

Effects of Demographic Factors for Fatigue Detection in Manufacturing

Arsalan Lambay*, Ying Liu**, Ze Ji**, Phillip Morgan***

*Cardiff University, Cardiff, United Kingdom (e-mail: lambaya@cardiff.ac.uk).

** School of Engineering, Cardiff University, Cardiff, United Kingdom

(e-mail: liuy81@cardiff.ac.uk). *** (e-mail: jiz1@cardiff.ac.uk).

*** School of Psychology, Cardiff University, Cardiff, United Kingdom (e-mail: morganphil@cardiff.ac.uk).

Abstract: Over the years, advancement in automation technology is allowed the increased integration of humans and machines in a manufacturing environment, these days fewer humans. The use of Knowledge-based Systems in improving and converting human overall performance has been restrained in truth because of a lack of expertise of the way an individual's overall performance deteriorates with fatigue buildup, which may range from employees to the work environment. As a result, the performance benefits of increased automation in a manufacturing environment, as well as the impact of human factors, must be taken into account. To predict fatigue in physically demanding tasks, this study takes a data-driven strategy. The influence of demographic characteristics, their physical fatigue states, detected workloads, and reactivity to physiological changes are investigated through sensors (Inertial Measurement Unit; IMU and Heart Rate Variability; HRV) in this paper. A framework is established for the selection of key features, machine learning algorithms, and evaluating subjective measures. To attain that, specific application scenarios of the framework are shown, each for different sorts of manufacturing-related tasks.

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1. INTRODUCTION

The advancements in automation, computer, information, sensing, and knowledge engineering systems are changing the landscape of employment and workplaces at an unprecedented rate. Significant technological automation has increased the usage of robotic systems in manufacturing and warehousing. (Lu L., Megahed, Sesek, & Cavuoto, 2017). Nevertheless, each operator may be seen as an integral component of modern industrial systems from this vantage point. However, over the years, in terms of industrial context, the process/product quality has been given more emphasis rather than the influence of human operators. A research article by (Kolus, Wells, & Neumann, 2018) uncovered several empirical studies on the impact of human factors (HF) in manufacturing processes on system quality performance, they state that quality inadequacies were linked with poor human effects of workload such as fatigue and injury-related risk factors. The researchers write, forty-six per cent of studies reported on efforts to improve HF in operations systems for quality improvements.

Fatigue has been one of the major contributors to the cause of quality inefficiency and accidents. Fatigue in the workplace is a multifaceted concept that reduces a worker's performance. It is caused by repetitive and everyday physical activities and is linked to psychological, economical, and environmental variables (Barker & Nussbaum, 2011). Fatigue must be handled from the standpoint of occupational health and safety since it has substantial short- and long-term consequences. Physical fatigue is defined as a decrease in capacity to

complete a physical task as a result of previous physical activity (Gawron, French, & Funke, 2001). Physical fatigue may be especially dangerous in production situations since it can induce pain, impaired motor control, and a decreased strength capacity in the short term. The consequences may result in decreased performance, decreased productivity, deficiencies in job quality, and an increase in the number of accidents and human mistakes. Physical exhaustion can also have long-term negative health consequences, such as chronic fatigue syndrome and decreased immunological function (Kajimoto, 2008). (Yung, 2016) his report states “These consequences have been linked to future illness and mortality, job disability, occupational accidents, increased absenteeism, unemployment, lower quality of life, and disruptions in social connections and activities.” The aforementioned effects of fatigue are not similar in every individual and differ from person to person due to its multidimensional nature. Several works of the literature suggest that the causes of fatigue range from (1) lack of sleep attributed to weariness (Shen, Barbera, & Shapiro, 2006) (2) mental fatigue as defined by Van der Linden (Linden, Frese, & Meijman, 2003) (3) effects linked to diseases such as cancer, Parkinson's disease, depression, anxiety, and multiple sclerosis (Dittner, Wessely, & Brown, 2004) (4) whole-body fatigue (Davila, et al., 2010) (5) localized muscle fatigue (Chaffin, 1973). The impact of fatigue is not only on an individual's social life but also on the business economy as well (Ricci, Chee, Lorandau, & Berger, 2007), (NSC, 2017). These findings demonstrate that, while our understanding of fatigue and its consequences has improved over time, the problem still looms large.

2. RELATED STUDIES

There are now several ways for evaluating fatigue, which may be roughly classified into an objective and subjective evaluation (Balasubramanian, 2021). Objective fatigue evaluation tries to measure the quantitative consequences of exhaustion, whereas subjective fatigue assessment aims to capture the qualitative impacts that reflect the individual's viewpoint of the event.

2.1 *Qualitative Fatigue Analysis*

The questionnaire-based analysis is subjective in nature, with a self-report approach for assessing an individual's discomfort. These place a premium on the workers' emotions. Wiktorin et al. established a technique for assessing worker fatigue that included questionnaires and interviews (Wiktorin, Karlqvist, & Winkel, 1993). To evaluate human fatigue, the Swedish Occupational Fatigue Inventory (SOFI) uses a similar principle and takes into consideration five major factors: lack of desire, bodily pain, physical exertion, drowsiness, and energy/effort (Ahsberg & Gamberale, 1998). The 'Fatigue Scale for Motor and Cognition' (FSMC) is the most recent self-administered questionnaire method for distinguishing between motor and cognitive fatigue (Calabrese, et al., 2009). These approaches take feeling into consideration, but they lack quick results and are limited to intermittent recording techniques, which are not helpful in real-time. The most frequently adopted and utilized is the 'Perceived Rating Exertion' scale, a tool used to quantify Muscle Fatigue, often known as the 'Borg Test' (Borg, 2004). Fatigue is determined by an individual's self-perceived assessment, which varies from person to person. Some of the alternative methods are by assessing the posture of the operator. In 1999, three posture-based analysis tools were developed: 'Posturegram,' 'Ovako Working Posture Analyzing System (OWAS)' as well as 'Quick Exposure Check' (Li & Buckle, 1999). However, these tools focused only on posture. Some focusing on musculoskeletal stress of hand movement coordination are 'Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), 'Hand-Arm-Movement Analysis' (HAMA), and 'PLIBEL (Stanton, N, Hedge A, Brookhuis K, Salas E, & Hendricks, 2004). These approaches were restricted to posture analysis and were not specific in diagnosing fatigue state. Alternatively, Williams and Rogers developed 'Muscle Fatigue Analysis' (MFA), which uses a similar premise but focuses on fatigue analysis (Rodgers, 2005). Overall the subjective measures have advantages of accurate fatigue predictions but have numerous disadvantages including use in real-time and are restricted to lab-based, and also did not consider different demographics of a person.

2.2 *Quantifiable Fatigue Analysis*

As the name suggests, this type of analysis is data-driven via the use of sensors to collect metabolic changes about the body. These variations are observed by the sensor, and a machine learning system is utilized to identify an individual's fatigue level. EMG sensors, often known as electromyography, are the most commonly utilized. EMG records the electrical activity (pulse) generated by the central nervous system (motor units) under the skin. Isa et al. conducted a study in 2014 to

investigate muscular fatigue in a manual material handling activity. Similarly, the Principal component analysis classification approach was applied to analyze upper arm fatigue using a fusion of EMG and 3D accelerometer (Brown, Bichler, Fiedler, & Alt, 2016). Various approaches, including force plate sensors, motion capture cameras, and behavioural analysis, were also employed. To get better results, motion capture is sometimes paired with other invasive sensors and a machine learning system. (Kider, Pollock, & Safonova, 2011). This method is used in driver fatigue assessment. Pradip et al. used force sensors to estimate fatigue as an alternative and used the CUSUM algorithm. Force sensors in plates were utilized to measure ground and foot response forces. The disadvantage was that a large number of plates were necessary since a person moves in a straight continuous way, making it difficult for modelling to integrate successive plates. Alternative approaches for predicting fatigue includes using behavioural characteristics such as keyboard dynamics, gait, and so on. Such as wearable sensors, which are less intrusive and may be worn while working while causing less discomfort. Inertial Measurement Unit is a well-known example of wearable (IMU). It evaluates an individual's gait parameters to anticipate the onset of fatigue (Maman, et al., 2020). Although, It does not predict localized muscle fatigue which can be one of contributing reasons for fatigue. Objective analysis literature provides different machine learning models but does not include how many sensors are to be used and how demographics affect the results.

2.3 *Demographic Characteristic Variables*

A significant number of studies have been conducted to investigate the function of fatigue in connection to chosen traditional demographic factors. There are not many pieces of research that have looked at the impact of a big variety of demographic variables at the same time, such as socioeconomic status, circadian cycle, and so on. (Milia, et al., 2011). Although the majority of the research examined in terms of driving accidents indicates correlations between an individual's demographic characteristics and tiredness, sleep length, and quality of work, they are far from conclusive in essence to how they affect when all taken into account. Normally, these studies fail to investigate the influence and weighting of each demographic variable on the dependent variable in the same research population. The research samples are lab-based samples that may not be appropriately representative of the population. (Milia, et al., 2011). As a result, in many cases, the literature is simply suggestive of methodological flaws, limiting one's capacity to be conclusive.

The differences in the kind of job done, degree of supervision, depth of training to work obligations, and specific socio-demographic characteristics between men and women confound knowledge of the association between sex and fatigue. Females from low socioeconomic positions were 1.4 times more likely to complain of fatigue than females from other socioeconomic strata, according to a study of 1180 Swedish employees. This link was not apparent in males. Within that study, the existence of kids at home was not taken into consideration of the impact on female employees' fatigue. (Fjell, Alexanderson, Nordenmark, & Bildt, 2008). Several

studies consider sleep as one of the major contributors to fatigue feeling in individuals. Alternatively, the shift pattern is affected. Gender differences in 'total' working hours were compared in research. Women worked significantly more domestic hours per week than men, even though males worked more hours per week. Although logistic regression could not classify between gender differences in the total work-hours worked effectively. However, there was a link between total hours worked per week and lower work capacity in women. Although some research suggests that women take longer to recover from shiftwork than men, the difference is minor (Milia, et al., 2011) However, it's unclear if the disparity is truly sex-related, given women are more likely than men to sense and admit fatigue.

Age is also a widely researched demographic variable in many industrialized nations. Although fatigue is an issue for all ages of employees, it is more in the elderly. However, there is no set age for getting fatigued, but it is believed that the human body starts to get more fatigued as age increases. Most studies simply include age as a sequential variable. The dynamic interplay of an individual's cognitive and emotional resources (e.g., health, motivation), workplace (e.g., workload, work schedules), and social mores are characterised as job ability. (Milia, et al., 2011). The aforementioned causes show that age and fatigue are related. However, numerous studies contain methodological flaws that make it difficult to draw definitive conclusions about cause and effect, and because the association between age and fatigue can be altered by a range of factors. Overall, it is not clear how different demographics will affect a manufacturing environment.

3. METHODOLOGY

3.1 Human Fatigue Modelling

As mentioned in section 1, many researchers have suggested the nature of fatigue is to be multifaced, sensation based according to an individual's perspective. In order to detect the onset of fatigue, machine learning models are used to classify between fatigue vs non-fatigued. Several authors suggest the amalgamation of multiple sensors. However, we argue whether we require multiple sensors for the detection of the onset of fatigue and which machine learning model works the best with different sensors. In order to find out, this study includes two stages in which hypothesized. 1) how do different machine learning models work with different sensors, i.e., how accurately can it detect the onset of fatigue with lesser sensors? How significant would it be to detect fatigue using one sensor (H2)? Stage one includes using different binary classifiers to classify between fatigue vs non-fatigued. Stage two includes using the results of classification and analyzing them to understand the significance of using one sensor. Figure one depicts the framework that has been proposed. To evaluate fatigue, a physical exertion job, such as manual material handling, is undertaken. This activity requires the user to perform a physically tiring task that includes pushing and pulling, picking up, bending, and walking. These tasks comprise the most commonly undertaken work in the manufacturing environment. This task involves repetitive actions and exertion of physical force. As the task progresses,

an individual's gait changes due to the onset of fatigue. This can be captured via the use of sensors.

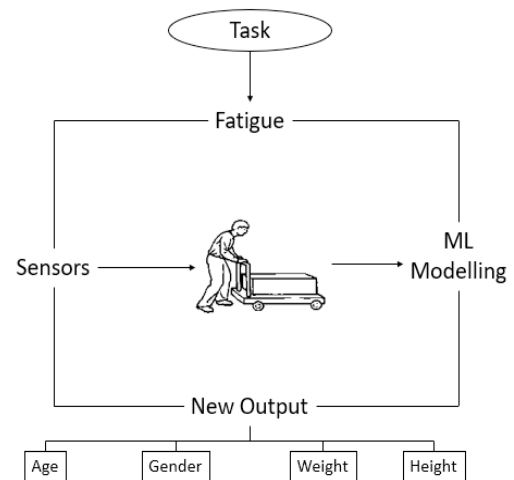


Figure 1 Framework of the impact of demographic variables.

The data for fatigue prediction comes from sensors that are connected to five different body locations and provide real-time data depending on physical activity. Wrist, Torso, Hip, Ankle and Heart Rate are the five components. These five body locations are the most affected due to the onset of fatigue. After that, the data is preprocessed to remove any missing/null values. As demonstrated in the framework, all of the data, including acceleration, jerk, and gait factors (step duration, step length, and so on), are combined with the demographics and anthropometric information of the people. This data collection is further separated into two parts: training and testing. To distinguish between fatigue and non-fatigued, the data is evaluated using a binary classifier machine learning model. Furthermore, it was established how many sensors are required to distinguish between fatigue and non-fatigued after categorising and analysing the machine learning model. Initially, in the framework, all five sensors were used to classify between fatigue vs non-fatigued. Then, with each iteration, a combination of four sensors was used, with one sensor being left out. Similarly, three sensors were used, with each iteration including a mixture of two sensors that were not part of the experiment. Analysis was then carried out employing a combination of two sensor data sets. Finally, only one sensor was employed. The classifier's output will be analysed further using statistical significance testing to determine the number of sensors necessary for fatigue prediction.

3.2 Demographic Characteristic Analysis

Through the construction of various machine learning models, it will help to classify between fatigue vs non-fatigued. However, as mentioned in section 2.3 many demographic variables are not considered during occupational fatigue. Demographic characteristic variables such as gender and age, which play a significant role in the onset of fatigue, does not show how the parameters change over time while sensors are used. Several anthropometric demographics of an individual such as weight, height, etc are not considered while predicting

fatigue. Furthermore, there is less evidence of how this will affect the onset of fatigue. For example weight, obesity is one of the causes of fatigue which could change the perception of individual fatigue. These parameters are not considered and their significance is not evaluated. In this section, we evaluate the significance of how different demographic variables have an impact on the onset of fatigue(H2). How does the perceived rating of an individual change with respect to the changes in the input sensor data(H3). Hence, we use exploratory statistical data analysis for examining the different demographic characteristics and how they affect an occupational task. It included significance testing to understand how significant are age, gender, weight, height, and body mass index in the onset of fatigue.

4. PRELIMINARY STUDY

4.1 Data Set Construction

The participant wore an Inertial Measurement Unit (IMU). Throughout the exercise, the IMU collected data at a rate of 51.2 Hz. A total of 4 IMU sensors were used which were placed at the wrist, hip, torso, and ankle. Additionally, a heart rate monitor (HR) was used throughout the experiment and was placed on the chest via an elastic strap belt. The study was completed by a group of 14 people. The individuals' average and standard deviation ages were 37.6 (16.7) years, the weight of 74.2 (14.4) kg, and height 170.8 (9.2) cm. There were seven men and seven women among the participants. These participants were a mix of students with prior experience performing manual activities and local employees, as is common in much ergonomic research (Baghdadi, et al., 2021) The task involved was a manual material handling activity. The task was divided into three stages; a) Picking up the weights(Boxes), b) Loading the weights onto a trolley and c) pulling the weights along the pathway and repeating it. The entire duration of the task lasted 180 mins without any breaks. In between the task, the participants gave their rating of perceived exertions (RPE) which was designed according to the Borg test.

4.2 Experiment

Machine Learning models are employed to classify between fatigue state vs non-fatigued state to the sensory data acquired by participants. This helps to understand the state of the participants from the sensors employed. There were seven models used to classify. They are a) Decision Tree (DT) b) Random Forest (RF) c) Gradient Boosting (GB) d) Naive Bayes (NB) e) K-Nearest Neighbor (KNN) f) Logistic Regression (LR) g) Support vector machine (SVM). These seven models are used to classify because it was used and recommended in many pieces of literature (Rescio, Leone, & Siciliano, 2018) (Maman, et al., 2020). Additionally, these classifiers are known for handling sporadic datasets and dichotomous outcomes. To evaluate the performance of these machine learning models accuracy metrics were used. This score may be used by us to assess if the model is equally capable of predicting fatigued and non-fatigued states.

4.3 Statistical Analysis.

Statistical significance was evaluated on all dependent responses using separate repeated-measures analysis of variance (RM ANOVA), with significance stated $\alpha = 0.05$ and marginal significance 0.5. (i.e. $0.05 < \alpha < 0.01$). A single-factor analysis of variance test was run to understand the significance of using only one sensor, i.e. to check whether the hypothesis mentioned in the above section (3.1) was true and had significant evidence. Secondly, we hypothesized that demographic characteristic variables (gender, age, height, and weight) had an impact on the sensor-based development for the prediction of fatigue (H2). To evaluate separate RM ANOVA tests were performed to test the effect of all the independent variables of the demographic characteristic. This helped to understand the impact of demographic characteristic variables on the prediction of fatigue. Thirdly linear regression analysis was performed to understand how the subjective fatigue rating changes to sensor-based changes.

4.4 Human Fatigue Model Performance

Table 1 shows the results for the machine learning model performed on the fatigue data sets. This showed that the Torso sensor worked out to be the best when employed with the Random Forest algorithm compared to the rest of them.

Table 1. One Sensor Used

Sensors Used	DT	RF	GB	NB	KNN	LR	SVM
TORSO	0.65	0.91	0.79	0.80	0.80	0.80	0.69
ANKLE	0.60	0.75	0.81	0.51	0.65	0.56	0.54
HIP	0.69	0.85	0.82	0.64	0.86	0.66	0.65
WRIST	0.69	0.69	0.65	0.67	0.69	0.75	0.71

Table 2. All 5 Sensor Used

LR	DT	RF	GB	NB	KNN	SVM
0.814	0.851	0.957	0.925	0.740	0.814	0.754

Similarly, when a combination of two sensors was used, the ankle and hip sensor gave the best results by achieving the highest accuracy of 0.95 followed by torso and hip, which gave the accuracy of 0.94. The algorithm used for these results was Random Forest. Additionally, ankle and hip combined sensors also performed well with the Gradient Boosting algorithm by achieving an accuracy of 0.92. The results for the combination of three and four sensors also gave a similar result, with the best combinations of the wrist, hip, and torso and ankle, hip, wrist, and torso respectively. Lastly when all five sensors were used RF and GB performed the best as shown in table 2. However, the results of the single factor ANOVA test showed that there was no significant evidence of using only one sensor. The ‘p-value’ was 0.081 compared to α 0.05. This proves that only one sensor cannot be used to predict fatigue.

4.5 Impact of Demographic Characteristic Variables

The demographic characteristic variables showed a significant impact on the development of fatigue during the activity. The p-value showed an impact of 0.0475 as compared to α of 0.05 i.e., $0.0475 < 0.05$. This showed that as the demographic variable of an individual changes the fatigue level changes as well. It was observed that females get more fatigue as compared to males in the manual material handling activity. The graph images below show the difference in the fatigue level.

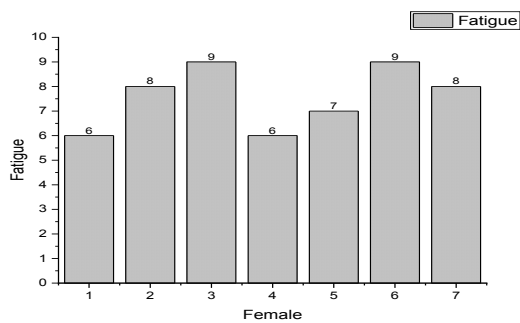


Figure 2 Fatigue level in female participants.

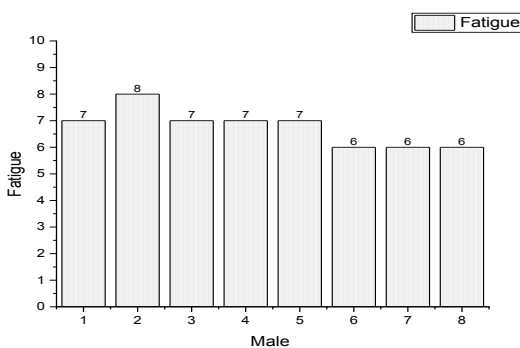


Figure 3 Fatigue level in male participants.

However, the graph above shows that the age group between 20 to 30 displayed higher fatigue as compared to the other cluster of age groups.

4.3 Subjective Responses

Linear regression analysis was performed to understand how the subjective fatigue rating (RPE) changes concerning sensor-based changes. Additionally, it shows how individual gait characteristics change over the duration of the activity concerning the individual's subjective rating. As fatigue is sensation-based and it purely depends on how an individual feels this impacts its gait characteristics as well. This shows that with every increase in the subjective fatigue rating the impact on the work and the gait characteristic increase which can cause less efficiency in work. The linear regression analysis showed that the coefficient linear relationship of the average step time and the number of steps taken has a negative value of -0.401 and -0.0268 respectively. This shows that as the fatigue increases the time taken to complete the steps and the number of steps decreases. This eventually will affect the time taken to complete the task and will have decreased

efficiency. However, the coefficient of linear regression analysis for the distance of step is a positive value, which is 4.026. This shows that as the fatigue increase during the activity the person tends to increase the distance between its steps. Thus taken larger steps during the task as the fatigue increases. This shows that it has an increase in its fatigue level and the step distance taken. Furthermore, the leg rotational velocity and the leg rotational position also have negative value which is -0.021 and -0.641. This has an impact on the velocity generated by the leg for walking decrease as the fatigue increases. Thus, the individual will take more time to come to the task as the work progress and also impact his fatigue level. In addition to that, the mean foot oscillation also shows an increase as the fatigue increases. In essence, the changes in the sensor from the hip it has a consequential impact on the individual subjective fatigue rating.

5. DISCUSSION

In this study, data from 5 sensors (4 X IMU and 1 HR) from a manual material handling task was investigated for three main studies: a) Which machine learning model performs the best for binary classification and how many sensors are required to classify a fatigued and a non-fatigued state of an individual b) how the demographic characteristic variables of an individual impact the fatigue prediction and c) how does an individual subjective fatigue rating changes to the sensor-based changes and the gait parameter of the individual. Furthermore, how does it impact the work and fatigue state of the individual. The key takeaways for this study: Fatigue classification cannot be carried out through one sensor as the evidence shows through the ANOVA testing and as stated in (Maman, et al., 2020) that only one sensor is enough to detect fatigue. However, the results from it are just marginally above the threshold i.e. the p-value compared to α , and thus cannot be substantial to predict the level of fatigue state an individual in complex tasks.

The demographic characteristic variables such as gender, age, weight, and height directly impact the amount of fatigue induced during physical activity. It is observed that females get more fatigue as compared to the male participants. The younger age group (20-25) of people are more fatigued during the activity as compared to the people from the higher age group, this may be due to lesser experience. A year of experience was not considered. The subjective fatigue rating of an individual showed the changes in the gait and sensor-based changes on an individual. Such as, when the fatigue-induced increase as the duration of the task increases the gait parameters change as well. Like the walking speed and the velocity of the leg, rotation is impacted when fatigued i.e. the velocity and the average step time decrease. This can impact the efficiency of the task to be completed.

6. CONCLUSIONS

The current study was designed to examine how different demographic variables affect fatigue prediction. Additionally, we examined if only one sensor could be used to classify between fatigue vs non-fatigued state. Lastly, how subjective fatigue rating changes as per the changes in the sensor data. There were seven machine learning algorithms employed to perform a binary classification among which Random Forest

and Gradient Boosting achieved the highest accuracy of over 90 %. Followed by which ANOVA testing was carried out, which showed that it is not significant to use only one sensor, and fail to reject the null hypothesis(H1). The study also observed that demographic variables have a significant impact on fatigue prediction. It also showed that females are more prone to fatigue as compared to males. The lower age group is more fatigued than the higher age group. This exhibit that demographic variables must be included while predicting fatigue. The limitation of this study must be acknowledged. It considered gender, age, height, and weight. However, these are not the only variables that govern fatigue-induced in an individual. Other socio-demographic variables such as workload, sleep cycle, medical condition, etc into predict fatigue state. As fatigue is sensation-based every individual feels differently and reacts differently. Furthermore, using IMU sensors provide gait information to predict fatigue and thus does not consider localized muscle fatigue which can be important when treating fatigue-related diseases. So amalgamation of different sensors could be used. Lastly, the study was conducted in a lab-based environment, while a real-life manufacturing environment will have different factors such as heat, vibrations, etc which will account for fatigue.

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