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Reducing Workers' Back, Shoulder, and Leg Stresses Using Low-Cost Wearables

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Abstract: The recent labour shortage in the construction industry has been exacerbated by health and safety issues due to the harsh work environment, long hours, and intense physical stresses. In a step towards better health, safety, and productivity, this paper presents an evaluation of several low-cost wearable devices for construction workers. First, a statistical analysis assessed the stresses on various body parts during construction and found that workers' backs, shoulders, and legs are most affected. An assessment of 11 wearable support devices was then carried out. This study included 18 participants, with each participant conducting specific load-carrying exercises targeting these body parts with and without wearables. Data was collected on the number of repetitions or time spent on each task prior to fatigue, heart rates, and ergonomic scores. Using this data, the relative improvements in stress levels were analysed. Clustering analysis was then performed to categorize each wearable as providing low, medium, or high levels of support. Additionally, the direct correlation between wearable price and level of support was investigated. Finally, a neural network model was trained using the participants' physical characteristics and their performance metrics during the experiments to predict the needed support for individual workers. Future work includes expanding experimentation to field workers and developing an optimization model to personalize the selection of low-cost wearables to suit specific worker and task characteristics while meeting budget constraints. This research will improve worker safety and productivity and reduce injury-related costs, making the industry more attractive to young participants.

1. INTRODUCTION

The construction industry is currently facing serious challenges in terms of project delays, cost overruns and labour shortages (Saeed et al. 2024). Labour shortages have been a major barrier to the construction industry's ability to reclaim its pivotal role in national economies in recent years (Associated General Contractors of America 2022). This can be largely attributed to the high prevalence of musculoskeletal disorders (MSDs) among workers, lessening the industry's ability to attract a young generation of workers (Ibrahim et al. 2023; Albers et al. 2005). These MSDs are largely caused by repetitive motions and the physical strain associated with various construction tasks. Wearable support devices offer a potential solution for alleviating worker stress, reducing the occurrences of these MSDs among workers, and therefore mitigating the labour shortage. Traditionally, the construction industry has been slow to adopt wearables for task support, due to cost constraints and the large variability of construction tasks (Balamurugan et al. 2022). However, with the recent availability of several low-cost wearable devices for commercial use, the utilization of wearable devices to support workers in the construction industry has become more feasible. To support the widespread implementation of these wearables in the industry to alleviate worker stress and reduce MSDs, this paper presents an evaluation of several low-cost wearable devices for construction workers. The level of efficacy of each wearable is determined for various construction tasks and various worker physical and physiological characteristics. These wearables are then presented as cost-effective solutions for their respective construction tasks. This approach paves the way for data-driven, personalized procurement of wearable devices in the construction industry.

2. BACKGROUND

Construction workers are exposed to prolonged physical stress due to repetitive movements, uncomfortable postures, and heavy lifting, leading to a high prevalence of work-related injuries. This physically demanding nature of construction tasks contributes to high injury rates, reduced productivity, and an increasing reluctance among younger workers to enter the industry (De Bock et al. 2023). Data from WorkSafeBC (2023), from 2014 to 2022, highlights that MSDs consistently accounted for 30% and 25% of all Long-Term Injuries (LTIs) for mechanical and electrical workers respectively. The report also indicates that overexertion/repetitive motion is a significant contributor to injury claim costs for both trades. Specifically, injury claims related to overexertion and repetitive motion accounted for $24 million (22% of total claim costs) in the mechanical trade and $13 million (26% of total claim costs) in the electrical trade (WorkSafeBC 2023). Furthermore, overexertion/repetitive motion was the leading cause of the lost workdays in both trades, surpassing falls from elevation and contributing to approximately one-third of all lost workdays (36% or 78k days for mechanical, 30% or 29k days for electrical) (WorkSafeBC 2023).

One of the major health concerns in construction is the strain placed on workers' backs, legs, and shoulders, which are among the most frequently affected body parts. Figure 1 presents the total MSDs by body part from 2018-2022, as recorded by WorkSafeBC (2023). The data indicates that, for both mechanical and electrical workers, the most affected body part by MSDs is the back, which constitutes nearly half of all MSDs experienced by workers. Additionally, the back, shoulder, and together comprise more than two-thirds of MSDs (70% for mechanical and 68% for electrical). The cumulative impact of these stressors often leads to chronic pain, fatigue, and long-term disabilities, further intensifying workforce shortages as experienced workers exit the industry (Abuwarda et al. 2022). Addressing these challenges requires innovative solutions that enhance worker safety, reduce physical strain, and improve overall job satisfaction.

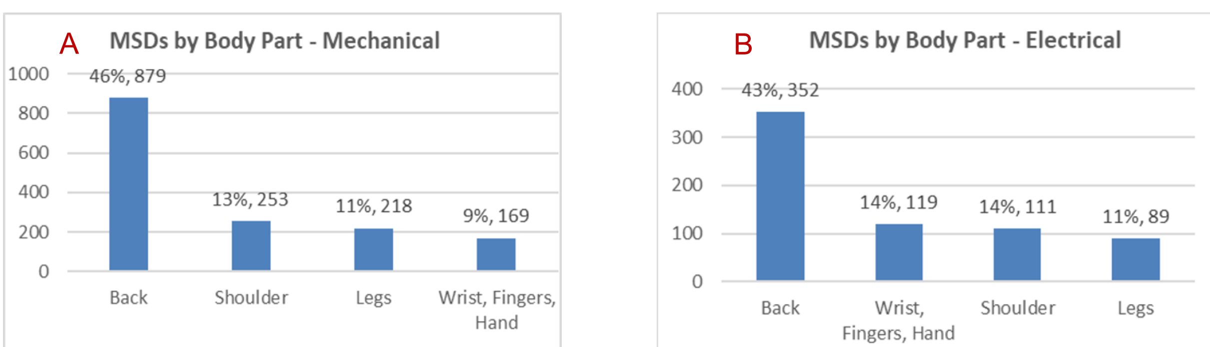


Figure 1: MSDs by body part and proportion of total MSDs from 2018 to 2022 (a) mechanical and (b) electrical trades (Source: WorkSafeBC)

Wearable support devices have emerged as promising tools to mitigate physical stress and enhance construction workers' endurance (Okpala et al. 2022). These devices are designed to redistribute loads, support key muscle groups, and reduce the risk of injuries. Previous research has demonstrated that wearable assistive technologies can lower muscle activity in key regions, decrease perceived discomfort, and extend endurance time in physically demanding tasks (Balamurugan et al. 2022; De Bock et al. 2023).

However, despite their potential benefits, the widespread adoption of wearables in construction remains limited due to factors such as cost, usability, and lack of personalization.

This study builds upon existing research by evaluating the efficacy of various low-cost wearable devices in reducing the risk of injury for construction workers. By analyzing their impact on muscle stress, endurance, and ergonomic support, this work aims to provide data-driven insights into optimizing wearable selection for individual workers based on their physical characteristics and task demands. The findings from this research can contribute to reducing injury-related costs, improving worker retention, and making the construction industry more attractive to new entrants, thereby addressing the ongoing labour shortage.

3. EXPERIMENT DESIGN AND DATA COLLECTION

The first step towards reducing injuries among construction workers is to determine the efficacy of each wearable device at reducing the risk of injury for various construction tasks and various workers. This will allow subsequent selection of the optimal wearable device based on the specific task and worker profile. An experiment was developed in which multiple participants would perform a set of simulated construction tasks using a pre-selected set of wearables. The results of this experiment will enable subsequent data analysis using the WEKA© machine learning software to classify the efficacy of each wearable device and to develop a machine learning model to predict the required level of support for each user.

Recent literature and comprehensive analysis from various databases, such as WorkSafeBC and the Workplace Safety and Insurance Board (WSIB), form the basis for designing the experiment. The objective of the experimentation is to determine the efficacy of various wearable support devices in reducing muscle strain experienced by different muscle groups. Therefore, the experimentation focuses on the muscle groups most impacted by MSDs, as these have the greatest potential for quantifiable improvement. This will not only provide a strong foundation for experimentation and analysis of results but also maximize the benefit of this research on the industry via reduced MSD-related lost time injuries and costs.

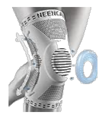
3.1. Selection of Body Parts

Based on WSIB (2018) data from 2015-2017, back, shoulders, and legs constitute 80% of all MSD injuries for construction workers. The WorkSafeBC data from 2018-2022 further confirms this trend, with these same 3 body parts constituting 70% of all MSDs for mechanical workers and 68% of all MSDs for electrical workers. Thus, based on data spanning multiple provinces and multiple time periods within the last decade, it is evident that the back, shoulders, and legs are consistently the most affected body parts by MSDs among mechanical and electrical workers. Therefore, the experiment was designed to involve tasks that primarily strain these three body parts and utilize wearable support devices designed to alleviate muscular load from them.

3.2 Wearable Devices Selection

The selection process for the wearable devices was designed to identify products offering varying levels of support, specifically targeting the back, shoulders, and legs. This initial assessment was based on educated inferences from supplier marketing data and an examination of the devices' design features (e.g., pulleys, straps, compression mechanisms). The actual level of support provided by each device was subsequently evaluated independently as part of this experiment. For this study, 11 wearable devices were selected that cover a variety of price and support ranges, shown in Table 1. Given the focus of this study on low-cost wearables, the price for the wearables ranges from $30 - $250 (except wearables 4 and 11). While wearables 4 and 11 are markedly more expensive (particularly wearable 11), they are marketed as providing significantly more support than their lower-priced counterparts in this study. For example, the Hilti EXO-S (wearable 11) is well-known for providing strong support at an affordable price. The high cost is understandable due to the complex design of these wearables; wearable 11 has a pulley system while wearable 4 uses tensioned backstraps to store energy. Furthermore, these wearables are more affordable than other similar commercial products for the level of support they provide.

Table 1: Wearable devices selected for experimentation and assessment

Body Part	Back				Leg				Shoulder		
Name	BraceUP Back Brace	CopperFit Elite Back Brace	BraceAbility Back Brace	Mediaid Textile Exoskeleton Suit	NEENCA Knee Brace	TIMTAKBO Hinged Knee Brace	Z1 K6 Dezire Hinged Knee Brace	WRUIOY Wearable Chair	Suptrust Shoulder Brace	Kuangmi Double Shoulder Brace	Hilti EXO-S
Code	1	2	3	4	5	6	7	8	9	10	11
Price ($)	31.08	50.00	146.46	422.63	31.69	100.45	215.58	111.87	28.80	47.79	1998.97
Image											

3.3 Task Design for Simulated Construction Activities

For each body part, a task was designed for the participants to perform which simulates a real-world construction activity. A description and image of each experimental task is listed in Table 2, as well as a list of sample construction tasks that are simulated by these experimental tasks.

Table 2: Experiment tasks performed and relevant construction tasks

Body Part	Experiment Tasks (steps) *	Construction Task	Experimental Task Image
Back	1. Bend and lift a 4 kg box from ~30cm off the floor. Keep back straight and knees slightly bent. 2. Lower slowly (back to ~30cm point), repeat until onset of muscle fatigue. Count total repetitions.	• Lift ACU compressors onto mounting platforms	
Leg	1. Go down to a squatting position with both hands together. 2. Count the seconds in this position until onset of leg muscle fatigue.	• Inspect refrigerant line • Install outlet receptacle	
Shoulder	1. Stand and hold right arm up with elbow at 90°, with 2 kg object in hand. 2. Count the seconds in this position until onset of shoulder muscle fatigue.	• Weld overhead steel pipes • Drill overhead holes	

* Participants have at least a 3-minute break between exercises.

3.4 Participant Characteristics

Eighteen participants were involved in the experiment. Each participant performed the leg, back, and shoulder task without any wearable support device, and then repeated each task with a wearable. Various physical characteristics were gathered from the participants, including height, weight, age, and gender. The average height of participants was 175 cm, ranging from 155 cm to 190 cm. The average weight was 166 lbs, ranging from 130 lbs to 225 lbs. Each participant's health status for each tested body part was also documented in the form of an Overall Health Score (0 for existing pain, 1 for no pain, 2 if they are highly athletic/active). These ranges of physical characteristics were selected to offer a wide range of body types to evaluate the wearable comfort levels and efficacy. 14 (78%) of the participants identified as male and 4 (22%) identified as female. This gender ratio closely aligns with Ontario's construction workforce, which is comprised of 89% males and 11% females (Government of Canada, 2023). The average age was 28 years old, ranging from 22 to 39, with 89% of participants aged below 34. This age group was selected as it is the age group most affected by MSDs, as supported by Infrastructure Health & Safety Association (IHSA) data.

Figure 2 presents annual MSDs by age group, collected by the IHSA (IHSA 2020a, IHSA 2020b, IHSA 2020c). These graphs demonstrate that for both, mechanical and electrical workers, the age group most affected by MSDs is 25 to 34 years old. Approximately 40% of annual MSDs are experienced by workers aged under 34 in the mechanical trade, and approximately 50% within the electrical trade.

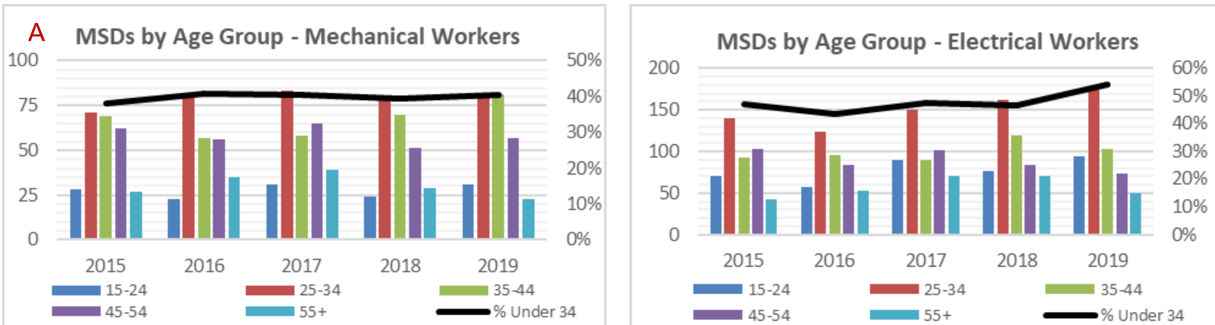


Figure 2: MSDs by age group and proportion of young workers from 2015-2019 (a) mechanical and (b) electrical trades (Source: IHSA)

3.5 Data Collection and Metrics

Metrics were selected based on previous studies to comprehensively quantify the physiological improvement each wearable device resulted in for the participant performing the task (Golabchi 2022). The Heart Rate Change was measured by using an Apple Watch to determine the heart rate before and after each task was completed. The Count to Fatigue was manually recorded by participants other than the user conducting the test. This approach improves accuracy compared to having only the user perform the counting. The Ergonomic Score was determined using the TuMeke© ergonomic software, which uses artificial intelligence to conduct image analysis of user-submitted videos of physical activities. The software then uses built-in ergonomic algorithms to provide a final ergonomic score. These three metrics and the data collection format are shown in Table 3:

Table 3: Metrics recorded to support quantification of wearable performance

		Without Wearable			With Wearable		
Participant	Wearable	Heart Rate Change (HR When Stressed – HR Before Start)	Count to Fatigue*	Ergonomic Score (TuMeke)	Heart Rate Change (HR When Stressed – HR Before Start)	Count to Fatigue*	Ergonomic Score (TuMeke)

*Count to Fatigue is measured as the time elapsed between the start of task performance and the onset of user fatigue

Following the data collection, percentage change values were calculated for Heart Rate Change, Count to Fatigue, and Ergonomic Score, for use during the data analysis.

3.6 Data Preprocessing

To ensure the accuracy and reliability of the machine learning model, the dataset was first preprocessed to handle outliers. The dataset contained a small number of instances in which negative values were recorded for Heart Rate Change (i.e., heart rate before start was higher than heart rate when stressed). Negative values in this context were illogical, as they suggested highly unlikely reductions in heart rates during task performance and were most likely caused by external factors (e.g., the participant receives a distressing message just before starting the task, thus artificially elevating their HR Before Start). The data preprocessing involved several steps to ensure that the adjustments were systematic and consistent across the dataset:

1. Calculation of Averages: Average Heart Rate Change from all positive values in the dataset.
2. Replacement of Negative Values: For each record with a negative Heart Rate Change, the negative value was substituted with the computed average of the positive heart rate differences.
3. Validation of Corrections: Post-correction, the dataset was re-evaluated to ensure that no negative values remained and that the overall data distribution remained intact.

4. DATA ANALYSIS AND CLASSIFICATION

Following data collection and cleaning, the data was analyzed in order to classify each of the tested wearable devices as providing either a “Low”, “Medium”, or “High” level of support. This was done using clustering analysis with the WEKA software, specifically the Expectation Maximization Clustering technique. The Count to Fatigue, Heart Rate, and Tumeke data metrics were used as the basis of the clustering algorithm. The clustering was done three separate times, once for each body part (shoulder, leg, back). All of the user data entries for each body part were clustered into three distinct clusters, with each cluster representing a different level of support (Low, Medium, High). The number of instances of each wearable in each cluster was noted down, with the results listed in Table 4. The back and leg wearables had three distinct clusters, with the average metrics in each cluster clearly indicating three different levels of support, namely Low, Medium, and High support. The shoulder wearables only had 2 distinct clusters based on the average metrics, as two of the three clusters had average metrics that clearly indicated much higher support when compared to the third cluster. Thus, it was clear that shoulder wearables 9 and 10 provided almost equally “Low” support, compared to the “High” support provided by wearable 11.

Table 4: WEKA clustering results

Body Part	Wearable Code	LOW	MEDIUM	HIGH
Back	1	10	3	0
	2	8	5	0
	3	5	6	0
	4	0	3	9
Leg	5	11	0	0
	6	11	1	0
	7	9	1	2
	8	1	2	9
Shoulder	9	11	0	0
	10	13	0	0
	11	0	8	10

The number of instances of each wearable in the different level of support categories was converted to percentages. These percentages were used to calculate a final level of support index for each wearable, which in turn was used to classify each wearable in a single level of support category of Low, Medium, or High. These results are outlined in Table 5, along with the price of each wearable.

Table 5: Classification of wearables

Body Part	Wearable Code	Percentage of Occurrences			Level of Support Index	Classification	Price $
		Low %	Med %	High %			
Back	1	77	23	0	1.23	LOW	31
	2	62	38	0	1.38	LOW	50
	3	45	55	0	1.55	MED	146
	4	0	25	75	2.75	HIGH	423
Leg	5	100	0	0	1.00	LOW	32
	6	92	8	0	1.08	LOW	100
	7	75	8	17	1.42	MED	216
	8	8	17	75	2.67	HIGH	112
Shoulder	9	100	0	0	1.00	LOW	29
	10	100	0	0	1.00	LOW	48
	11	0	0	100	3.00	HIGH	1,999

The cost of the wearables versus the level of support provided by the wearable was compared for each body part by plotting the cost of each wearable against its previously calculated level of support value. A strong positive correlation was found for the shoulder and back wearables, with the level of support increasing as the cost of the wearable increased. R-squared values for the shoulder and back wearables were close to 1. For the leg wearables, a positive correlation also existed, albeit weaker, with a low R-squared value. This was due to the High-support leg wearable being less costly than the Medium-support wearable. The graph in Figure 3 compiles all wearables for all body parts and displays cost versus level of support.

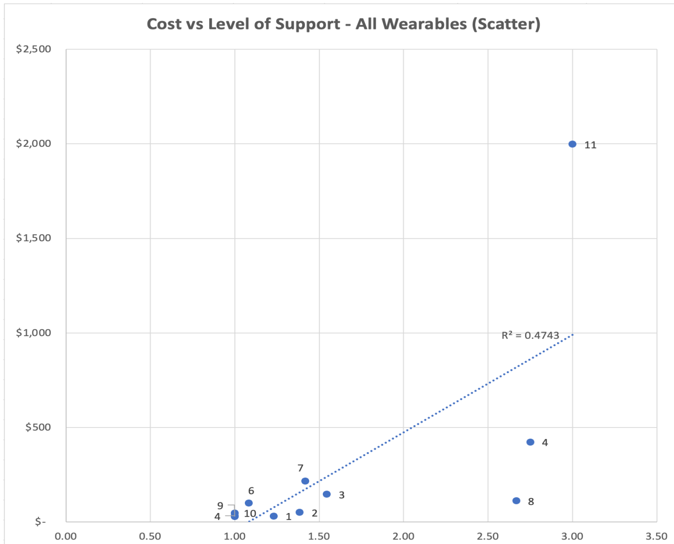


Figure 3: Cost of wearables versus level of support provided by the wearables

5. PREDICTING USER REQUIRED LEVEL OF SUPPORT

Following the classification of wearables into Low, Medium, and High support categories, a WEKA-based model was developed to predict the level of support that individual users required based on their physical characteristics and capabilities. The predicted Required Level of Support for each user would then inform the selection of the best-suited wearable level of support to assign that user. For example, if a user is predicted to require a “High” level of support for their shoulder, they would require a shoulder wearable that provides “High” support (in this example, wearable 11). The end goal is to understand which wearable(s) should be recommended to each user to best fit their specific needs while optimizing cost. Based on the previous findings, as the level of support of the wearable increases, the cost of the wearable also increases. Thus, if a user only requires a “Low” level of support, they will save cost by selecting a “Low” support wearable in lieu of a higher support wearable. To this end, an artificial neural network (ANN) model was developed and trained using the collected user data. This model was developed using the Multilayer Perceptron tool on the WEKA software. The neural network, shown in Figure 4, included the following inputs: Height, Weight, Age, Gender, Heart Rate (Before and After exercise), Heart Rate Change, Count Until Fatigue, Tumeke Index, and an Overall Health Score.

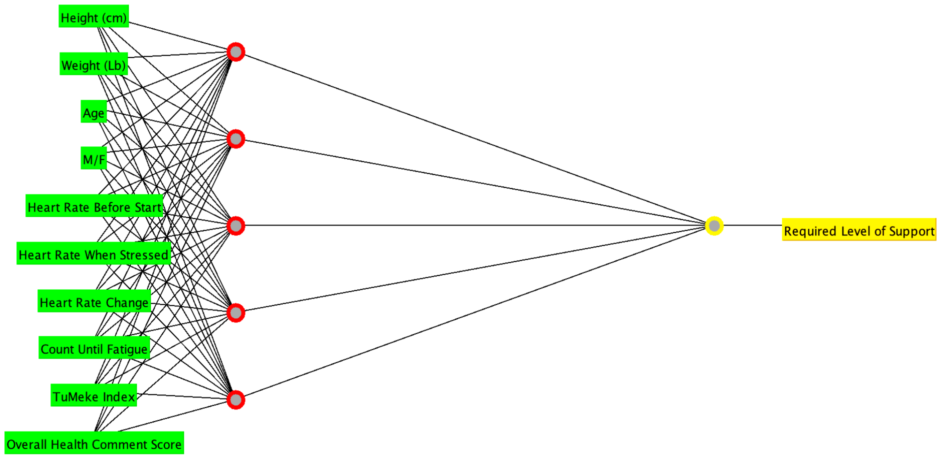


Figure 4: ANN model to predict required level of support

A total of three individual ANN models were developed, one for each assessed body part (shoulder, back, leg). The models were each run at a 66% split between training and test data (i.e. 66% of user entries were used to train the model, and 33% of entries were used to test the model). The models would then predict the required level of support to the nearest hundredth decimal place. Each value was then rounded to the nearest integer to provide the final required level of support for that test case. For the back and leg models, the models were 83% accurate (5 out of 6 test instances were correct), while the shoulder model was 67% accurate (4 out of 6 test instances were correct). Figure 5 displays the WEKA results for the Back.

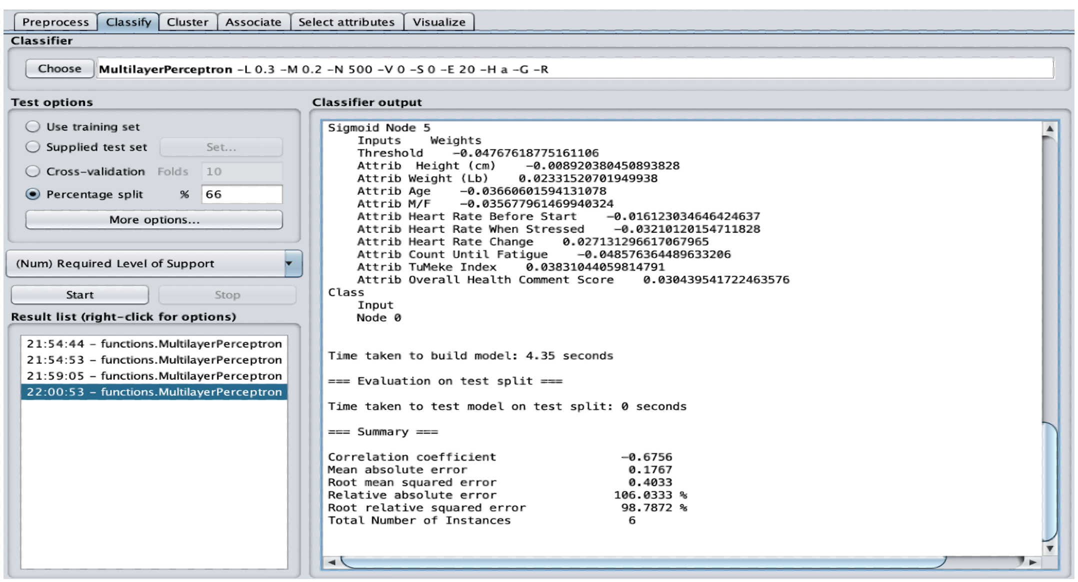


Figure 5: Results of test instances for Back ANN

6. DISCUSSION

This study demonstrates an effective methodology to evaluate wearable performance in various construction activities by simulating construction tasks while using the wearables and using the collected data to classify the wearables using machine learning clustering analysis. The results of this study demonstrate that low-cost wearable devices can provide varying degrees of support in reducing musculoskeletal stress among mechanical and electrical construction workers. The classification of wearables based on support level (low, medium, and high) indicates that while all tested devices offered some degree of assistance, their efficacy differed significantly depending on their design and cost. More expensive and complex devices generally provided greater support, highlighting the trade-off between affordability and performance. A key finding is the strong correlation between wearable price and support level, particularly for back and shoulder wearables, where higher-cost devices exhibited significantly better performance. However, this trend was less pronounced for leg support devices, suggesting that cost alone is not always a definitive indicator of efficacy. Given that not all users require the same level of support for the same task, it is important to be able to predict what level of support each user requires for a specific task given their physical capabilities and characteristics. This would enable cost efficiency when selecting the wearables required by users.

The development of a predictive model using artificial neural networks (ANNs) further underscores the potential of data-driven approaches in optimizing wearable selection. The model demonstrated an accuracy of 67-83% in predicting the required level of support for individual workers based on their physical characteristics and capabilities. This suggests that wearables can be personalized to each worker's specific needs, ensuring both cost efficiency and improved ergonomic support. Despite these promising results, a limitation of this study is the relatively small sample size of participants. Expanding the dataset significantly in both size and diversity is essential to enhancing the model's generalizability and facilitate its use in practical settings. It would also be ideal to eliminate the Count to Fatigue and Heart Rate inputs from the model, instead relying on the user's physical attributes and health history as the primary inputs. This would eliminate the need for any physical testing and substantially improve ease of use in real-world applications. However, additional studies with a significantly expanded dataset would be required to determine the feasibility of this. Additionally, incorporating task type as an input to the model would broaden the application of the model and enable it to finetune the required level of support based on the physical demands of specific tasks (for example, drilling directly overhead would require more shoulder support than drilling at shoulder height level). This would require additional data collection to expand the pool of available data and enable the model to detect and learn new patterns.

7. CONCLUSIONS AND FUTURE WORK

This paper evaluates the efficacy of various low-cost wearable devices in reducing physical stress on the back, legs, and shoulders. These three body parts were found to be most commonly affected by musculoskeletal disorders (MSDs) in mechanical and electrical construction work. The findings indicate that while wearables offer meaningful support, their efficacy varies based on task type and the physical characteristics of workers. Additionally, the wearable devices provided varying levels of support, with more expensive and complex devices generally providing higher support. A neural network model was developed to estimate the required level of support for users, revealing that wearable selection should be tailored to workers' physical characteristics and needs to maximize the benefits. To enhance the model's accuracy and applicability, future research will expand testing to include a broader range of age groups and significantly increase the dataset size. Field testing will also be conducted to assess wearables under real-world conditions, where environmental factors may impact their effectiveness. Additionally, a wider variety of tasks with different durations will be examined to evaluate how wearables perform across diverse job demands and worker positions. This will assist in optimizing the selection of wearables for practical and cost efficiencies based on worker needs and budget constraints. This optimization will in turn ensure a practical and sustainable means of supporting workers and reducing injuries, which will also provide the added benefits of improved productivity in the industry and reduced costs due to injury claims.

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