Evaluating the Feasibility of Personalized Health Status Feedback to Enhance Worker Safety and Well-Being at Construction Jobsites

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ABSTRACT

Advancements in wearable sensor technology and AI provide an excellent opportunity to monitor the health status of construction workers on-site. However, there is still a lack of efficient means of promptly communicating this information to workers without violating their privacy. This study evaluates the feasibility of providing personal feedback to construction workers regarding their health status while carrying out routine tasks. The proposed mechanism employs machine learning models and a decision tree to provide workers with timely private feedback and corresponding recommendations or risk mitigation strategies. As such, an experiment was conducted to evaluate the performance of the proposed feedback system as well as users' perception of its usability. The findings revealed that the proposed feedback system could provide the workers with accurate and effective feedback regarding their health status, indicating the great potential to enhance worker safety and well-being at construction jobsites.

INTRODUCTION

Construction workers often face challenging work conditions that can damage their physical and mental health. Harsh environmental conditions, such as loud noise, dust, vibration, and extreme temperatures, along with heavy physical exertion, can increase the risk of injuries, illnesses, and long-term health problems among construction workers (Ojha et al. 2020). Accordingly, statistics have shown that construction workers suffer from higher rates of injuries and fatalities compared to workers in other industries (U.S. Bureau of Labor Statistics 2022a). Furthermore, severe work conditions can be combined with poor training, lack of situational awareness, and inadequate safety equipment, resulting in lost workdays, decreased productivity, and potential legal liabilities (Mitropoulos et al. 2005). As a result, it is critical to implement effective practices to improve workers' health and safety at construction job sites.

Despite the significance of workforce health monitoring, there is a lack of effective health monitoring approaches at construction job sites. This is primarily because the traditional worker health monitoring methods often rely on periodic assessments, which are not suitable for detecting early signs of occupational fatality or injury (Hinze and Godfrey 2003). These methods are also subjective and intrusive, making their practical implementation more challenging. Additionally, traditional worker health assessment methods do not consider the variability in work conditions and individual characteristics that can impact workers' overall health status (Awolusi et al. 2018). As a result, there is a need for more effective and personalized approaches for assessing worker health status in construction.

Recent advances in wearable biosensor technology and artificial intelligence (AI) provide an excellent opportunity to continuously monitor and evaluate worker health status on construction job sites (Abuwarda et al. 2022). In this regard, wearable biosensors can capture physiological data in real-time and provide objective measures of workers' health status. AI algorithms can analyze and interpret this data to identify patterns and predict various health and safety risks, enabling the adoption of proactive interventions to prevent injuries and fatalities. In such cases, workers can leverage this information to protect themselves and make necessary adjustments to their working environments. While physiological sensing methods have great potential to facilitate continuous and objective health monitoring of construction workers, there is still a lack of effective means to communicate the results of health assessments to workers in a timely manner. As such, a lack of situational awareness regarding their current health status may lead to workers being unable to take appropriate actions or make necessary arrangements on time.

To address this issue, this study aims to assess the feasibility of generating and transmitting personalized feedback to construction workers regarding their health status during construction activities. The proposed feedback mechanism employs the prediction results of machine learning models and infuses them into a decision tree to provide workers with timely private feedback and corresponding recommendations or risk mitigation strategies. The results of the study provided evidence for the feasibility and effectiveness of the proposed feedback system to enhance workers' understanding of their health status. This study contributes to the current body of knowledge by examining the feasibility of a personalized health status feedback system to improve construction workers' health and safety on job sites.

WORKER HEALTH MONITORING AT CONSTRUCTION SITES

The construction industry is recognized for its high number of work-related injuries and fatalities. The inherent safety risks associated with construction work, such as falls, struck-by incidents, electrical incidents, and exposure to hazardous substances, make this industry one of the most dangerous industries to work in (Mohammadi et al. 2018). Based on the U.S. Bureau of Labor Statistics report (2022a), 986 workers lost their lives on U.S. construction job sites in 2021. In addition, the industry was responsible for 169,200 non-fatal work-related injuries and illnesses in 2021 (U.S. Bureau of Labor Statistics 2022b). Accordingly, it is critical to prioritize and promote occupational health and safety in the construction industry to protect workers, prevent injuries and fatalities, and create a thriving and sustainable work environment. In this context, effective health and safety monitoring of construction workers is crucial for identifying and addressing potential health and safety issues. Given the limitations of traditional health monitoring approaches, such as construction site observations and safety inspections, there is an increasing need for objective and non-intrusive techniques to continuously monitor workers' health status on job sites (Ojha et al. 2023).

The emergence of wearable sensing technologies has opened up new opportunities for objectively and non-intrusively monitoring the safety and well-being of construction workers on-site (Hwang and Lee 2017; Jebelli and Choi 2018). In this regard, various physiological data (e.g., heart rate, breathing rate, body temperature, brain activity) can be captured using different sensors and analyzed to assess the overall health status of the workers in real-time. Therefore, there is great potential to employ wearable sensing technologies to reduce injuries and fatalities in construction. However, previous studies have suggested that a significant proportion of injuries and fatalities at construction job sites can be associated with the workers' limited ability to predict, recognize, and respond to workplace hazards (Choudhry and Fang 2008). This issue can limit the effectiveness of applying physiological-based health monitoring methods at construction sites. Therefore, effective communication of health information to workers is essential to enhance their situational awareness and promote occupational health and safety on construction job sites.

In this regard, various methods of communicating health information to workers have been implemented at construction sites, ranging from paper-based systems to mobile applications and wearable devices. Paper-based systems involve distributing safety observation reports to workers in person or via noticeboards (Oswald et al. 2018). While these systems are convenient to employ, they may be impractical given the risk of reports being lost or ignored and the urgent nature of some health and safety hazards. To address such issues, mobile applications and wearable devices can be implemented to offer a more automated and real-time means of communicating health status information to workers. However, integrating these technologies with AI-based physiological sensing is not fully explored in the construction field. These technologies can potentially transmit biosensor data and results of predictive models to provide workers with personalized feedback on their health status and risk mitigation strategies. As a result, the improved situational awareness of the workers regarding their health status can enable them to anticipate potential health hazards and take proactive measures to prevent injuries and illnesses. For example, based on the received feedback, workers can adjust their work practices, take rest breaks, hydrate, and use personal protective equipment to mitigate identified risks to their health. Therefore, it is essential to examine the feasibility and effectiveness of mobile applications and wearable devices in communicating personalized, health-related feedback to workers.

METHODOLOGY

This study proposes a framework for generating and transmitting personalized health feedback to construction workers. To that end, a physiological sensing module is developed to measure the physical fatigue of the workers by capturing and analyzing their electromyography (EMG) signals during construction task performance. Subsequently, a fault-tolerant mechanism is used to filter inaccurate prediction results of the physiological sensing module and enhance the reliability of the feedback system. The proposed fault-tolerant mechanism is founded on the principle that human physiological conditions remain invariant in a relatively short period of time (Paas et al. 2003). Lastly, a feedback generation module is established to send workers private feedback regarding their health status. Figure 1 demonstrates an overview of the proposed framework.

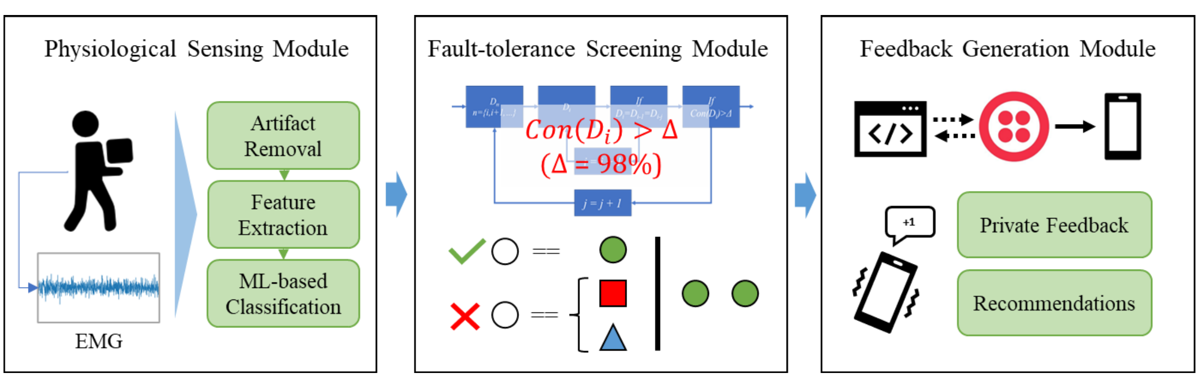

Figure 1. Overview of the proposed framework

Physiological Sensing Module. In this study, EMG signals are used to assess the physical fatigue of the workers during task performance. The EMG sensor can provide valuable information about the electrical activity of muscles, which can help identify the physical fatigue of workers during construction activities (Shair et al. 2017). However, these signals are contaminated by artifacts from various sources, such as movement artifacts and electromagnetic interferences, which can result in reducing the quality of the captured signals. To remove these artifacts from EMG signals, the authors employed different filters on the recorded signals, including a bandpass filter and a Hampel filter (Jebelli and Lee 2019). The bandpass filter allows a specific range of frequencies to pass through while attenuating frequencies outside that range. On the other hand, the Hampel filter detects outliers and replaces them with more reliable values to deal with noisy data. It uses a moving window approach and compares each data point to the median within the window. A data point is regarded as an outlier if the difference between it and the median exceeds a certain threshold. In this study, a bandpass filter with a lower cutoff frequency of 0.5 Hz and a higher cutoff frequency of 250 Hz was employed to minimize external signal artifacts. In addition, the Hampel filter was employed to remove any signal outliers and achieve clean data.

Following removing signal artifacts and acquiring clean data, several informative features were extracted from the data in time and frequency domains, including root mean square, mean absolute value, standard deviation, zero crossing, median frequency, and mean frequency. These features were calculated from segmented EMG signals divided into windows with a size of 2 seconds (2000 data points). The window size was determined based on the results of our previous work. The resulting features were then employed to predict the physical fatigue of the workers during construction task performance. After the construction of the training dataset, the authors applied multiple supervised machine learning algorithms as training classifiers, including the Support Vector Machine (SVM) with Gaussian kernel, Linear SVM, Logistic Regression (LR), and Random Forest (RF). These algorithms were selected based on their robustness and flexibility in classifying physiological data. This study employed a 10-fold cross-validation method, which involved dividing the training data into ten equal-sized folds and using each fold as the validation set, to verify classifiers' accuracy. The performance of the classifiers in detecting physical fatigue was then compared to determine the optimal classifier for feedback generation.

Fault-tolerance Screening Module. Given that physiological variations in the human body typically happen slowly over time (compared to physiological signal alterations that can occur in milliseconds or less), the results of physiological-based predictive classifiers may lead to incorrect classification and erroneous feedback regarding workers' health status (Liu et al. 2022), which can severely impact worker safety on site. To overcome this limitation, the authors proposed a fault-tolerant screening algorithm. The term fault tolerant refers to the fact that the module can make the framework function reasonably well even when the data it receives contains mistakes, outliers, or unexpected variations. This algorithm operates by receiving the prediction results from the machine learning model, modulating the data, and generating logically sound predictions. In this case, the rapid changes in the classification results, which are more likely due to prediction errors rather than actual variations in physiological states (Paas et al. 2003), are filtered to deliver a more accurate prediction regarding workers' health status.

The proposed fault-tolerant mechanism consists of four main elements. First, the receiver module obtains the classification outcomes from the predictive model. These outcomes are indexed as $D_i (i = \{1, 2, \dots, n\})$ and prepared for comparative analysis. Second, the comparison module compares the i^{th} classification result of workers' physiological signals to its j previous consecutive data, $\{D_{i-1}, \ldots, D_{j-1}\}$. Third, the confidence evaluation module assesses the classification confidence ($Con(D_i)$) by evaluating the number of consecutive points required to meet a predetermined confidence level. Fourth, the fault tolerance level j determines the number of consecutive data points (classification results) that must be considered in the comparison module. If the $j+1$ predecessors of D_i are equal, then the classification confidence of D_i will be evaluated using Eq 1. Otherwise, the mechanism will increment i by one unit until it finds $j+1$ identical consecutive results.

$$Con\ (D_i) = \frac{P(D_i = D_{i+1} = \ldots = D_{i+j} = C)}{P(D_i = D_{i+1} = \ldots = D_{i+j} = C) + P(D_i = D_{i+1} = \ldots = D_{i+j} = W)} \quad (1)$$

Where C indicates correct classification results that align with the actual physiological states of the worker, and W shows wrong classification results. The probability of getting j consecutive correct classifications, $P(D_i = D_{i+1} = \ldots = D_{i+j} = C)$, and the probability of getting j consecutive misclassifications, $P(D_i = D_{i+1} = \ldots = D_{i+j} = W)$, can be calculated as the product of the probability of the correct and wrong classifications from D_i to D_{i+j}, respectively. For each classification result, the probability of the correct classification is equivalent to the classification accuracy of the machine learning classifier, while the probability of misclassification is 100% minus the classification accuracy of the classifier. Once the value of $Con(D_i)$ is calculated, it can be compared with a user-defined threshold (98% in this study). If $Con(D_i)$ exceeds the threshold, D_i is accepted as a correct prediction outcome and transmitted to the feedback generation module. If $Con(D_i)$ does not exceed the threshold, the fault tolerance level will be incremented by one unit to re-evaluate $Con(D_i)$ accordingly. As such, the proposed fault-tolerant mechanism can regulate the feedback generation system with high confidence and minimal prediction result variations.

Feedback Generation Module. Once the predictions that were unlikely to be correct were filtered, health-related feedback messages could be generated to signal the actual alterations in the current physiological status of the workers. As such, the results of the decision tree were passed to the feedback module to send private feedback to workers. In this study, the authors employed a text messaging system to transmit feedback to the workers during task performance. Twilio service was integrated into the system, allowing authors to send short messages through its Application Programming Interface (API). To that end, the Twilio Python library was used to import the Twilio REST (Representational State Transfer) Client and create an instance of it using created account SID (Security Identifier) and authentication token. A phone number was provided to the API along with the content of the message. The content of the message included an alert of "high risk of physical fatigue," followed by risk mitigation recommendations to cope with that. In this work, the recommendations included taking a break, maintaining proper posture, staying hydrated, and reporting any concerns promptly. For instance, one of the feedback workers could receive was "Our monitoring systems have detected signs of high physical fatigue during your current shift. Your well-being is our priority, and we encourage you to take a break to recharge. Consider stepping away from your current task, stretching, and hydrating." It is worth mentioning that in real-world use cases, the responsibility for preparing and delivering such feedback would likely fall to safety managers and designated personnel responsible for worker well-being. As such, their role would require interpreting data derived from various sensors to provide actionable insights to workers. This strategy is in line with the broader industry vision, which seeks to use data and information to foster a culture of proactive safety management within the industrial context.

SYSTEM PERFORMANCE ASSESSMENT

The proposed personalized health status feedback system was examined in an experiment designed to replicate a construction task. Six healthy subjects participated in the experimental process to evaluate the performance of the proposed feedback system. A material handling task was selected for the experiment because it is a common construction activity and puts considerable levels of physical pressure on workers' bodies. During task performance, subjects were required to carry two different types of heavy loads, including 14 kg (30lb.) soil bags and 4.5 kg (10 lb.) cement bags, for a distance of 10 meters. Accordingly, carrying 14 kg bags could lead to a high level of physical fatigue, and carrying 10 kg bags could lead to a low level of physical fatigue. Meanwhile, an EMG sensor (Biosignalsplux EMG), capable of capturing data at a rate of 1000 Hz, was attached to their back muscles to monitor muscle activity. The subjects were required to perform both material handling tasks in random order. The physical fatigue of the subjects was also measured using the Borg rating of perceived exertion (Borg 1998) to confirm the labeling process of the collected physiological data. The rating is a subjective assessment scale that assigns a numerical value to how hard an individual perceives their exertion during physical activities.

Once subjects were prepared, they were instructed to start the material handling tasks. Each task lasted 5 minutes, during which subjects' EMG data were collected to train the predictive models and assess their physical fatigue. Each subject performed both material handling tasks (i.e., low physical fatigue and high physical fatigue) in random order. Figure 2 shows the experimental procedure for collecting the training data in this study. Afterward, the authors applied the trained model and asked the subjects to perform the same material handling task. During this session, subjects were provided with generated feedback regarding their health status in the form of a short message. Subsequently, subjects were asked to complete a system usability self-assessment (i.e., a modified version of the System Usability Scale [SUS] (Brooke 1996)) to indicate their perception of the proposed feedback system's usability. The self-assessment consisted of 10 statements (Table 1) rated on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree). The analysis and reporting of the SUS results could allow for an evaluation of the performance of the proposed personalized health status feedback during the material handling task.

RESULTS AND DISCUSSION

Following the data collection process, the performance of the selected machine learning algorithms to differentiate two levels of physical fatigue based on EMG data was evaluated. The collected data were randomly split into 90% training and 10% testing sets. The results were computed using a 10-fold cross-validation method, which involved dividing the training data into ten equal-sized folds and using each fold as the validation set once. Accordingly, the authors evaluated the performance of SVM with the Gaussian kernel, linear SVM, logistic regression, and random forest. The results showed that SVM with the Gaussian kernel outperformed the other algorithms with an accuracy of 86.5%. The accuracy of other selected algorithms is presented in Table 2. The high accuracy of SVM with the Gaussian kernel can be attributed to its ability to capture complex non-linear relations between the data. In addition, the Gaussian kernel allows for flexible modeling of the decision boundary, which can better represent the underlying structure of the employed EMG data.

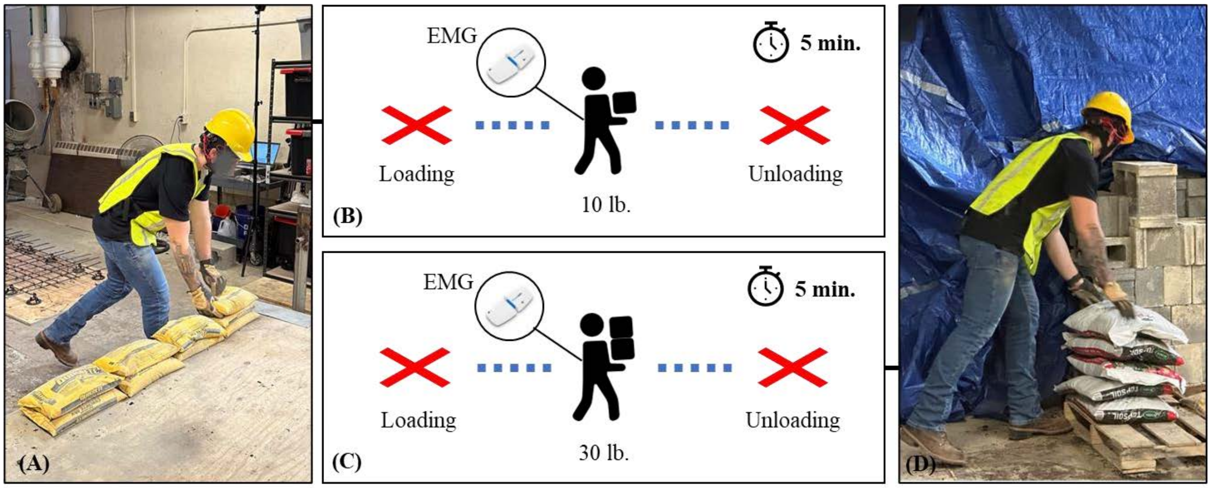

Figure 2. Experimental procedure; (A) and (B) Low physical fatigue task; (C) and (D) High physical fatigue task

Table 1. Modified System Usability Scale (SUS) statements based on (Brooke 1996)

	Statement
1.	I think that I would like to use this feedback system frequently.
2.	I found the feedback system unnecessarily complex.
3.	I thought the feedback system was easy to use.
4.	I think that I would need the support of a technical person to be able to use this system.
5.	I found the various functions in this feedback system were well integrated.
6.	I thought there was too much inconsistency in this feedback system.
7.	I would imagine that most people would learn to use this feedback system very quickly.
8.	I found the feedback system very cumbersome to use.
9.	I felt very confident using the feedback system.
10.	I needed to learn a lot of things before I could get going with this feedback system.

Table 2. Performance of the selected supervised machine learning algorithms in classifying collected EMG data.

Supervised Learning Algorithm	Accuracy (%)
SVM with the Gaussian Kernel	86.5
Linear SVM	79.8
Logistic Regression (LR)	73.3
Random Forest (RF)	81.2

Based on the presented results, applied supervised machine learning algorithms could be effectively used for classifying EMG data. The findings are consistent with previous studies in the field that used such algorithms in physiological data classification tasks (Mokri et al. 2022; Di Nardo et al. 2022). Accordingly, the optimal machine learning algorithm (SVM with the Gaussian kernel) was selected and employed in the feedback generation process. While EMG signals offer valuable information about muscle activity and physical fatigue, the results can support the feasibility of adopting a more comprehensive approach that includes multiple types of sensors and physiological signals to monitor an individual's performance and health status. As such, further research is required to explore the integration of various sensor modalities to offer a holistic and comprehensive approach to delivering targeted personalized feedback to workers.

In order to evaluate the performance of the deployed fault-tolerant mechanism, the authors compared the accuracy of the generated health-related feedback with and without employing that module. To that end, subjects were asked to perform the same task while receiving timely feedback based on the results of the predictive model and indicate their agreement with the generated health-related feedback. As such, inaccurate feedback based on the erroneous prediction of the previous module could be identified. As shown in Figure 3, compared to the condition of not applying the proposed fault-tolerant mechanism, using the mechanism in the feedback generation process led to an increase in the percentage of accurate feedback among the subjects. Therefore, it was revealed that the personalized health status feedback system, augmented with the proposed fault-tolerant mechanism, could enhance the accuracy and reliability of the generated feedback during task performance.

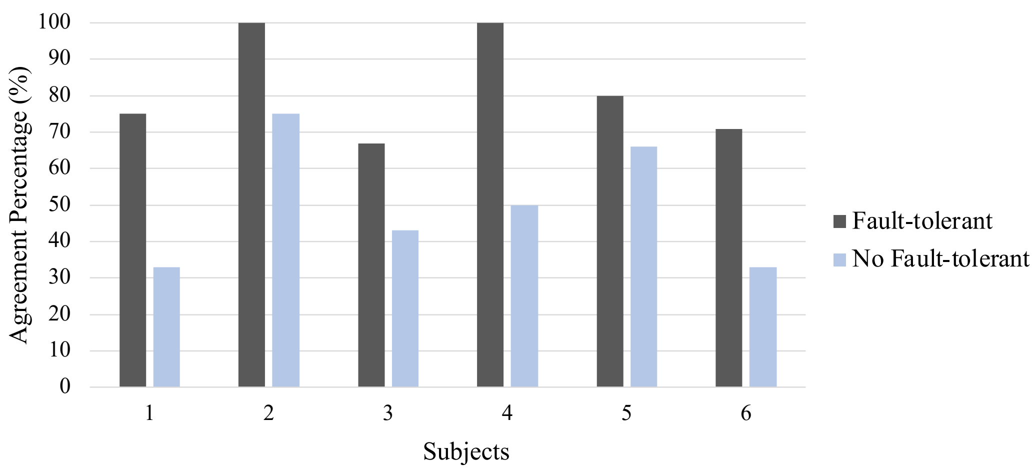

Figure 3. Performance of the fault-tolerant mechanism based on the subjects' agreement with the generated health status feedback

In addition to the performance results of the selected machine learning algorithms and the fault-tolerance screening mechanism, the usability of the proposed personalized health status feedback system was assessed using a modified version of the System Usability Scale (SUS). This widely adopted questionnaire measures user perception of a system's ease of use and learnability. Accordingly, the final SUS score, ranging from 0 to 100 (with higher scores indicating greater usability), reflects the perceived usability of the feedback system. To account for the alternating positive and negative statements, adjustments were made in calculating the final score using Eq. 2:

$$Final\ Score = 2.5(S_{odd} - S_{even} + 20) \quad (2)$$

The final SUS score was calculated for six subjects. The mean SUS score was found to be 73.75, with a standard deviation of 7.49. According to Bangor et al. (2008), a SUS score above 70 indicates good usability. Therefore, the high SUS score obtained suggests that the subjects found the implemented feedback system user-friendly and easy to use. Additionally, the reliability of the collected data was assessed to ensure its validity. As such, Cronbach's Alpha reliability coefficient, a measure of internal consistency and item interchangeability, was employed for this purpose. The analysis yielded a reliability coefficient of 0.868, indicating the high data reliability in this study. This outcome further supports the feasibility of employing the proposed personalized health status feedback system in the field. The results provide evidence supporting the viability of implementing worker feedback to proactively enhance safety measures at construction sites. In light of these findings, it is necessary to conduct additional research to assess the feasibility and effectiveness of personalized health feedback in real-world operational contexts.

CONCLUSION

This study highlights the potential of wearable sensor technology and AI in providing personalized health status feedback to construction workers while carrying out their routine tasks. The proposed feedback mechanism, which uses machine learning models and a decision tree, could provide workers with timely and private feedback regarding their health status, with recommendations and risk mitigation strategies. The results of the experiment revealed that the proposed feedback system is feasible and has the potential to enhance workers' understanding regarding their health status on job sites. The findings of this study have important implications for the construction industry, where the safety and well-being of workers are of utmost importance. Therefore, further research in this area can lead to the development of more advanced and efficient systems that can improve workers' situational awareness and ultimately contribute to reducing occupational injuries and fatalities in the construction industry.

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