technologies in construction is a must for workers to excel in the technologically driven construction sector. As construction sites become more technologically advanced, maintaining vigilance about potential hazards is also increasingly and equally important [43]. Workers need to be continuously aware of both safety hazards and new risks introduced by technology. This involves staying vigilant in the operational aspects of technology, understanding its limitation, and being prepared for unexpected scenarios that might arise from technological integration. When safety hazards go unrecognized, workers are prone to engaging in unsafe behaviors, facing unexpected exposure to hazards, and potentially suffering severe injuries. Conversely, identifying safety hazards enables workers to evade such exposures, implement proper safety protocols, and prevent injuries at the workplace. Distracting technology can hinder the performance of construction tasks, impairing workers' ability to detect and address hazards effectively. Such technology not only affects their productivity but also compromises overall safety at the construction site.

2.2 Psychophysiological Challenges of Powered Exoskeletons in the Construction Domain

As powered exoskeleton systems become more prevalent on construction sites, novel challenges are likely to emerge due to the shift from a work environment centered solely around human workers to one where humans and technological aids like exoskeletons collaborate. The introduction of this human-technology partnership in the workplace will necessitate addressing new issues and considerations. The adoption of powered exoskeletons could introduce new psychophysiological risk factors, which include cognitive overload [11], lack of trust [12], and decreased vigilance [44]. The deployment of an exoskeleton on a job site can inevitably cause additional cognitive demands, imposing excessive cognitive workload on users [16–19]. The increased cognitive demands placed on workers from interacting with and operating exoskeleton systems could potentially hinder work efficiency if the users do not have sufficient cognitive resources available to properly control the exoskeleton while simultaneously performing their job

tasks. The introduction of exoskeletons may add a new layer of complexity, requiring workers to divide their cognitive resources between their primary tasks and the operation of the exoskeleton. This cognitive resource allocation could strain the user's mental capacities, leading to cognitive overload if the demands exceed their available cognitive resources. Similarly, for human-robot teams to function effectively and sustainably, it's crucial to consider human factors during interactions and incorporate them into the development of collaboration strategies [42]. In such a setting, human trust in robots is a key factor for the success and efficiency of these teams. If there isn't sufficient trust, there's a risk that robots could be misused or underutilized, which could undermine their potential benefits and the overall effectiveness of the team. Without trust, workers are likely to underutilize the exoskeletons or even disregard them completely, which negates the potential benefits such as reduced physical strain and increased productivity. Likewise, the deployment of an exoskeleton on a job site can inevitably cause additional distractions, negatively impacting their vigilance (situational awareness) [18–20]. As exoskeletons provide physical support and assistive capabilities, there is a risk that workers may become overly reliant on these aids, potentially leading to decreased awareness of their environment. This reliance can be particularly dangerous in a construction setting, where situational awareness is critical for safety. Reduced vigilance can increase the risk of accidents, as workers might not be as quick to react to dynamic changes or potential hazards in their surroundings. Moreover, the additional sensory input and feedback from the exoskeleton could serve as a distraction, further diminishing the worker's ability to stay alert to external factors. As the construction industry continues to adopt powered exoskeletons, it is essential to evaluate their effects on users' cognitive load, trust, and vigilance.

Prior studies have explored the psycho-physiological impact of exoskeleton on users. Studies have suggested that exoskeletons can reduce cognitive load by reducing workers' physical demands and allowing workers to focus more on the task [45]. Kim et al. [45] evaluated the impact of unpowered exoskeleton on cognitive performance during a fatigue inducing posture maintenance task and found that the exosuit was effective at reducing perceived workload. However, other researchers have argued that the use of exoskeletons may increase the cognitive load on workers due to the manual operation of the device [23]. For instance, Bequette et al. [23], found that the cognitive workload for subjects performing tasks with powered exoskeletons was higher than the subjects performing the tasks without exoskeletons. Moreover, studies like that of Karunakaran and Foulds [22] assessed the cognitive demand of walking with hand-controlled unpowered exoskeleton and found no significant impact on cognitive load. These varying results underscore the lack of consensus about how exoskeletons influence cognitive functions. One primary reason for such a lack of consensus can be the use of subjective measures (self-assessment surveys, i.e. NASA-TLX [46]) amongst the subjects to assess the cognitive load level. Such surveys are susceptible to self-reported biases inherent in subjective scales. Specifically, these methods depend entirely on the worker's ability to accurately recognize and assess the severity of their health condition. This reliance makes such surveys less suitable for a fair and objective assessment of an individual's actual safety status. Similar concerns arise regarding the assessment of workers' trust levels in exoskeletons. Turja et al. [21] investigated the user experience with unpowered exoskeleton and found that the user trusted the reliability of exoskeleton. Also, Kim et al. [47] examined the usability of powered exoskeleton robot assessing the trust and overall satisfaction and found the users have higher trust with the exoskeleton robot. While studies like

those by Turja et al. [21] and Kim et al. [47] have found that users generally trust the reliability and usability of exoskeletons, these findings provide limited objective evidence due to their reliance on self-report measures, which are prone to biases and lack reproducibility. Recent advancements in wearable technology enable non-intrusive, objective, and continuous real-time monitoring of psychological status [27–29]. Several researchers have leveraged wearable technologies to examine the psychophysiological impacts of an exoskeleton [30,31]. For instance, Zhu et al. [30], leveraged fNIRS-based brain connectivity analyses to assess the neural tradeoffs of an unpowered exoskeleton during asymmetrical lifting. Their findings indicated that the exoskeleton required greater neurocognitive and motor adaptation efforts by engaging action-monitoring and error-processing brain networks [30]. Likewise, Bonnal et al. [31] leveraged fNIRS to assess the cortical activation during powered exoskeleton-assisted walking and found that the neural activation increased with the increase in effort (less assistance from exoskeleton). However, it is important to note that these studies were conducted in controlled lab environments, using simulated tasks of lifting, which may not accurately reflect the dynamic and hazardous environments encountered in industries like construction. In construction settings, workers often utilize exoskeletons in challenging locations, such as elevated heights, and engage in various postures like squatting, walking, lifting, or stooping. In this vein, the findings from prior studies [30,31] through controlled experiments may not be directly applicable to real-world construction scenarios. Furthermore, most of the studies have focused on the impact of unpowered exoskeletons. The unique challenges posed by powered exoskeletons, such as their increased complexity, and power assistance, may introduce additional cognitive demands on workers, which couldn't be explained by the psychophysiological assessment of users wearing unpowered exoskeletons. Current research has not yet fully explored the potential psychophysiological risks associated with the use of powered exoskeletons in construction environments.

3 Psychophysiological Risk Assessment of Powered Exoskeletons in Construction

This research seeks to examine the psychophysiological effects of powered exoskeletons during construction tasks. The proposed approach consists of two main components: Virtual Testbed Development and Worker-centered Psychophysiological Assessment. In the first component, an immersive VR was created to realistically simulate a construction environment, allowing for the safe and effective evaluation of psychophysiological risks associated with interactions with powered exoskeletons. The immersive environment served as a platform for collecting PPG, EDA, and EEG signals, along with eye-tracking data. In the second module, user-centered assessment frameworks were developed to assess cognitive load, trust level, and vigilance of the users based on the collected physiological signals. A multimodal physiological sensing framework was developed to assess the impact of powered exoskeletons on users' cognitive load from the collected EDA and EEG signals. Additionally, a trust measurement model was developed to interpret the trust level of users from the collected PPG, EDA, and EEG signals. Lastly, a vigilance detection model was developed to measure the vigilance level of users by analyzing collected eye-tracking data from predefined areas of interest corresponding to task locations, hazards, and distractions in the simulated virtual testbed. Figure 1 presents a summary of the proposed methodology. A more detailed description of the components within this methodology is provided in the following subsections.

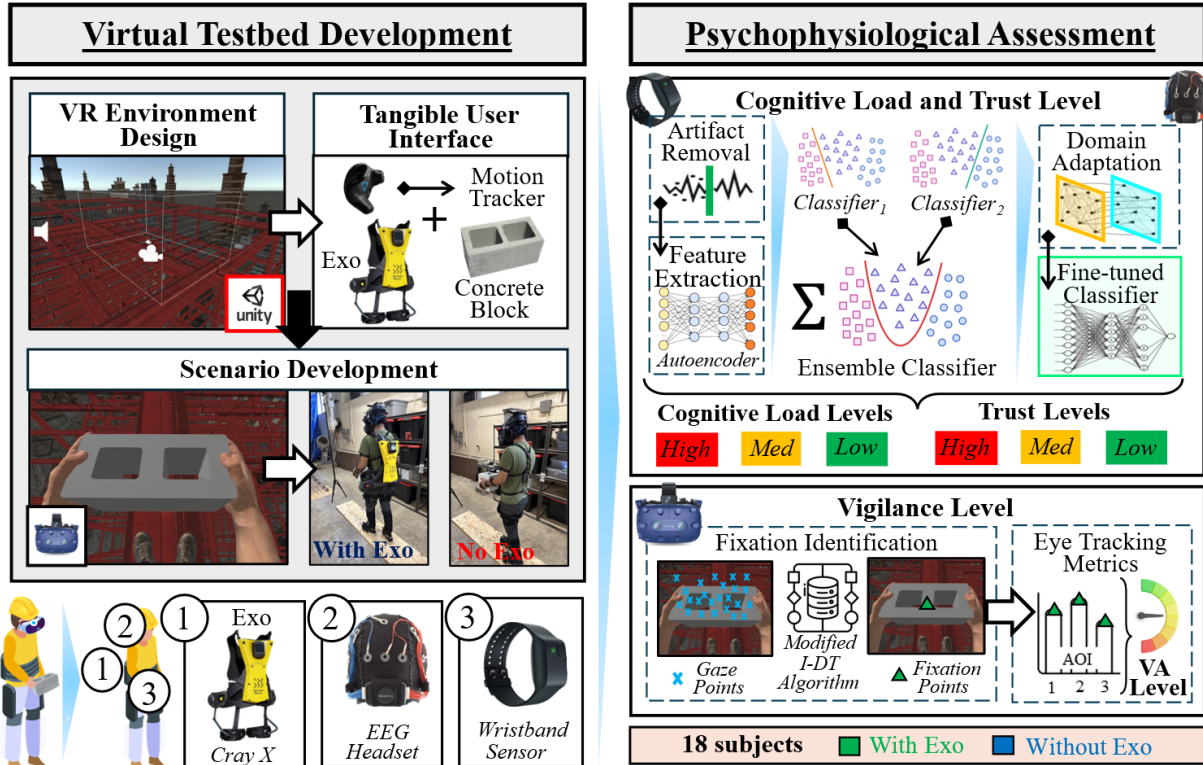


Figure 1. Research methodology

3.1 Virtual Testbed Development

The first component of the methodology involves the design and development of an immersive VR testbed tailored for evaluating psychophysiological risks associated with the use of powered exoskeletons during construction tasks. The subsections below provide a detailed description of the immersive environment design, the integration of tangible user interfaces, and the development of task scenarios used for psychophysiological risk assessment.

3.1.1 Immersive Environment Design

In the first component, a VR environment was created to replicate material handling tasks. Virtual simulations offer the advantage of providing lifelike experiences in a risk-free environment [48,49]. This is essential for testing powered exoskeletons since construction sites are not safe environments to experiment with, and conventional lab settings lack the characteristics of actual workplaces. To that end, a high-fidelity simulation of a construction job site integrated with an actual powered exoskeleton (i.e., Cray X) was created, as shown in Figure. 2-A. The model of the job site was created by 3D modeling in Building Information Modeling software (Autodesk Revit) and concurrently imported into the game engine (i.e., Unity). Notably, the spatial accuracy of the simulated job site was well-preserved to further enhance the user's spatial awareness. To replicate realistic construction job sites, the environment was enriched with numerous elements, including construction machinery, automated systems (drones, as seen in Figure 2-C), Personal Protective Equipment (PPE), and virtual workers were integrated into the environment as static and dynamic objects. To visualize the dynamic objects, scripts were developed in C# to add functionality and interactivity to various elements within the virtual environment. Particularly, the scripts were

responsible for initiating animations of the objects within the virtual environment based on certain conditions or user actions. As such, the scripts allow objects to respond to user inputs, follow specific rules or logic, and create a more realistic and immersive experience for the users interacting with the simulated environment. Auditory immersion was achieved by integrating spatial audio that replicated realistic construction site sounds such as machinery operation, tool noise, and ambient mechanical activity. These audio elements contributed to sensory fidelity and supported immersion during task execution. A virtual model of the powered exoskeleton was incorporated into the virtual environment, acting as the main interactive tool within the designed scenario. The virtual environment was developed on a high-performance computer with an Intel Core i7-13700F CPU at 2.10 GHz, 16 GB of RAM, and an Nvidia GeForce RTX 4070 GPU. To facilitate user interaction within this developed testbed, a tangible user interface was also generated.

3.1.2 Tangible User Interface in Virtual Environment

A virtual representation of the worker was simulated within the setting through an integrated system of tracking devices, which mapped the worker's physical movements onto a virtual character. To that end, a marker-less hand-tracking device (Leap Motion) was used to obtain stereoscopic images of the worker's hands and track the forearm, hand, and fingers. In addition, an inverse kinematics method was used to capture the worker's feet movements and mimic them through joint simulation in real-time [50]. By using inverse kinematics, the simulated environment back-calculates from the positions of the feet to the joints, allowing for accurate and realistic foot movements based on the desired end positions. The exploited motion data was obtained from motion tracking sensors (Vive tracker) attached to the feet and lower back of the user.

To make physical objects interactive in the immersive environment, a motion-tracking sensor was attached to each object, which was then rendered in the VR setting, as seen in Figure 2-A. Specifically, a real-powered exoskeleton was incorporated into the simulated testbed through a tangible interface. A motion-tracking sensor was affixed to the actual exoskeleton, allowing its movements to be simultaneously rendered in the virtual environment. To integrate the movement of the exoskeleton with human movement simulation, a closed loop inverse kinematics constraint was deployed for the exoskeleton model, as demonstrated in the corresponding objective equation:

$E(q) = \min \sum_i |F_i(q) - p_{i,target}|^2$. Here, q represents the vector of joint angles, which defines the positions of various joints in the exoskeleton or virtual avatar. $F_i(q)$ calculates the position of i^{th} chain end effector (hand or foot) based on the joint angles provided by q . $p_{i,target}$ are the target positions for each end effector. These targets are predefined positions that the end effectors should ideally reach, often determined by the desired interaction within the virtual environment or by tasks that the virtual avatar must perform. The objective function $E(q)$ is designed to minimize the discrepancy between where each end effector currently is and where it should be. By minimizing the objective function, the virtual testbed ensures that the movement of the exoskeleton aligns with the human movement.

In the virtual test environment, participants engaged in material handling tasks using powered exoskeletons, with a motion tracking sensor attached to a real concrete block. This sensor, incorporating an inertial measurement unit (IMU), estimated the block's position. The VR system employed (HTC Vive Pro) utilized dual laser emitters to correct IMU sensor errors by detecting variations in response times from the tracker's photodiodes. This ensured the virtual representations of the exoskeleton and concrete block accurately mirrored their physical counterparts in terms of position and orientation. The system delivered visual and haptic feedback, allowing users to interact naturally with the exoskeleton and concrete blocks, providing a realistic

perception of weight during task execution. The use of real concrete blocks allowed participants to experience physical exertion during material handling, resembling real-world lifting and carrying tasks. The combination of tangible interaction and haptic feedback ensured that the physical workload was preserved despite being situated in a virtual testbed. By utilizing this feedback, users can engage with virtual objects throughout the task, facilitating seamless interaction. This method integrates digital content with physical elements and equipment, further enhancing the user's immersion and sense of presence within the virtual environment.

3.1.3 Scenario Development

To analyze the impact of powered exoskeletons on the psychophysiological status of the workers, the authors developed material handling tasks. Particularly, the tasks involved a material handling activity where participants engaged in lifting and carrying concrete blocks to place them onto a material handling area while working at heights (walking on an iron beam), as seen in Figure 3-C. Due to the inherent physical demand of material handling, which includes intense manual labor and sustained poor posture, the authors simulated the material handling tasks, owing to the significant benefit enabled by the powered exoskeletons for the workers. Likewise, working at elevated heights can induce significant psychological stress beyond just the physical demands of manual labor. At heights, workers may experience increased anxiety, cognitive load, and other psychophysiological responses. These factors can contribute to safety risks and impaired performance. By incorporating the working at height scenario into the simulated material handling tasks, the authors could comprehensively evaluate how the use of powered exoskeletons might influence the cognitive load, trust level, and vigilance. Considering the inherent safety hazards associated with common construction tasks, the use of an immersive and interactive virtual testbed allows for a realistic yet safe experience.

Two scenarios for material handling tasks at virtual height were developed, differing only in the use of a powered exoskeleton. In the first scenario, users performed the material handling task at virtual height without the use of a powered exoskeleton, whereas, in the second scenario, users performed the material handling tasks with the use of a powered exoskeleton. To that end, participants interacted with real concrete blocks and an actual powered exoskeleton, which were presented as physical items within the VR environment. During each scenario, workers lifted, carried, and lowered the concrete blocks at height. For each scenario, users picked up the blocks, walked for 4 meters in a straight line while carrying the load and dropped the blocks in designated location. To replicate the feeling of walking on an iron beam at height during the material handling task at height, users walked on a 40 cm wide wooden plank superimposed on the virtual beam. Throughout the scenarios, all users were exposed to the same VR experience and sounds, eliminating any potential bias in the obtained results. Figure. 2-C illustrates the simulations of developed VR environment.

The structure and conditions of the experimental scenarios were grounded in foundational theories from applied cognitive psychology and human–automation interaction. Cognitive Load Theory [13] guided the inclusion of multitask demands and novel system operation to simulate realistic cognitive demands. Trust Calibration Model [16] informed the interactive elements requiring users to rely on the exoskeleton for task execution, mirroring real-world trust dynamics in technology use. Vigilance Decrement Theory [17,51] justified the inclusion of repetitive attention-requiring tasks under dynamic environmental stimuli. This theoretical grounding ensured

that the experimental setup was not only ecologically valid but also psychologically representative of the stressors encountered during real construction work.

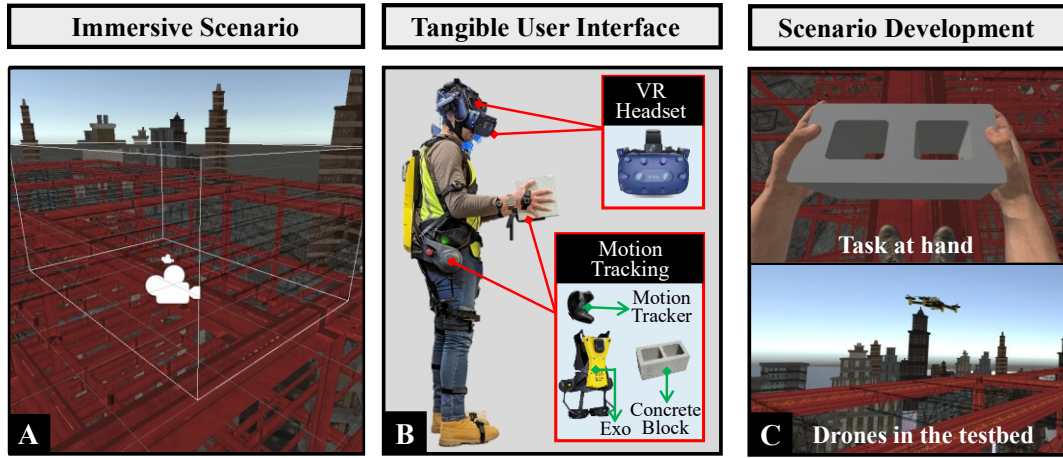


Figure 2. Developed VR environment: (A) Scenario design; (B) Tangible user interface in virtual environment; and (C) Scenario development of material handling task at height

3.2 User-Centered Psychophysiological Assessment

After developing the interactive immersive workspace, the authors proposed and implemented a series of frameworks to evaluate the impact of powered exoskeletons on workers' psychophysiological parameters, including cognitive load, trust, and vigilance. Detailed explanations of the specific frameworks implemented for each of these parameters will be elaborated on in the following subsections.

3.2.1 Cognitive Load

To evaluate the impact of powered exoskeletons on workers' cognitive load level, the authors utilized a multimodal physiological sensing framework, developed upon the authors' prior research [52–54]. This framework assessed the cognitive load by denoising, processing, and decoding workers' EEG and EDA signals captured by wearable biosensors. Figure 3 shows the structure of the framework. A signal denoising step was first applied to reduce signal artifacts from the physiological signals – the blind-source separation methods (ICA: Independent Component Analysis; DCA: Dependent Component Analysis) were used to remove the ocular and facial movements artifacts in EEG signals; and the discrete wavelet transforms adaptive predictor filtering (DWT-APF) technique was implemented for motion artifacts in EDA and EEG signals [53,55]. The selections of these signal denoising methods were based on the authors' previous research. In this paper, these techniques proved effective in eliminating relevant artifacts, which will be reported in the Results section.

In the second step, the authors designed a symmetric multilayer perceptron model (autoencoder) to extract the informative features from workers' physiological signals [56,57]. This feature engineering step produced auto-generated features superior to the traditional feature engineering approaches that need hand-crafted engineering with a higher computational cost and time [58]. The autoencoder component consisted of two main parts, the encoder, and the decoder. The encoder in the model featured three 1-D convolutional layers, with 32, 64, and 128 filters, respectively. The decoder comprised three transposed convolutional layers with 64, 32, and 1 filter. In addition, sigmoid function served as the activation function for each layer in both the encoder and the decoder. This autoencoder was trained using the objective function formulated in Equation (1). In this equation, $I_{denoised}$ indicates the input denoised physiological signals, $Decoder_{out}$

denotes the decoder's outputs, and W represents the weight matrix of the autoencoder, including all the weights from each layer of the decoder and encoder. Throughout the training process, the weight matrix (W) of the autoencoder was tuned and optimized. Post-training, the autoencoder was capable of automatically extracting features from the denoised signals and feeding these features into machine learning classifiers for the subsequent analysis (decoding) step.

$$Obj := \operatorname{argmin}_W \|\text{Decoder}_{out} - I_{denoised}\|_2 \quad (1)$$

In the third step of the framework, the extracted features were input into an array of machine learning classifiers [e.g., Support Vector Machine (SVM) with Gaussian Kernel, SVM with Polynomial Kernel, Linear SVM, k-Nearest Neighbor (k-NN), Random Forest (RF), Logistic Regression (LR), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA)]. These classifiers were trained to classify workers' cognitive load levels. Notably, the classifier exhibiting the highest training (validation) accuracy was then selected for further refinement using a domain adaptation (DA) mechanism. The domain adaptation process was applied to enhance the performances of the machine learning classifier in assessing workers' cognitive states from signals with non-stationary statistical properties triggered by the subject variability characteristic [59]. More specifically, the objective function of the applied domain adaptation mechanism was formulated as $\epsilon_k = \sum_{i=1}^q w_i^k \cdot \text{norm}_1(\sum_{j=1}^n (h_i^k(x'_j) - c(x'_j)))$. This function measures the classification error, where $h_k(x_i)$ represents the predicted label (worker's cognitive load levels) of the selected machine learning classifier, $c(x_i)$ is the actual label of x_i , and t_i^k indicates the weight of each input data (the i^{th} data), initially set to 1. The error ϵ_k was then used to generate domain-adaptation parameters $\beta_k = \frac{1-\epsilon_k}{\epsilon_k}$. β_k was then used to update the weight t_i^k of each input data. This update increased the weights of the data misclassified due to the subject variability, applying a factor of $\beta_k^{|h_k(x_i)-c(x_i)|}$. Conversely, it decreased the weights of the data points unaffected by subject variability by the same factor. As such, the machine learning classifier was able to learn from the statistical distributions of the misclassified data during the domain adaptation process. This targeted learning process addressed the subject-variability issue, thereby enhancing the performance of the classifier in assessing cognitive load levels.

The training and evaluation of this framework will be detailed in section 4. Additionally, further information about the implemented framework, such as the ICA and DCA techniques, the architecture of the autoencoder, can be found in authors' prior publications [52,53,55,60].

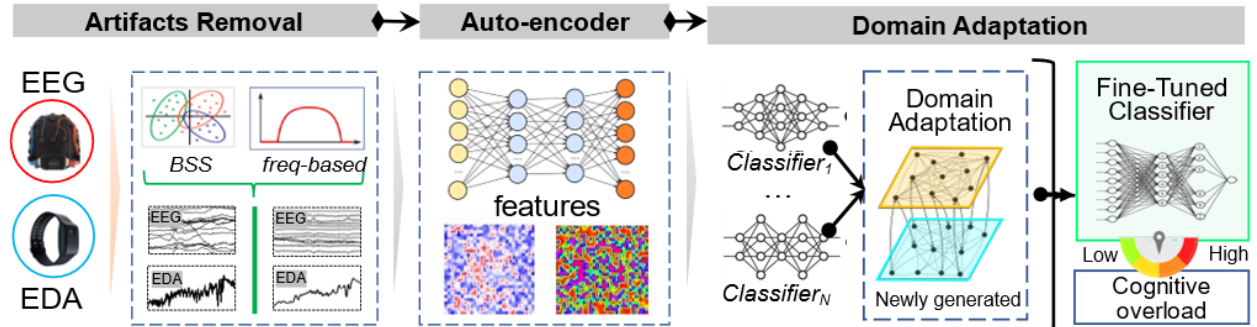


Figure 3. Overview of the proposed multimodal physiological sensing framework for cognitive load detection

3.2.2 Trust Level

To assess workers' trust in powered exoskeleton, the authors developed a non-invasive, trust measurement model that decodes the key physiological signals: PPG, EDA, and EEG. The selection of physiological signals draws on research studies reported in [61–63], which demonstrates the effectiveness of these signals in measuring human trust in robotics. The overall structure of this model is detailed in Figure 4. Like the framework introduced in Section 3.2.1, this model had three components. First, the model employed a signal processing component to capture high-quality, noise-reduced physiological signals. Second, a feature extraction component utilized the autoencoder technique to extract discriminative features from the denoised signals. Building on these features, a series of machine learning classifiers were calibrated to categorize the workers' trust into three trust levels, low trust level, neutral, and high trust level. The machine learning classifier, which presented the highest efficacy in measuring trust, was further fine-tuned via the domain adaptation mechanism. As stated, this mechanism could address the subject variability issues inherent in the physiological signals, ensuring robust performance across different subjects. By utilizing this process, the machine learning model was capable of consistently measuring workers' trust in powered exoskeleton during the worker-exoskeleton interaction.

In this paper, this trust measurement model adopted similar signal denoising techniques as described in Section 3.2.1, including blind-source separation methods for filtering out ocular and facial movements artifacts in EEG signals. Additionally, the DWT-APF technique was implemented for reducing motion artifacts in PPG, EDA, and EEG signals [53,55]. The autoencoder component mirrored the structure presented in Section 3.2.1 but with a slight variation. The encoder in this trust measurement model had two fully connected layers, containing 16 and 32 neurons respectively, while the decoder was comprised of three layers with 32, 16 and 1 neuron each. A sigmoid function was selected as the activation function for each layer. Equation (2) was formulated to train the autoencoder. As shown, this equation calculated both the Mean Square Error (MSE) loss and Mean Absolute Error (MAE) loss of the autoencoder. Here, $I_{denoised}$ indicates the input denoised signal matrix – comprising matrix contained EEG, EDA, and PPG signals), $decoder_{out}$ denotes the reconstructed signal matrix generated by the decoder, and W is the weight matrix of the autoencoder, optimized during the training. Notably, the decision to combine MSE and MAE loss functions stems from the collective robustness to variations in the input physiological signals, which can effectively enhance the capability of the autoencoder to extract discriminative features [60,61].

$$Obj: = argmin_W \|Decoder_{out} - I_{denoised}\|_2 + argmin_W \|Decoder_{out} - I_{denoised}\|_1 \quad (2)$$

Additionally, the classifier training and its subsequent domain adaptation process adhered to the settings introduced in Section 3.2.1. By doing this, the machine learning model could have a stable performance in measuring the trust level in exoskeleton use across a diverse range of workers. The evaluation of this trust measurement model will be detailed in section 4 as well. The performance of the model will be reported in section 5.

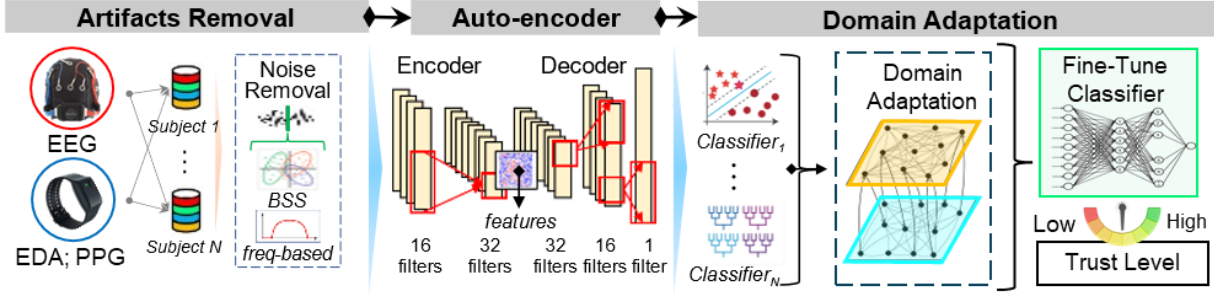


Figure 4. Overview of the proposed trust detection model

3.2.3 Vigilance

To assess the effect of powered exoskeletons on worker vigilance, the authors measured the selective attention level by analyzing eye-tracking data [tracked gaze points; (x_g, y_g, z_g)] captured from an eye tracker integrated into the VR headsets (Figure 5-A).

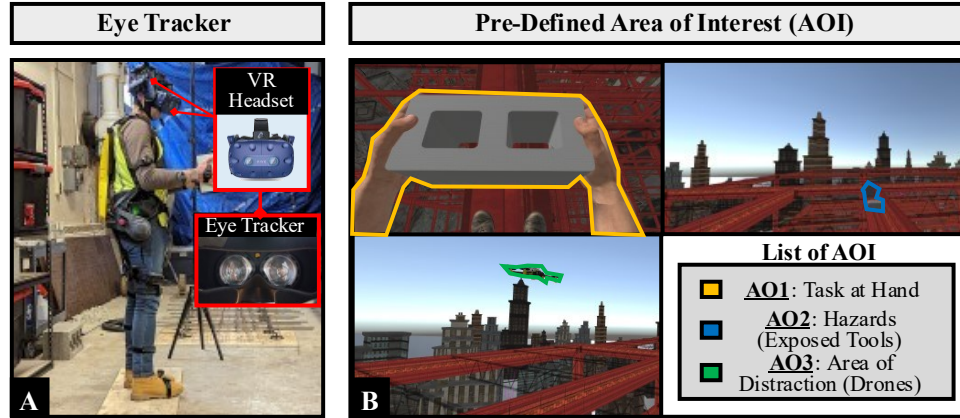


Figure 5. Eye-Tracking metric collection for vigilance detection: (A) Tobii eye tracker integrated with VR headset and (B) Sample for each Area of interest (AOI)

These gaze points were translated into meaningful visual information that can quantify selective attention towards predefined Areas of Interests (AOIs) in the immersive environment. Three specific AOIs were defined in this paper: AOI-1 is the location of the construction tasks that need to be completed by workers; AOI-2 is the location of the hazards in the VR scene; and AOI-3 are the areas of distractions in the virtual environment (other workers and automated machinery in the developed virtual testbed). Figure 5-B shows an example of each AOI. To measure the users' vigilance level, the authors measured fixation points for each AOI. These fixation points indicated the coordinates and duration in which the central foveal vision remained fixed on each AOI. For this purpose, the Identification-by-Dispersion Threshold (I-DT) algorithm was modified. The pseudo-code of the modified I-DT algorithm is shown in Algorithm 1.

Algorithm 1. Modified Identification-by-Dispersion Threshold

Input: Tracked gaze points (x_g, y_g, z_g) ; Thresholds: Dispersion δ ; and Frequency ω

1. **While** new generated gaze point has been tracked: coordinate (x_g, y_g, z_g)
 2. **If** Point generation frequency $> \omega = 30\text{Hz}$ **then**
 3. Calculate angle distance θ_{ij} between two arbitrary gaze points (i and j)
-

```

4.      Among all calculated  $\theta_{ij}$ 
5.      If  $\theta_{max} \leq \delta$  then
6.          Add the sample (new point) to the current set of points
7.          Average all samples into a fixation point
8.      Else
9.          Remove the sample.
10.     Else
11.         Remove the sample
12.     End

```

The modified I-DT algorithm processed raw eye-tracking data that captured the three-dimensional coordinates where the user's gaze intersected objects in the virtual environment, as outlined in Line 1 of Algorithm 1. In the virtual testbed simulation, these intersection points were tracked relative to the 3D position of the user's head, which served as the origin point. Each gaze measurement included metrics for both eyes that measured blink activity, with values ranging from 0 (eye open) to 1 (eye closed). The system removed data points where either eye registered a blink coefficient above 0.80, resulting in the exclusion of 0.75% of the collected data points. Computationally, if the highest angular distance (θ_{max}) in a set of gaze points is less than the dispersion threshold (ranging from $1^\circ - 1.6^\circ$, as referenced in [64]), the algorithm considered these points in such a group as fixation points (lines 6 and 7 of Algorithm 1). The angle distance θ_{ij} between any two gaze points (i and j) is calculated by $\theta_{ij} = \arccos(\frac{\vec{d}_i \cdot \vec{d}_j}{|\vec{d}_i||\vec{d}_j|})$ where $\vec{d}_i$ and $\vec{d}_j$ represent vectors from the subject's average head position to the subject's i^{th} and j^{th} gaze points. Vectors $\vec{d}_i$ and $\vec{d}_j$ are derived as $\vec{d}_s$ ($s \in \{i, j\}$) = $(x_g^s, y_g^s, z_g^s) - (\bar{h}_x, \bar{h}_y, \bar{h}_z)$. (x_g^i, y_g^i, z_g^i) are the coordinates of the worker's i^{th} gaze point, and $(\bar{h}_x, \bar{h}_y, \bar{h}_z)$ are the coordinates of the average head position obtained from the VR headset. According to the users' fixation points, several eye-tracking metrics were calculated, including fixation duration, and dwell time [65–69] for each AOIs. For each metric, higher value represents greater interest and more visual attention to the given AOI [70]. Accordingly, for each user, the authors calculated the ratio of the overall value of the eye-tracking metrics at AOI-2 to the overall value of AOI-1. Higher values indicate that the subject was more alert to potential hazards. The ratio served as a measure of vigilance level. Section 5 will present the performance of this vigilance detection model.

4 Case Study Setup

An experiment was designed and conducted in the developed immersive virtual testbed to evaluate the effectiveness of the developed framework while simultaneously examining the psychophysiological effects of powered exoskeletons. This experiment is comprised of two phases. In the first phase, the subjects' physiological data was collected during material handling tasks at height in the immersive environment under two scenarios: with powered exoskeleton and without exoskeleton. In this phase, the physiological data were collected to train and validate the multimodal physiological sensing framework for cognitive load assessment, as well as trust detection model. Further, the eye-tracking metrics collected during this step will be used to detect the vigilance level of the subjects. In the second phase of the experimental study, the validated framework was applied to evaluate the cognitive load and trust levels of participants during a material handling task at height, comparing two conditions: with and without the use of a powered exoskeleton. Figure 6. presents the schematic diagram of the experimental study.

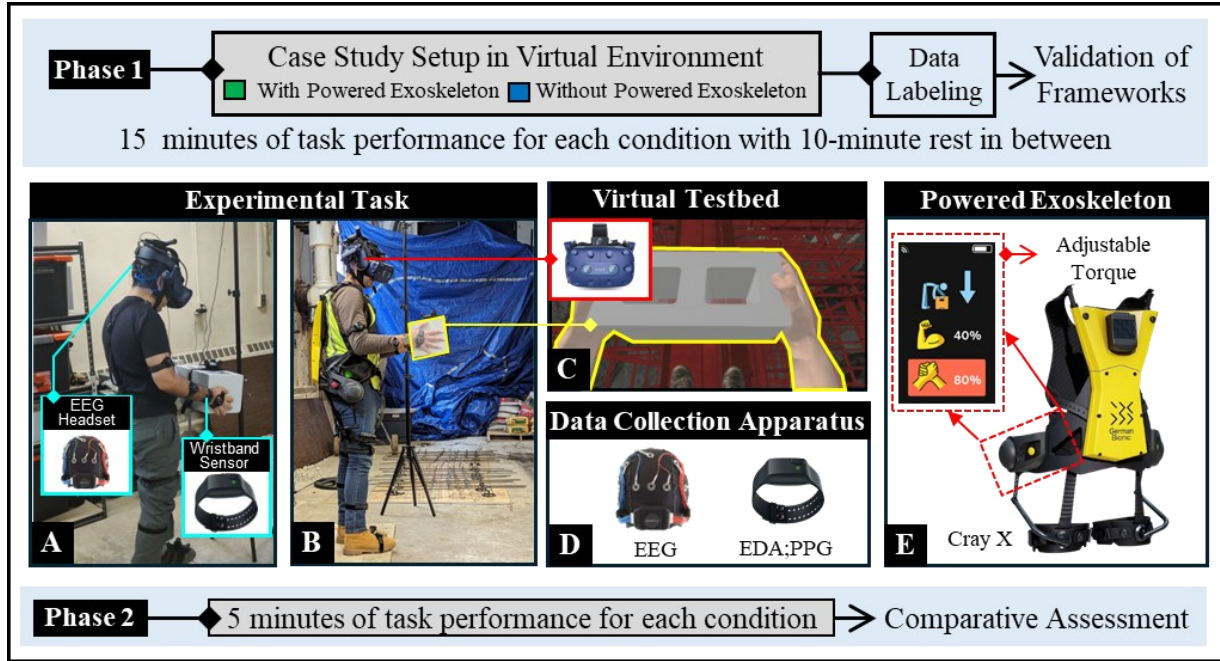


Figure 6. Schematic diagram of experimental study

4.1 Phase 1: Validating the Assessment Frameworks and Evaluating Vigilance.

In Phase 1, physiological data were collected from participants performing material handling tasks at height within the immersive environment to train and validate the proposed models for cognitive load and trust assessment. Concurrently, eye-tracking data were gathered to evaluate participants' vigilance levels during task execution. The subsections below provide detailed information on subject and device information, experimental procedures, and data labeling approach.

4.1.1 Subjects and Device Information

For the case study, eighteen physically capable participants (twelve male and six female) were asked to perform material handling tasks in the immersive VR environment, as shown in Figures 6-A and 6-B. The number of the participants was informed by the prior studies involving physiological sensing in human–robot interaction research [52,53,62,71–76]. Prior studies using comparable experimental setups have demonstrated reliable psychophysiological inference with similar participant counts. All participants were active construction workers with prior experience in material handling and elevated work tasks. Their familiarity with construction tools, PPE, and task procedures helped ensure realistic behavior and task execution within the simulation. Participants wore their own PPE (safety helmets, vests, gloves) and interacted with both real concrete blocks and an actual powered exoskeleton, each equipped with motion-tracking sensors. This setup preserved authentic physical exertion and body mechanics. The average age, height, body mass, and body mass index of the participants were 25.2 ± 4 years, 179 ± 5.5 cm, 74 ± 6.5 kg, and 23.1 ± 2.5 kg/m², respectively. Prior to the experiments, all participants were given informed consent forms detailing the purpose of the paper, the data collection process, confidentiality, and their rights. Informed written consent was obtained from all participants in accordance with the procedure approved by the Institutional Review Board at the University of Illinois Urbana-Champaign (IRB24-0938).

Once informed consent was obtained, participants were equipped with a wristband sensor (E4 Empatica™) and wearable EEG headset (Emotiv Epoc Flex™), as seen in Figure 6-D. The wristband sensor included a PPG sensor, an EDA sensor, and an infrared thermopile sensor to measure skin temperature, recording physiological signals at frequencies of 64, 4, and 4 Hz, respectively. The wristband was securely worn by the participants. Similarly, the EEG device, which had 32 channels placed on the participants' scalps, was wirelessly connected to a nearby computer to capture brainwave activity at a rate of 128 Hz. For subsequent analysis, EDA signal was up-sampled to 64 Hz, while EEG signals were down-sampled to 64 Hz to ensure compatibility with the data processing steps in the proposed framework. In addition to the physiological sensors, participants were provided with a VR headset (HTC Vive Pro Eye) equipped with a Tobii Pro eye tracker and motion tracking sensors (Vive Trackers and Leap Motion). The description of the physiological sensing devices used in the case study, including their signal type, sampling rate, and placement location, is provided in Table 1.

Table. 1. Specifications of physiological sensing devices used in the case study.

Sensor	Signal Type	Device	Sample rate	Location
EEG	Brain activity	Emotiv Epoc Flex™	128 Hz	Scalp
EDA	Electrodermal activity	Empatica E4™	4 Hz	Wrist
PPG	Blood volume pulse	Empatica E4™	64 Hz	Wrist
Eye-tracking	Gaze data	Tobii Pro	120 Hz	Head-mounted display

4.1.2 Data Collection Procedure

After setting up the wearable physiological sensors and the VR system, participants were asked to perform a material handling task at height within the immersive testbed. Participants are first given a short period to acclimate to the simulated environment, including learning the interaction mechanisms and the nature of the task. After familiarizing themselves, they were directed to begin the material handling tasks in the virtual testbed, which included two scenarios: one with the powered exoskeleton (Figure 6-A) and the other without it (Figure 6-B). The material handling tasks involved lifting, carrying, and lowering a 10 lb. concrete block, as shown in Figure 6-C. To closely replicate common construction tasks, participants were asked to physically handle a real concrete block at height, which was seamlessly integrated into the virtual testbed through a tangible user interface. In the scenario involving the powered exoskeleton, the actual Cray X exoskeleton was incorporated into the virtual environment, enabling participants to perform the material handling tasks with the assistance of the exoskeleton. This setup allowed for a realistic simulation of the exoskeleton's impact on task performance in a construction-like setting.

The authors implemented a randomized crossover study design, randomly assigning participants into two groups. Participants were randomly assigned to one of two groups: one group performed construction tasks without the powered exoskeleton (Figure 6-A), followed by performing the same tasks with powered exoskeleton condition (Figure 6-B), and the other group completed the conditions in reverse order. This counterbalancing procedure was implemented to reduce the risk of order effects. A 10-minute seated rest period, without task or VR exposure, was provided between the two conditions. This rest duration was selected based on prior psychophysiological studies demonstrating that a 10-minute interval is generally sufficient for

recovery of physiological baseline following moderate exertion [77,78]. The powered exoskeleton used in the case study was the Cray-X, shown in Figure 6-E.

In each scenario, participants were instructed to engage in the material handling tasks for 15 minutes, with a 10-minute break in between. Their movements were filmed using a video camera throughout the experiments. While performing the tasks, their physiological data was monitored continuously. The wearable biosensors recorded physiological signals, such as PPG, EDA, and EEG, which were then transmitted to a cloud server for detailed analysis. Additionally, the Tobii eye tracker integrated with the HMD VR headset captured the users' gaze points from predefined AOIs. These gaze points were processed using the modified I-DT algorithm to identify fixation points. To the end, first fixation duration, fixation duration, and dwell time were calculated from fixation points for each AOI and compared between two scenarios. Also, for each user, the authors the ratio of overall value of the eye-tracking metrics at AOI-2 (hazards location) to the overall value of AOI-1 (task at hand) were calculated and compared between two scenarios. The comparison results will be presented in section 5.

4.1.3 Data Labeling

After completing each scenario (and during the break in between), subjects were required to evaluate their cognitive load levels and trust levels by filling out the widely accepted cognitive load assessment questionnaire, NASA-TLX [79] and Trust Perception Scale for Human-Robot Interaction (HRI) questionnaire [80]. The NASA-TLX generated a score ranging from 0 to 100 based on subjects' self-evaluation, with scores over 67 considered high cognitive load, scores under 34 considered low cognitive load, and scores between 34 and 67 considered medium cognitive load, as per the research reported in [52]. The authors labeled the collected EDA and EEG signals as low, medium, and high levels of cognitive load based on the NASA-TLX score for each subject. These labeled signals were used to construct the dataset for training the proposed physiologically based cognitive load assessment framework. In this paper, a 14-item version of the Trust Perception Scale for HRI was used, with scores ranging from 0 to 100 percent [80]. The average score for each item was calculated to determine an overall trust score for each participant and scenario. These overall scores were then compared across scenarios and categorized into labels such as low trust level, neutral, and high trust level, which were used to classify the collected EEG, EDA, and PPG signals. The labeled signals were used to prepare the dataset to train the proposed trust detection model. To validate the performance of the proposed framework for cognitive load assessment and trust detection, a 5-fold cross validation process was conducted. The performance of the proposed frameworks will be presented in section 5.

4.2 Phase 2: Utilizing the Validated Framework to Assess Cognitive Load and Trust Level.

Once the framework for assessing cognitive load and detecting trust levels was trained and validated, the authors applied it to new physiological data obtained from participants performing material handling tasks at height within the immersive virtual testbed they developed. Each subject performed these tasks for 5 additional minutes, followed by a 5-minute break. This setup enabled continuous evaluation of cognitive load and trust levels under two scenarios: with and without the assistance of a powered exoskeleton. By analyzing and comparing these metrics, the authors assessed the impact of the powered exoskeleton on the subjects' cognitive load and trust levels. Detailed results of this comparison are presented in Section 5.

5 Results -Psychophysiological Impact of Powered exoskeleton on Construction Workers

5.1 Impact of Powered exoskeleton on Cognitive Load Level

As introduced in the previous section, the collected and labeled dataset was used to train and validate the proposed framework to assess the cognitive load level of subjects. The collected dataset was first used to train the single ML classifier, which includes SVM with Gaussian Kernel, SVM with Polynomial Kernel, Linear SVM, k-NN, RF, LR, LDA, and QDA. Table 1 presents the performance of the framework, showing the validation accuracy of the single ML classifiers. All reported accuracies were averaged from all 18 subjects. Given that the training dataset included three labels—low, medium, and high cognitive load level—the baseline accuracy for each classifier was set as 33.3%. Remarkably, the SVM with a Gaussian kernel achieved the highest validation accuracy of $82.2\% \pm 4.3\%$ in assessing the workers' cognitive load levels.

Table 2. Cognitive load assessment validation accuracy for single ML classifiers

Single ML Classifiers	Accuracy	Single ML Classifiers	Accuracy
SVM with Gaussian	82.2%	RF	80.1%
SVM with polynomial	76.5%	LR	77.2%
Linear SVM	79.2%	QDA	74.6%
kNN (K=3)	75.8%	LDA	78.3%

The authors selected the optimal single classifier, i.e., SVM with Gaussian for further refinement using DA mechanism. To validate the performance of the proposed framework for cognitive load assessment, a 5-fold cross validation process was conducted. To that end, the validation accuracy of the SVM with Gaussian (refined with DA) was 90.6%, averaged for all 18 subjects. To further evaluate the performance of the proposed multimodal physiological sensing framework in cognitive load assessment, the authors reported its validation accuracy for each subject in Figure 7. SVM with Gaussian (refined with DA) demonstrated a stable and robust performance across all 18 subjects, with a standard deviation of 1.78% in the validation accuracy, which performs better than the classifier without DA with a standard deviation of 4.3%. This stability and consistency across the subjects suggest that the proposed framework could robustly and accurately assess the cognitive load levels for subjects performing common construction tasks, with or without using the powered exoskeleton.

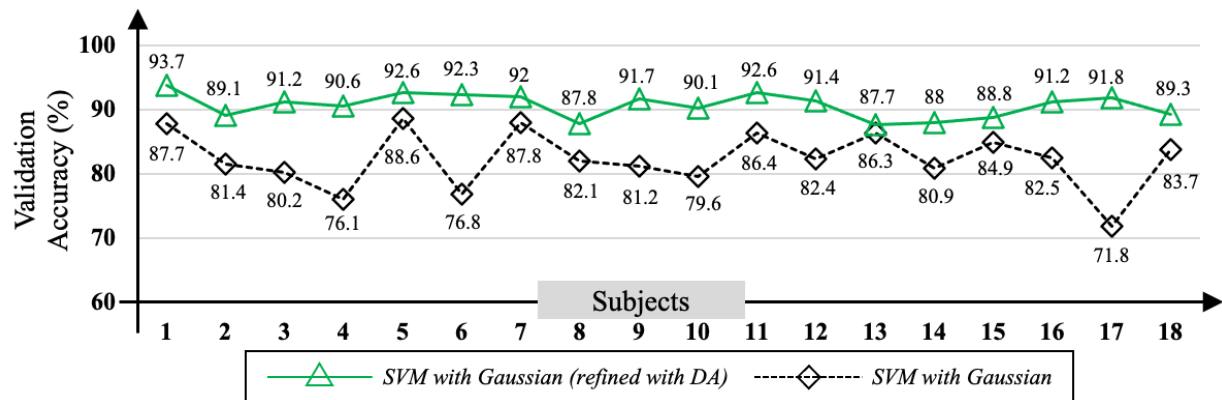


Figure 7. Performance of the multimodal physiological sensing framework for cognitive load

assessment for each subject

After obtaining the classifier refined with DA, the authors leveraged the proposed framework to evaluate the impact of the powered exoskeleton on the cognitive load levels of the subjects during the material handling tasks in the immersive virtual testbed. As mentioned, the framework was applied to an additional 5 minutes of the designated task for each scenario (with and without powered exoskeleton), as mentioned in Section 4.2. During each scenario, the developed multimodal physiological sensing framework assessed the cognitive load levels of each subject. The score of each subject was calculated by averaging the cognitive load levels (low:1, medium: 2, and high: 3) assessed by the framework. Figure 8 illustrates the comparison results of the assessed cognitive load levels between these two scenarios. The histogram in Figure 8 shows the cognitive load score of each of the 18 subjects while they performed the task with and without powered exoskeleton. The blue histogram in the figure shows the cognitive load level scores for all subjects while they performed the task with the powered exoskeleton. Likewise, the red histogram in the figure shows the cognitive load level scores for all the subjects while they performed the material handling task at height without the powered exoskeleton. On average for all subjects, the use of the exoskeleton increased subjects' cognitive load score from 1.84 to 2.56, a 39.1% increase. The use of the exoskeleton increased the cognitive load score for each subject during the task, with a maximum increase for the 16th subject (1.3) and a minimum increase for the 2nd subject (0.3). To determine the appropriate inferential statistical analysis method to analyze the differences, Shapiro-Wilk method was leveraged to examine the normality of the extracted metric. As the data did not satisfy the normal distribution ($p < 0.05$), a Wilcoxon-signed rank test was then adopted to evaluate the statistical difference of cognitive load on workers during common construction activities under two conditions (with and without using powered exoskeleton). The p-value obtained from the Wilcoxon-signed rank test was less than 0.05 (level of threshold = 0.05). The p-values indicate that the observed differences are statistically significant, suggesting that the use of powered exoskeleton could increase the cognitive load imposed on subjects.

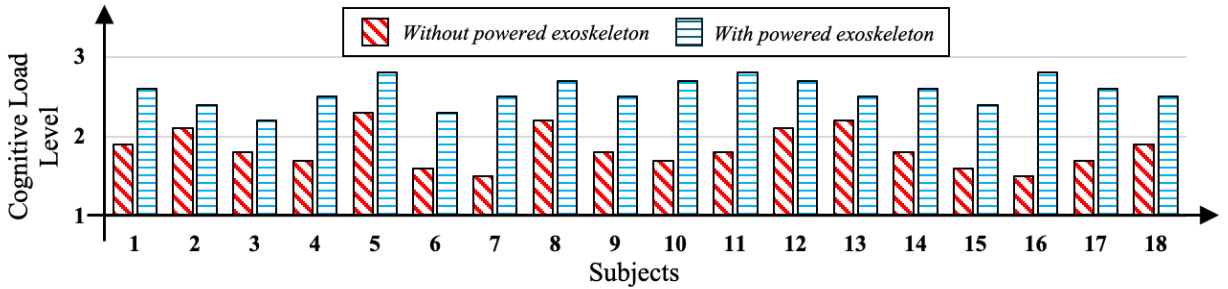


Figure 8. Comparative assessment of cognitive load level of subjects performing material handling task at height with and without using powered exoskeleton

5.2 Workers' Trust in Powered Exoskeleton

Similar to the multimodal physiological sensing framework for assessing cognitive load, the collected and labeled physiological signals-based dataset was used to train and validate the trust detection model. Firstly, the labeled PPG, EDA, and EEG dataset were leveraged to train the single

ML classifiers. Table 2 presents the validation accuracy of the single ML classifiers. showing the validation accuracy of the single ML classifiers. All reported accuracies were averaged from all 18 subjects. Particularly, the LR achieved the highest validation accuracy of 83.8%±6.2% in measuring the trust level of workers.

Table 3. Validation accuracy for single classifiers

Single ML Classifiers	Accuracy	Single ML Classifiers	Accuracy
SVM with Gaussian	82.1%	RF	80.5%
SVM with polynomial	79.1%	LR	83.8%*
Linear SVM	75.6%	QDA	77.6%
kNN (K=3)	78.3%	LDA	75.3%

In accordance with the validation accuracy of the single ML classifier, LR was selected for refinement with DA mechanism. To validate the performance of the proposed framework for cognitive load assessment, a 5-fold cross validation process was conducted. To that end, the validation accuracy of the LR refined with DA was 92.4%, averaged for all 18 subjects. To further evaluate the performance of the proposed trust detection model, the authors reported its validation accuracy for each subject in Figure 9. LR refined with DA demonstrated a stable and robust performance across all 18 subjects, with a standard deviation of 1.6% in the validation accuracy, which performs better than the classifier without DA with standard deviation of 6.2%. This stability and consistency across the subjects suggest that the proposed framework could robustly and accurately detect the trust level for subjects performing common construction tasks, with or without using the powered exoskeleton.

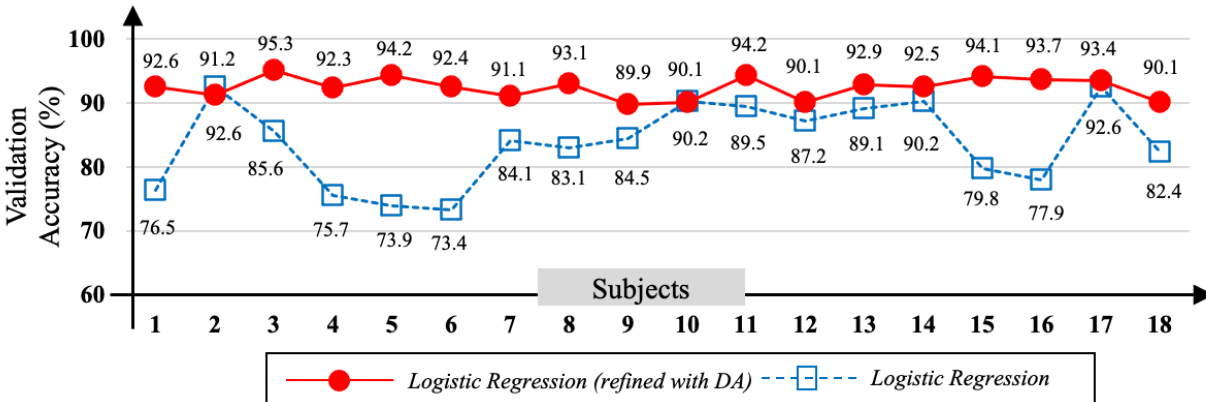


Figure 9. Performance of the trust detection model for detecting trust level for each subject

After obtaining the classifier refined with DA, the authors leveraged the proposed framework to evaluate the impact of the powered exoskeleton on the trust level of the subjects during the material handling tasks in the immersive virtual testbed under two scenarios: with and without powered exoskeleton. During each scenario, the validated trust detection model assessed the trust levels of each subject. The score of each subject was calculated by averaging the trust levels (low trust level:1, neutral: 2, and high trust level: 3) assessed by the model. Figure 10 depicts the comparison results of the assessed trust levels between these two scenarios. The red histogram in

Figure 10 shows the trust level score of each of the 18 subjects while they performed the task with and without powered exoskeleton. On average for all subjects, the use of the exoskeleton decreased subjects' trust level score from 2.56 to 1.64, a 35.9% decrease. The use of the powered exoskeleton decreased the trust level score for each subject during the task, with a maximum decrease for the 3rd subject (1.57) and a minimum decrease for the 15th subject (0.31). To evaluate statistical differences in trust levels across the two experimental scenarios, the Shapiro–Wilk test was first applied to examine the normality of the model-assessed trust scores. As the trust score distribution did not satisfy the assumption of normality ($p < 0.05$), the Wilcoxon signed-rank test was conducted to assess the significance of differences between the powered exoskeleton and non-exoskeleton conditions. The resulting p-value was less than 0.05, indicating that the difference in trust scores between the two conditions was statistically significant. This outcome confirms that the use of the powered exoskeleton was associated with a significant reduction in perceived trust. The decline in trust reflects user uncertainty, reduced perceived control, or cognitive friction introduced by the need to interact with a complex assistive system during physically demanding tasks.

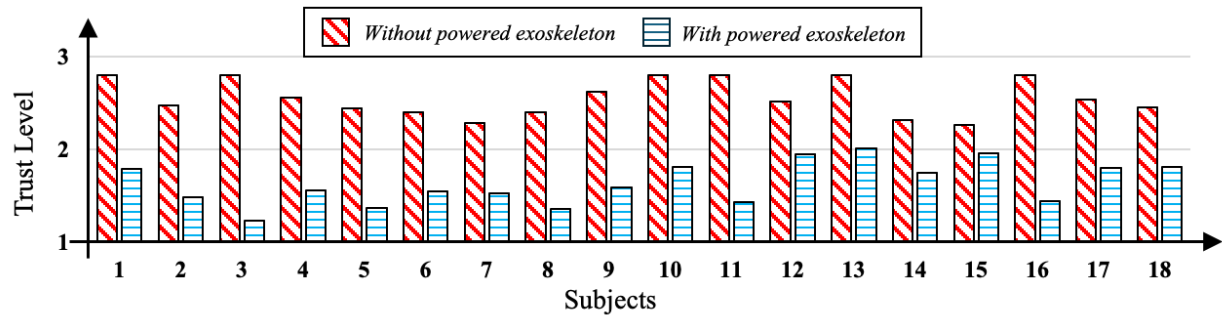


Figure 8. Comparative assessment of trust level of subjects performing material handling task at height with and without using powered exoskeleton

5.3 Impact on Workers' Vigilance in Presence of Powered Exoskeleton

Table 3 shows the results of calculated eye-tracking metrics from the fixation point for each AOI. The results showed a nuanced difference in how the attentional level was allocated during the material handling task at height in the simulated virtual testbed.

Table 3. Results of calculated eye-tracking metrics for each AOI

Area of Interest (AOI)	Metrics	With Exo (second)	Without Exo (second)
AO-1 (Task at Hand)	Fixation Duration	2.8±0.25	2.5±0.76
	Dwell time	3.1±0.25	2.7±0.45
AO-2 (Hazards)	Fixation Duration	2.5±0.56	2.4±0.35
	Dwell time	2.6±0.39	2.5±0.67
AO-3 (Distraction)	Fixation Duration	1.6±0.45	1.7±0.35
	Dwell time	2.1±0.27	1.8±0.26

With the use of powered exoskeleton, subjects demonstrated a mean fixation duration (per fixation basis) on the primary task (AO-1) of 2.8 seconds (± 0.25), indicative of sustained and

focused attention. This was complemented by a dwell time (per dwell basis) of 3.1 seconds (± 0.25), suggesting prolonged engagement with the task at hand. Attention to potential hazards (AO-2) was also robust, with a mean fixation duration of 2.5 seconds (± 0.56) and a dwell time of 2.6 seconds (± 0.39). In the absence of exoskeleton, the fixation duration on tasks slightly decreased to 2.5 seconds (± 0.76), and the dwell time was 2.7 seconds (± 0.45). Attention to hazards recorded a fixation duration of 2.4 seconds (± 0.35) and a dwell time of 2.5 seconds (± 0.67), indicating consistent attention to safety. For distractions (AO-3), fixation duration with exoskeleton was shorter, at 1.6 seconds (± 0.45), and the dwell time was 2.1 seconds (± 0.27), reflecting quicker shifts away from these stimuli. Without exoskeleton, the fixation duration was slightly longer at 1.7 seconds (± 0.35), and the dwell time decreased to 1.8 seconds (± 0.26). Overall, the ratio of overall eye tracking metrics between tasks (AOI-1) and hazards (AOI-2) was close to 1:1 in both scenarios, demonstrating consistent focus regardless of whether workers were equipped with powered exoskeleton. To examine the significance of these differences, the Shapiro–Wilk test was conducted to assess the normality of the extracted visual attention metrics. As the data violated the normality assumption ($p < 0.05$), the Wilcoxon signed-rank test was applied. The test results revealed no statistically significant differences in fixation duration or dwell time across any of the AOIs between the two experimental conditions ($p > 0.05$). These findings indicate that while slight variations in attention distribution occur with the use of exoskeleton, they do not adversely alter vigilance level of the workers between tasks and safety hazards.

6 Discussion

This paper sought to assess the psychophysiological effects of powered exoskeleton on construction workers performing various typical tasks. To begin, a highly realistic and immersive VR environment was developed to simulate a material handling task at an elevated height. This setup enabled the collection of physiological data, including EDA, PPG, EEG signals, and eye-tracking metrics, while providing a controlled, risk-free environment that eliminated injury risks and allowed for comprehensive data collection. Additionally, integrating tangible elements, such as a real concrete block and a powered exoskeleton, into the virtual environment enhanced the realism of the experience for participants, ensuring the data collected closely mirrored real-world scenarios. The risk-free simulated experience proved to be an effective method for eliciting authentic behavior and corresponding physiological responses from participants, thus facilitating the evaluation of the psychophysiological impact of powered exoskeleton on construction workers.

Secondly, user-centered assessment frameworks were developed to assess cognitive load, trust level, and vigilance of the users based on the collected physiological signals. A multimodal physiological sensing framework was developed to assess the impact of powered exoskeleton on users' cognitive load from the collected EDA and EEG signals. The framework successfully enabled the prompt estimation of cognitive load level with an accuracy of 90.6%. Such optimal accuracy outperforms the reported accuracies of other studies that developed physiological data-driven models to discern different levels of workers' cognitive load level [52,81]. The consistent reduction in training and testing losses indicates the stability and reliability of the cognitive load assessment framework. More specifically, the refinement of SVM with Gaussian classifier through a DA mechanism significantly enhanced the accuracy and stability of cognitive load assessments. The classifier's refined version, demonstrated through a 5-fold cross-validation process, showed improved performance with a standard deviation reduction in validation accuracy from 4.3% to 1.78%. This enhancement suggests a robust ability to assess cognitive load across different

subjects consistently. Guided by Cognitive Load Theory [13], which posits that increased task complexity or system novelty places greater demands on limited working memory resources, the findings indicated a statistically significant increase in cognitive load by 39.1%, from 1.84 without the exoskeleton to 2.56 with the powered exoskeleton. This significant increase suggests that while powered exoskeleton are designed to assist physically, they may add complexity to cognitive processing during tasks. The increased cognitive load associated with the use of the powered exoskeleton could be attributed to the additional cognitive resources required to operate and coordinate movements with the exoskeleton device. The increased cognitive load may reflect the dual-task burden workers experience when integrating the powered exoskeleton's assistance with their primary task, consistent with principles of divided attention under Cognitive Load Theory [13]. Wearing and interacting with the powered exoskeleton may introduce an additional cognitive burden, as the user needs to adapt to the new interface and integrate it with their natural movements. Furthermore, the exoskeleton's weight, assistance mechanisms, and potential limitations in freedom of movement could contribute to increased cognitive demand, as the user needs to actively monitor and adjust their actions while wearing the device.

Additionally, a trust measurement framework was developed to interpret the trust level of users from the collected PPG, EDA, and EEG signals. The trust measurement model was trained and validated within the developed VR-based experimental setup, ensuring high contextual relevance. The framework builds on authors' earlier work [62], which demonstrated the effectiveness of physiological sensing in estimating worker trust in collaborative construction robots in an immersive environment. The paper effectively used a dataset of physiological signals to train ML classifiers, achieving the highest validation accuracy with LR. The application of the DA mechanism to refine the LR classifier significantly improved its performance. This refinement, validated through a 5-fold cross-validation process, resulted in a marked decrease in the standard deviation of validation accuracy, dropping from 6.2% to 1.6% and increment in accuracy from 83.8% to 92.4%. This high level of accuracy surpasses those reported in other studies that have utilized AI and physiological data to distinguish various trust levels among workers [62]. This substantial enhancement underscores the model's capability to provide stable and consistent trust assessments across a diverse group of subjects. These results indicate both the technical reliability and contextual validity of the trust assessment approach. To further verify the validity of the developed trust measurement framework in the VR environment, trust predictions from the model were cross-referenced with participants' responses to the Trust Perception Scale for HRI [80]. The alignment between physiological indicators and subjective ratings confirmed that the model outputs accurately reflected participants' trust perceptions. Further, the paper also addressed VR-specific confounding factors such as the novelty effect, allowing participants to become familiar with the simulated environment before data collection. The close alignment of the results from this paper with the previous studies conducted in traditional laboratory settings [61,62,82,83] further supports the robustness of the developed trust level measurement approach. The assessment of trust levels from the validated framework indicated a statistically significant decrease in trust scores when subjects used powered exoskeleton, dropping from an average of 2.56 to 1.64. This reduction suggests that while powered exoskeleton are intended to aid physical tasks, they may inadvertently induce distrust. This decline could be attributed to several factors: the complexity of operating the exoskeleton, potential reliability concerns, and the psychological impact of relying

on mechanical assistance for routine tasks. Additionally, the initial unfamiliarity with the exoskeleton's controls and feedback mechanisms may lead to discomfort or skepticism regarding its efficacy and safety. Furthermore, the adjustment period required to become skillful in using the exoskeleton could temporarily increase the users' cognitive load, thereby affecting their trust levels. These findings align with Trust Calibration Model [16], where insufficient understanding or inconsistent system performance can lead to under-trust, reducing the effectiveness of human-machine teaming.

Lastly, a vigilance detection model was developed to measure the vigilance level of users by analyzing collected eye-tracking data from predefined AOIs corresponding to task locations, hazards, and distractions in the simulated virtual testbed. Three AOIs were defined: AOI-1, where construction tasks were located; AOI-2, where potential hazards were present in the VR scene; and AOI-3, areas of distraction such as the presence of other workers or construction equipment. With the exoskeleton, workers in AOI-1 (Task at Hand) showed increased fixation duration of 2.8 seconds and dwell time of 3.1 seconds, indicating enhanced sustained attention. This improvement is likely to be due to the physical support provided by the exoskeleton, which could reduce fatigue and allow workers to allocate their attention to the task. In AOI-2, fixation duration remained relatively stable with and without exoskeleton, indicating that the use of this assistive technology does not detract from the workers' awareness of potential dangers. This stability in hazard attention, with a fixation duration of 2.5 seconds with the exoskeleton and 2.4 seconds without, is critical in ensuring that the benefits of physical assistance do not compromise safety. Distraction (AOI-3) fixation was shorter with the exoskeleton at 1.6 seconds, pointing to better task focus. The ratio of attention between tasks (AOI-1) and hazards (AOI-2) remains nearly equal in both scenarios, demonstrating that workers consistently allocate their focus between these critical aspects of their work environment, regardless of exoskeleton use. This pattern aligns with Vigilance Decrement Theory [17,51], which predicts that attentional fatigue can impair hazard detection; however, in this case, the physical relief provided by the exoskeleton may have buffered against such decrements. Particularly, the result of the Wilcoxon-signed ranked test suggests that the primary function of the exoskeleton to assist physically does not compromise the vigilance level.

This research significantly contributes to understanding the psychophysiological impacts of powered exoskeletons on construction workers by employing a highly realistic and immersive VR environment to simulate material handling tasks at height. By integrating physiological data collection, including EDA, PPG, EEG signals, and eye-tracking metrics, the paper provides a comprehensive analysis of how powered exoskeleton affect cognitive load, trust, and vigilance. The findings reveal that while powered exoskeleton enhances physical support, leading to improved sustained attention and task focus, they also increase cognitive load and may reduce trust. These results highlight the dual influence of powered exoskeleton, assisting in physical tasks while potentially adding cognitive complexity and inducing skepticism due to unfamiliarity and operational complexity. Moreover, the robust assessment frameworks developed for cognitive load and trust, refined through domain adaptation technique, offer precise, reliable measurements that surpass the accuracies reported in previous studies. Ultimately, this research advances the field by providing a nuanced view of the benefits and challenges of exoskeleton usage in high-risk

environments, guiding future development and integration of assistive technologies in the workplace.

The research findings, while informative, contain several limitations that could be addressed in future research. Firstly, the primary limitation stems from the relatively homogeneous participant pool. The recruitment choices were shaped by both methodological and logistical considerations. The selection of younger individuals with similar physical capabilities was intended to minimize confounding variables, such as wide variations in fitness levels or medical conditions to isolate and accurately assess potential psychophysiological risks to powered exoskeleton use under controlled conditions. Additionally, factors such as the availability of local construction personnel influenced the composition of the participant pool. While necessary for internal validity and operational feasibility, this approach resulted in a relatively homogeneous sample that may not fully represent the diversity of the construction workforce. However, construction sites typically employ individuals with diverse backgrounds, physical capabilities, and professional experience levels, suggesting that a broader demographic representation in future research would yield more comprehensive insights into the performance of the developed psychophysiological assessment frameworks across different worker populations. Secondly, the research focused exclusively on a single powered exoskeleton model, potentially limiting the broader applicability of the findings to other assistive devices in the market. Future research could consider incorporating multiple powered exoskeleton models to understand how various designs impact worker performance and comfort. Thirdly, although the developed trust measurement framework builds on previously verified protocols, virtual simulations may introduce unique contextual challenges, such as heightened novelty, motion discomfort, or differences in perceived presence. While these factors were addressed by limiting session durations, allowing participants sufficient time to acclimate, and validating trust predictions against subjective self-report scores, future research could evaluate the framework under more varied VR conditions or deploy it in real-world construction settings to reinforce external validity. Fourthly, the VR testbed did not simulate environmental stressors such as temperature, humidity, or wind. The exclusion of such variables was a deliberate design decision intended to preserve internal validity by ensuring consistent environmental parameters across all experimental conditions. While the simulated environment provided necessary safety controls, it may have oversimplified the inherent complexities of actual construction environments, where workers must navigate unpredictable conditions, varying weather patterns, and dynamic site layouts. Future studies should be counted in authentic construction sites to better capture the conditions and challenges workers face on actual job sites. Lastly, the temporal scope of the investigation is another limitation. Future investigations would also benefit from longitudinal studies that track the impact across extended periods of regular use in authentic construction environments.

7 Conclusion

The paper effectively examined the psychophysiological effects of powered exoskeletons on construction workers, focusing on cognitive load, trust, and vigilance. For this purpose, VR environment was created to simulate realistic construction tasks and gather physiological data, including EDA, PPG, EEG signals, and eye-tracking metrics. The collected physiological responses were then analyzed to assess how the use of powered exoskeleton influenced cognitive load, trust, and vigilance in users. A multimodal physiological sensing framework was developed

to assess the impact of powered exoskeleton on users' cognitive load from the collected EDA and EEG signals. Likewise, a trust detection model was developed to evaluate the impact of powered exoskeleton on users' trust level from the collected PPG, EDA, and EEG signals. Similarly, a vigilance detection model was developed to measure the vigilance level of users by analyzing collected eye-tracking data. The results indicated that the use of powered exoskeleton would increase subjects' cognitive load levels and induce distrust during worker-exoskeleton interaction. Further, the findings also illustrate that powered exoskeleton does not impair vigilance level, which is critical for safety. The integration of advanced physiological sensing technologies with artificial intelligence allowed for precise and reliable assessments, paving the way for robust automated assessment of impacts of wearable technology in industrial settings. The findings of the paper indicate that powered exoskeleton hold substantial potential to improve safety and efficiency in the workplace but also emphasize the need for designs that consider the cognitive and trust implications of their use. The findings offer valuable insights for safety managers and ergonomic specialists, underlining the importance of balancing the support provided by powered exoskeleton with any potential risks. This paper contributes valuable knowledge to the field of human-robot interaction, specifically in understanding the nuanced ways in which powered exoskeleton affect cognitive load, trust, and vigilance. While the paper yielded encouraging outcomes, its reliance on virtual reality simulation, though necessary for precise data collection, potentially falls short of capturing the full complexity inherent in actual construction environments. To address these limitations, subsequent research endeavors should prioritize extended field-based investigations that examine the sustained impact of powered exoskeleton usage. Such studies should encompass a more comprehensive range of construction activities and recruit participants from diverse demographic backgrounds, thereby enhancing our understanding of how these devices perform in real-world applications. Furthermore, expanding the scope to evaluate multiple commercial exoskeleton models would provide valuable insights into how specific design elements and features influence both psychological and physiological responses among construction workers.

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