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Advancing Safety Surveillance Using Individualized Sensor Technology (ASSIST): Final Progress Report

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Principal Investigator:
Lora Cavuoto, Ph.D.
loracavu@buffalo.edu
(716) 645-4696

Co-Investigator:
Fadel Megahed, Ph.D., Miami University

Department of Industrial & Systems Engineering
School of Engineering and Applied Sciences
Bell Hall, Room 324
University at Buffalo, State University of New York

Project Team

Lead Faculty:

Lora Cavuoto, Ph.D. (PI)
Fadel Megahed, Ph.D. (Co-I)

Graduate Student Assistants:

Zahra Sedighi Maman, Auburn University
Amir Baghdadi, University at Buffalo
Lin Lu, Auburn University

Collaborating Faculty:

Tessa Chen, Ph.D., University of Dayton
Richard Sesek, Ph.D., Auburn University
Allison Jones-Farmer, Ph.D., Miami University
Steve Rigdon, Ph.D., Saint Louis University
Ehsan Esfahani, Ph.D., University at Buffalo
Hongyue Sun, Ph.D., University at Buffalo

Summary of Significant Findings

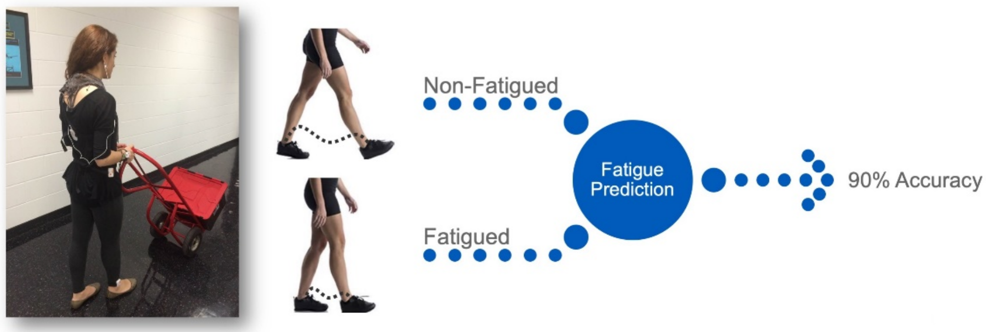
Importance of Fatigue

- Advanced manufacturing has resulted in significant changes on the shop-floor, influencing work demands and the working environment while the corresponding safety-related effects, including fatigue, have not been captured on an industry-wide scale.
- Our survey toward the U.S. manufacturing workers found that 57.9% of respondents indicated that they were somewhat fatigued during the past week.
- Ankles/feet, lower back and eyes were reported to be frequently affected body parts and a lack of sleep, work stress and shift schedule were top selected root causes for fatigue.
- To respond to fatigue when it is present, respondents reported coping by drinking caffeinated drinks, stretching/doing exercises and talking with coworkers.
- Our results from the survey may inform the design of fatigue monitoring and mitigation strategies and future research related to fatigue development.

Use of Sensors for Monitoring Fatigue

- No need for full set of sensors for accurate physical fatigue monitoring in manufacturing tasks.
- Fusing the data from multiple wearable sensors can highly improve the accuracy of movement information estimation for fatigue monitoring.
- The on-body sensor layout for fatigue monitoring can be optimized by sensor fusion techniques.
- Use of heart rate sensor to detect, identify and diagnose physical fatigue for tasks similar to supply insertion.

- Use of torso sensor to detect, identify and diagnose physical fatigue for the manual material handling task.
- Fatigue induced through a simulated MMH task resulted in changes in both the temporal and spatial characteristics of gait kinematics, which is detectable with a single sensor.
- Analytical models are able to detect physical fatigue in multiple occupationally relevant settings.
- This research makes an encouragement to invest in data-driven assessment in the manufacturing sector to prevent occupational injury.
- Prolonged fatigue monitoring is possible using body movement parameters from wearables with the prediction of the fatigue start point and for an individualized intervention.



Fatigue Interventions

- While it has been well-documented that the prevalence of physical fatigue is high in many industries and it has adverse health outcomes, there is limited research on the prescription of interventions.
- Our systematic review presented a total of 23 controlled trials examining 14 physical fatigue interventions.
- Using the PEDro scale to evaluate the methodological quality of the studies, 15 studies were deemed of high quality (and the remaining eight were of low quality).
- Only three interventions (posture variation, chemical supplements and rest-breaks) had strong evidence of efficacy; the remaining 11 had limited to minimal evidence.
- More high-quality randomized controlled trials are needed to examine the effectiveness of the aforementioned 11 interventions in mitigating/reducing physical fatigue.

Recommendations for the Implementation of Wearables in the Workplace

- It is critical to choose the right wearable – both sensor type and wear location – for the industry and problem of interest.
- Provide employees with detailed information on how the data will and will not be used.
- Do not use the wearable sensors for productivity monitoring; limit their application to safety and wellness.
- Work through unions and employee organizations to gain buy-in.
- Provide employees with the option to not share their data or to opt-out of a monitoring program.

- Conduct data collection and monitoring for limited durations and to answer a well-defined question (e.g., at the implementation of a new task or production line) – continuous monitoring is not needed and leaves more room for data misuse.
- Integrate data collection with existing wellness programs where possible to support a Total Worker Health approach – prevents competing efforts for similar data.
- Train users on proper wear and maintenance of the sensors.
- Assess user perceptions pre- and post-introduction of the sensors.

Detailed Description of Project Work and Outcomes

Summary of Methods Employed

The incidence of workplace incidents and injuries can be significantly reduced with the accurate and timely identification of fatigue by quantifying a worker's level of physical and physiological exposure. With advances in technology, sensor systems have begun to be applied in the workplace. Current uses have focused on posture analysis, task classification, fall detection and computerized application of traditional observational tools (e.g., automated checklists).

However, these systems have had limited utility for exposure assessment and safety surveillance. Improved systems and the analysis approaches for interpreting the data are, thus, needed to accurately quantify an individual's level of exposure to determine fatigue and subsequent risk. The long-term goal of this work was to enable the individualized quantification of fatigue and subsequent risk in a manufacturing environment for intervention prescription. The specific objective of this project was to develop a sensor system that quantifies the physical and physiological impact of work, to develop models of fatigue estimation, and to determine appropriate interventions. To achieve this objective, the specific aims were carried out as described below.

Specific Aim 1: Identify the Appropriate Combination of Sensors and On-Body Locations for Optimal, Real-Time Fatigue Monitoring

Survey of Manufacturing Workers on the Prevalence of Fatigue

To survey the prevalence of fatigue, its drivers and individual coping mechanisms among U.S. manufacturing workers, we constructed an online survey. Workers currently employed in manufacturing industries and aged 19 or older were invited to participate. They were recruited through two main channels: a) e-mails sent to over 25 manufacturing company contacts, where we asked them to share the link to our survey to their employees; and b) survey invitation emails that were sent through the membership list of several American Society of Safety Engineers (ASSE; now known as American Society of Safety Professionals or ASSP) listservs. In total, we distributed 38 emails to safety professionals asking their assistance to share our survey with their manufacturing employees.

This survey was designed as a cross-sectional study. To address the research questions, the survey collected data on: a) respondent demographics; b) fatigue-related individual characteristics; c) work-related exposures; d) worker-perceived fatigue causes; e) perceived fatigue level, frequency and interference; f) body parts affected; and g) individual fatigue coping mechanisms. The survey was completed by 451 individuals (i.e., a completion rate of 55.9%).

Survey of Safety Professionals for the Use of Wearables

A custom, electronic survey was developed using the Qualtrics (Provo, UT, USA) survey engine. Questions regarding basic demographic information including age and gender of the respondent, current occupation and industry sector, years worked in current occupation as well as total years in any OSH-related position, highest degree, and current OSH certifications comprised the first part of the survey. Respondents were then asked a series of questions about the types of wearable devices they use at work and away from work. Questions included listing any personal fitness technologies that they owned [make(s) and model(s)], if they wear any of those technologies at work, and describing what they use their personal fitness technologies for at work (if they reported wearing them at work). Respondents were also asked to estimate what percentage of employees at their workplace use wearable sensors at work (although, not necessarily for work purposes).

Finally, respondents were asked a series of questions regarding their perceptions of using wearable devices while at work. Questions included asking if they would be in favor of using wearable technologies at their workplace to track OSH risk factors and ranking the types of risk factors respondents were most interested in capturing at work with a wearable device (among six typical ergonomic risk factors potentially capable of being assessed with wearable technologies). Respondents were also asked if they would be interested in using a "dashboard" display to track group or departmental exposures to physical risk factors as well as to describe the single biggest concern with using wearable sensors at their workplace. The survey concluded with a free response section for respondents to list any additional comments they had regarding wearable devices and/or the survey.

An electronic invitation to the survey was emailed to 28,428 registered members of ASSP and 1,302 professionals certified by the Board of Certification in Professional Ergonomics (BCPE). Of the 28,428 email invitations sent to registered ASSP members, 7,867 (27.7%) of the emails were opened and 996 responses were recorded (12.7% of opened emails, 3.5% of emails sent). Of the 1,316 emails sent to BCPE members, 155 responses were recorded (11.8% of emails sent). It is unknown how many emails distributed to BCPE members were opened. Of the 1,151 survey responses, 952 responses were considered sufficiently complete (i.e., valid) for subsequent analyses. The mean age of the respondents was 48.7 years (SD=12.2) and 70.4% were male.

Experimental Study of the Use of Wearables for Fatigue Monitoring

Twenty-eight participants, 10 females and 18 males, were recruited from the Buffalo, New York, community. Detailed demographic information is presented in Table 1. The study involved healthy adults who reported to have no cardiovascular diseases, metabolic conditions, or musculoskeletal disorders that would interfere with completion of the study procedures. The protocol was approved by the Institutional Review Board at the University at Buffalo, and all participants provided informed consent prior to participation.

Table 1. Participants demographics (mean ± SD)

	Males	Females
N	18	10
Age (years)	38.4 ± 18.5	28.4 ± 9.4
Height (cm)	174.5 ± 7.8	165.9 ± 8.1
Weight (kg)	79.4 ± 13.3	64.0 ± 12.6
Body mass index (BMI; kg/m^2)	26.0 ± 3.4	23.4 ± 5.7

The study was designed as a cross-sectional laboratory study with a one-factor within-subjects design. The designed factor was the physical level of the task at three levels (low, medium, and high) based on postural, biomechanical, and physiological demand. The low-level task included an assembly task completed in a standing position at a workstation, the medium level task involved supply pickup and delivery with sustained back flexion at the delivery point, and the high-level task involved manual materials handling with order picking. These tasks represent the range of tasks performed regularly and repeatedly in complex manufacturing environments (Lu et al., 2017). Picture representing each task are shown in Figures 1 and 2. Each task level was performed in a separate session and the session involved three hours of continuous work. The three-hour period was selected to represent a typical period of continuous work in a manufacturing environment.

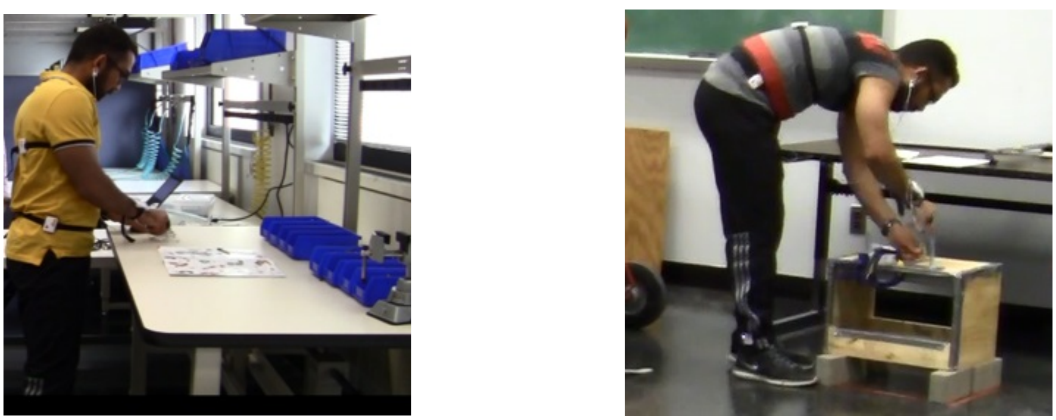
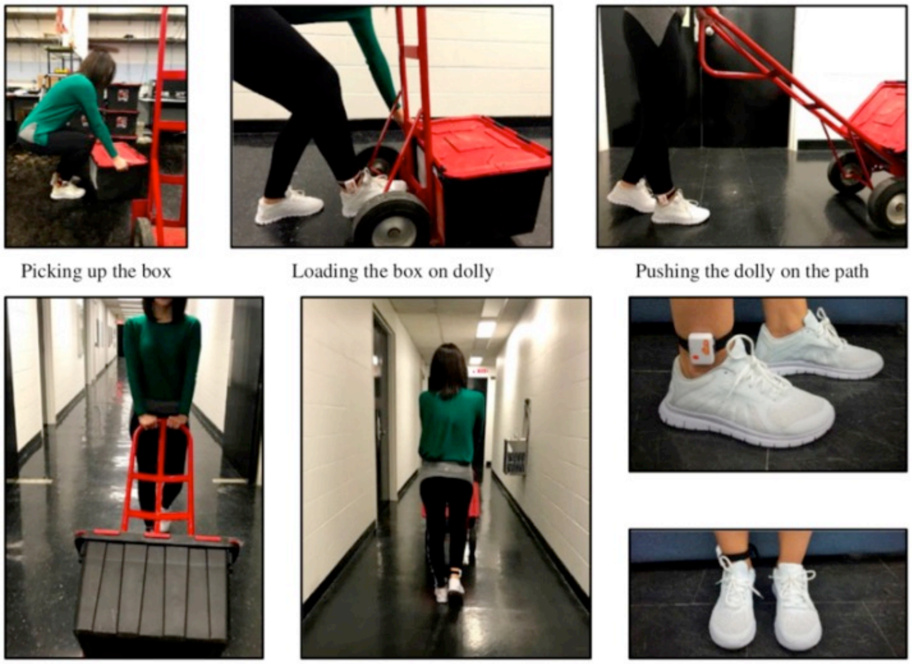


Figure 1. Pictures of the assembly task (left) and the supply pickup and insertion task (right)



Picking up the box | Loading the box on dolly | Pushing the dolly on the path

Pushing the dolly on side 1 of the walkway (front view) | Pushing the dolly on side 2 of the walkway (back view) | The type of footwear and placement of the IMU at the ankle

Figure 2. Pictures representing the manual materials handling task

Each participant was instrumented with four inertial measurement units (IMUs) while performing the tasks. Each IMU was a Shimmer3 (Shimmer, Dublin, Ireland, www.shimmersensing.com), which is small-sized, low-power-using and equipped with wireless transmission capabilities. The sensor contains a low-noise analog accelerometer, a digital wide-range accelerometer and magnetometer, and a digital gyroscope. The acceleration, angular velocity and magnetic field data were recorded at a sampling rate of 51.2 Hz throughout the tasks. Each sensor was oriented with the internal y-axis directed along the segment. The sensors were attached by an elastic strap. A heart rate monitor chest strap was also worn throughout the experiment (Polar CR800X, Polar). Figure 3 below shows the locations of the sensors on the body.

Each three-hour task was divided into three one-hour periods representing a replicated task, with a one-minute rest period between to allow for subjective rating collection. At the start of the session, participants completed a sleep quality questionnaire, a risk-taking behavior task [Balloon Analogue Risk Task (BART)], and a psychomotor vigilance task (using PC-PVT). These measures were used as a baseline of sleepiness and behavior.

In addition, the subject was asked to lay in a supine position to measure resting heart rate. After baseline measurements, the participant was provided with instructions on the relevant fatiguing task for the session. Participants were given target performance levels for each task. Participants provided their subjective rating of perceived exertion using the Borg 6-20 scale every 10 minutes. At the end of each hour, participants completed the NASA-TLX workload assessment. Then, after three-hours of task performance they did the BART and PC-PVT tasks as a postassessment. Table 2 summarizes the average subjective ratings, sleep quality, PVT, and BART assessment results.

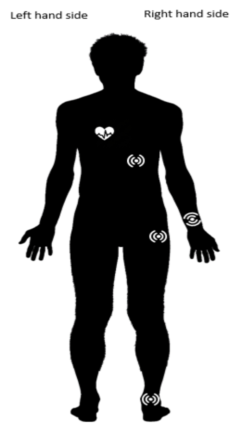


Figure 3. Location of the sensors on the body

Table 2. Average (SD) results at the end of three hours for each task

Task	Reported Sleep Quality	PVT (ms)	ΔPVT (ms)	Final Borg RPE	Fatigue Rating (max 10)	NASA-TLX Mental Demand (max 20)	NASA-TLX Physical Demand (max 20)
Parts Assembly	4.8 (2.7)	279 (74)	-5 (59)	12 (3.1)	5.3 (1.9)	8.8 (5.4)	7.3 (5.0)
Materials Handling	5.0 (2.7)	257 (50)	16 (37)	14.2 (2.6)	6.8 (4.7)	7.0 (4.7)	11.4 (4.9)
Supply Insertion	4.7 (2.6)	270 (51)	10 (43)	14.5 (3)	6.8 (1.5)	5.8 (4.6)	10.7 (5.4)

Specific Aim 2: Model Fatigue Development to Distinguish Between a Worker's Normal (In-Control) State and Fatigued (Out-Of-Control) State

Using the data collected through the experiment described above, a large portion of the effort for the project was dedicated to modeling fatigue development to: detect the presence/absence of fatigue in a participant, and to evaluate whether it was feasible to identify when the individual became fatigued. One main challenge with wearable sensors is the large quantities of data that are now available and that require advanced statistical analysis approaches to make meaningful interpretation of worker behavior from the data.

This aim focused on comparing different approaches for fatigue classification and monitoring. Four main approaches were implemented: 1) regression-based analysis to predict changes in subjective response of the participant as they completed the three tasks, 2) machine learning methods for detecting differences between the non-fatigued and fatigued states based on features defined from the sensor data, 3) template-based matching of the gait cycle for the walking portions of the materials handling task, and 4) change point analysis for gait parameters extracted from each step taken over the three-hour task. For each approach, a consistent series of steps for analysis were performed: 1) data cleaning, where missing/erroneous data were detected, the data from all sensors was synchronized, and all data was sampled to an equivalent frequency; 2) data filtering, to eliminate outliers in the captured sensor signals; and 3) feature extraction of potential predictors of fatigue from the multiple sensors.

For the first method, several penalized regression models were applied to the data. Penalized logistic regression and penalized regression models were used for fatigue detection and development, respectively. For the second method, several single classifier and ensemble machine learning approaches were applied to the materials handling and supply insertion task data separately to determine the best model for fatigue diagnosis.

The third and fourth methods focused on just the gait data from the materials handling task. Gait parameters, including stride length, stride height, duration, velocity, acceleration, and jerk were extracted for each step. For fatigue classification, a series of steps from the start and end of the task were used for analysis. For change point analysis, all steps were segmented from the filtered sensor data and used as input for analysis. The last phase of each method involved model evaluation and testing to showcase the utility of the approach.

Specific Aim 3: Determine the Effect of Individual Worker Interventions by Measuring Work Exposures and Recovery Time to Return to In-Control State

Systematic Review of Intervention Efficacy
Several interventions have been designed to lower the injury risks and lost productivity associated with fatigue. However, as stated in the U.S.'s National Occupational Research Agenda (NORA):

> [The] adoption of these interventions by employers is slow. There is a need to conduct additional intervention research that demonstrates the effectiveness of workplace changes in improving musculoskeletal health across a variety of outcomes, and to understand the facilitators and barriers to adoption of existing interventions by employers. Research to speed the adoption of effective interventions has the potential to dramatically reduce the frequency and severity of MSDs in the workplace. (National Occupational Research Agenda for Musculoskeletal Health, 2018, p. 11)

A first step towards addressing this NORA objective is to first survey and assess the existing literature for workplace interventions that target physical fatigue. There are no published reviews that examine the efficacy of physical fatigue interventions in workplace settings. The overarching objective of this aim is to bring into better focus the literature that focuses on designing, developing and/or implementing interventions that reduce fatigue development and/or improve fatigue recovery. Our approach utilized a standard systematic review of the workplace fatigue intervention literature, focusing on articles that utilized randomized controlled trials (RCT) or controlled clinical trials (CCT). The following three main research questions were examined in this review:

1) What are the characteristics of current workplace physical fatigue intervention studies?
2) What is the methodological quality for each intervention study?
3) What is the strength of evidence for each intervention?

From the systematic review, we aimed to: a) present practitioners with some insight on the effectiveness of examined interventions in the literature; and b) highlight gaps that need to be further studied by researchers.

Two popular databases (PubMed and Google Scholar) were used to identify relevant studies of workplace physical fatigue interventions. The first search was performed in July 2017, limited to articles written in English, and used terms to capture the overlap between three fields: a) interventions; b) health outcomes; and c) workplace. In July 2018, we conducted our second search, where we excluded all terms within the intervention field to expand our search results. Note that we also excluded several non-physical and/or non-workplace terms that occurred in the previous search including: “sleep,” “mental,” “cancer,” “driver,” “patient,” “alarm,” “children” and “compassion.”

For this systematic review, five inclusion criteria were chosen: a) the intervention study was based on a RCT or CCT; b) the interventions were related to occupational settings (whether it is field-based or lab-based studies that mimic occupational tasks/work); c) the study attempted to address physical fatigue; d) the study was published in a journal (we excluded conference proceedings and book chapters since their peer review is often not detailed); and e) we excluded any papers that were not written in English. A breakdown of the search strategy and the included articles is provided in Figure 4.

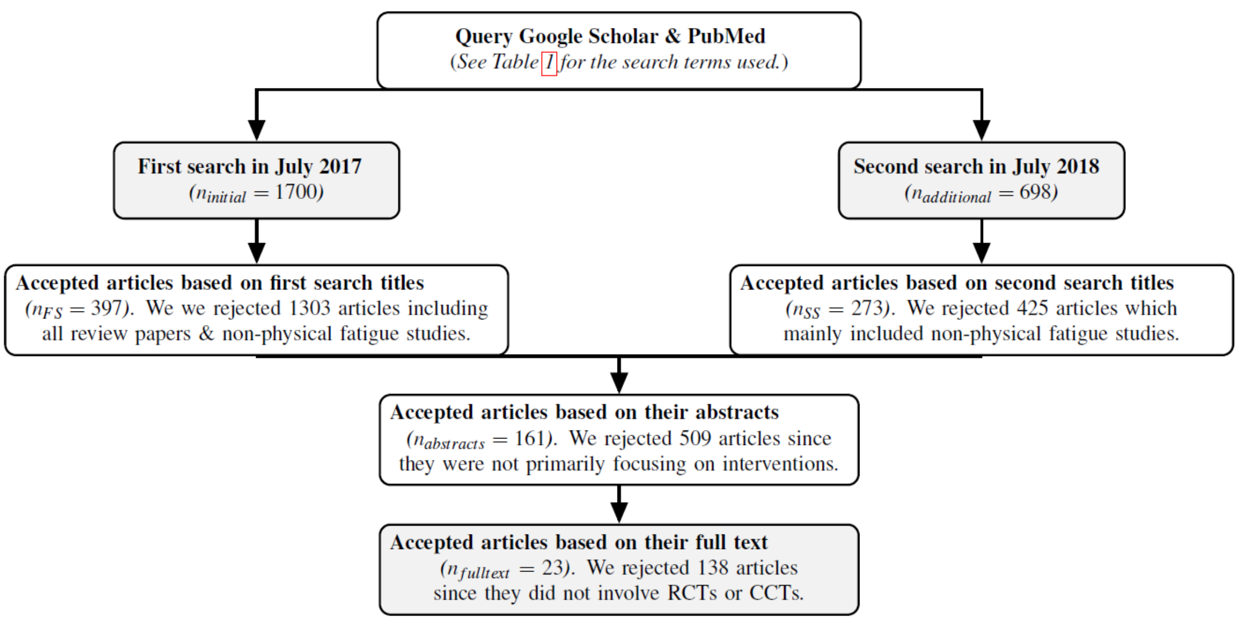


Figure 4. An overview of the sequential procedure for selecting relevant intervention papers

Summary of Research Findings

Over Half of Respondents Would Be in Favor of Using Wearable Technologies to Track Safety Risk Factors

However, overcoming the issue of employee privacy and confidentiality of the data would need to be addressed first. Other barriers for implementation included employee compliance, sensor durability, cost, accuracy of the data, and workplace safety standards around worn items. About half of the safety professionals own a wearable device, with most if them using the wearable for fitness tracking.

Table 3. Responses on favorability of using wearables to track safety risk factors

		Own a Personal Fitness Technology	Wear Their Personal Fitness Technology at Work	In Favor of Using Wearable Technologies at Work to Track OSH Risk Factors
Industry Sector	*N*	*n* (%)	*n* (%)	*n* (%)
Manufacturing	244	122 (50.0)	92 (75.4)	132 (54.1)
Construction	117	47 (40.2)	33 (70.2)	67 (57.3)
Oil, energy, or gas	84	42 (50.0)	30 (71.4)	44 (52.4)
Insurance	81	47 (58.0)	32 (68.1)	40 (49.4)
Academia/research	80	47 (58.8)	39 (83.0)	45 (56.3)
Government	67	27 (40.3)	18 (66.7)	40 (59.7)
Health care	36	20 (55.6)	15 (75.0)	14 (38.9)
Transportation	20	12 (60.0)	10 (83.3)	12 (60.0)
Food processing	20	8 (40.0)	7 (87.5)	8 (40.0)

Note. OSH = occupational safety and health.

Table 4. Risk factor prioritization by industry

Rank	Risk Factor	Average Rank	1		2	
			%	*n*	%	*n*
1	Awkward postures	2.7	22.8	209	28.1	258
2	Forceful exertions	2.8	29.3	269	20.3	186
3	Repetition	3.1	19.2	176	20.0	184
4	Physical fatigue	3.3	15.4	141	16.1	148
5	Mental fatigue	4.2	10.8	99	10.5	96
6	Vibration	4.9	2.6	24	5.0	46

Rank	Risk Factor	Manu-facturing	Health Care	Food Process-ing
1	Awkward postures	2.6	2.1	2.4
2	Forceful exertions	2.6	3.0	2.3
3	Repetition	2.9	2.7	1.8
4	Physical fatigue	3.6	3.6	4.2
5	Mental fatigue	4.6	4.1	5.0
6	Vibration	4.8	5.6	5.3

Rank: 1 = Most Interested; 6 = Least Interested

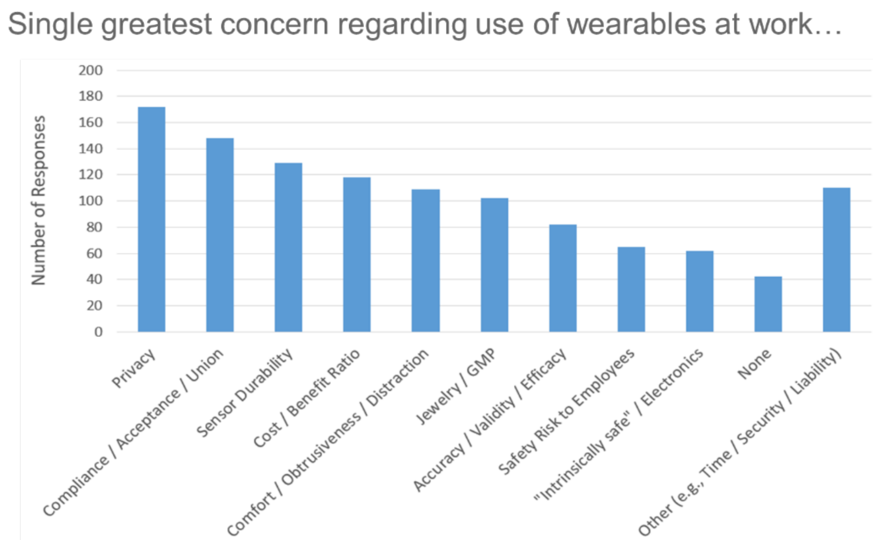


Figure 5. Response on the single greatest concern for the use of wearables at work

As an example, these are some concerns expressed by respondents:

- "I would not want employees to feel their jobs are threatened by not moving correctly or fast enough."
- "We are a very large employer (~5,000 employees at one location). The cost to deploy devices to such a large population would likely be very high compared to relatively low losses."
- "My employees do real life activities with real hazards . . . . I don't want people looking at a device screen while they are engaged in hazardous activities . . . ."

These concerns are valid and need to be addressed before implementing a monitoring program in the workplace.

Movement Patterns Change with Fatigue. These Changes can be Measured Using Wearables. Machine Learning Models can be Used to Better Identify and Diagnose Fatigue.

For the regression and machine learning analysis, a balanced dataset for training was desirable, so only a portion of data from the start (non-fatigued) and end (fatigued) periods were included. As a first step for feature selection, time series plots of all features were constructed to evaluate which features were virtually unchanged from the non-fatigued to fatigued states.

Based on the visualizations, 15 (of the 55 candidate) features were dropped. The second step (where wrapper or embedded methods are used) of feature selection is applied after the training and test samples are generated using the leave p-participants out cross validation approach. Then the last step of variable selection was deployed using two popular methods: best subset selection and LASSO. For our analysis, we used 200 bootstrap samples (each having n = 234).

To develop the fatigue prediction models, several methods were applied during our preliminary analysis of the data. The models evaluated included: logistic regression, penalized logistic regression, decision trees (DT), naive Bayes (NB), k-Nearest Neighbors (kNN), support vector machines (SVM), and three ensemble models (random forest (RF), bagging, and boosting). Due to their relatively poor performance, DT, NB and kNN were eliminated. In addition, models using best subset selection typically had better prediction performance with less features than their LASSO counterparts.

Therefore, our case study focused on using the best subset selection with the following five analytical models: a) logistic regression; b) SVM; c) RF; d) RF with bagging (hereafter bagging); and e) RF with boosting (hereafter boosting). In addition, we compared these five models to the approach of [20] since it was the only paper that considered multiple tasks in the context of occupational fatigue (Table 2).

To ensure that the comparison is fair, we considered two different variants of the penalized logistic regression approach with LASSO. The first is utilizing their approach and features (on our data), and the second involves using their methodology with our features and data. In our estimation, this allows us to better evaluate whether our proposed method is superior to theirs. The reader should note that they did not consider model interpretation in their feature generation and thus we expect that our features are easier to interpret by practitioners.

In Table 5 (below), the predictive performance of our five models is compared with the two variants from our regression analysis. The table shows the mean (and standard deviation in parentheses) for each of our four metrics. In addition, the average number of features selected by each model is also presented. The reported results are based on 105 constructed test datasets from the two-participants-out cross-validation. For the first three numeric columns, a higher value is desired since it reflects a better prediction performance. The consistency column captures the average absolute difference between the sensitivity and specificity for each model, evaluated on the 105 test datasets. It is noted that the smaller the consistency is, the similar performance in detecting fatigued and no-fatigued states simultaneously would be. Moreover, a smaller number of features facilitates the interpretation of the model, which is important in the fatigue identification and diagnosis phases.

Four main observations from the table need to be highlighted.

1) As expected from the preliminary analysis, the number of features selected with the best subset selection are much less than those selected by the LASSO model. This means that the usability of the analytical models with the BSS model is much higher than that with LASSO since practitioners' need to monitor and understand approximately five features (instead of 11 or 19).
2) The the performance of all seven models is relatively high with an overall average accuracy greater than 0.77.
3) The performance of the three ensembles is better than the remaining models.
4) The penalized logistic regression of our prior work outperforms its variant with our features from a prediction perspective. However, this comes at the cost of adding eight features to the model (i.e., ~70% increase in the variables used). Based on these observations and this case study, one can conclude that our framework has shown higher detection performance (with less features) when compared to our regression approach.

The next logical research question is to examine how the prediction performance varies while limiting the number of sensors used. To evaluate this question, we utilize the bagging model since the results showed that it had the lowest consistency and had similar prediction performance to the two other ensembles. Table 6 reports the prediction results, when features are limited to those from one, two, three, four and all sensor combinations. Note that the values that are not shown in the table (e.g. Ankle, Hip, Wrist and HR sensors) reflect scenarios when a prediction was not possible. This means that the main features that detected the fatigue were eliminated with the added constraints on which possible features to select from.

From the results in the table, one can see that the prediction performance does not vary significantly as the number of sensors are changed. For example, the average accuracy varies from 0.850 to 0.871 (with a standard deviation υ 0.09) as the number of sensors vary. This is only true if the torso IMU is included in the analysis. Based on this observation, we recommend only using the torso IMU sensor for detecting fatigue in manual material handling environments (that are similar to those analyzed in our case study). While the prediction performance is almost the same, the costs incurred by the firm are much lower, and the usability of the system by using only one sensor is significantly improved. This is an important practical takeaway, which has not been reported in previous studies investigating fatigue in MMH tasks.

Table 5. Mean performance and corresponding standard deviation of the classification models for fatigue detection for the materials handling task (recommended model is in bold)

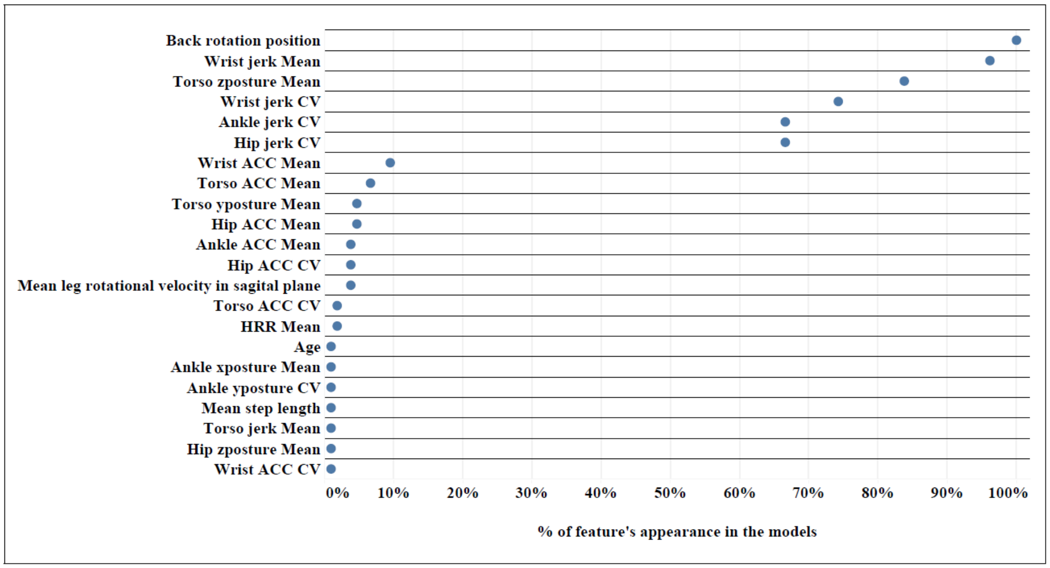
Category	Model	Sensitivity	Specificity	Accuracy	Consistency	# of Features
BSS	**Bagging**	**0.872 (0.13)**	**0.869 (0.15)**	**0.870 (0.09)**	**0.143 (0.17)**	**5.35**
	Boosting	0.871 (0.13)	0.872 (0.15)	0.870 (0.08)	0.147 (0.17)	5.352
	Random Forest	0.879 (0.14)	0.879 (0.15)	0.879 (0.09)	0.152 (0.18)	5.352
	Support Vector Machine	0.811 (0.18)	0.828 (0.17)	0.820 (0.11)	0.198 (0.19)	5.352
	Logistic Regression	0.790 (0.17)	0.766 (0.20)	0.778 (0.11)	0.227 (0.20)	5.352
LASSO	Penalized Logistic Regression*	0.802 (0.20)	0.916 (0.11)	0.859 (0.11)	0.175 (0.20)	18.943
	Penalized Logistic Regression	0.810 (0.13)	0.775 (0.17)	0.793 (0.08)	0.197 (0.16)	11.133

Table 6. Mean performance and the corresponding standard deviation of the Bagging model for fatigue detection using different sensor combinations for the materials handling task

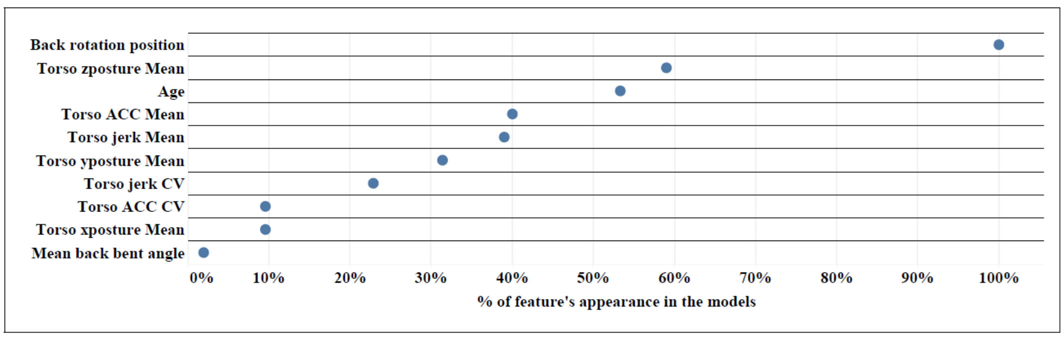
# sensors	Sensor Combination					Sensitivity	Specificity	Accuracy	Consistency
5	Ankle	Hip	Wrist	Torso	HR	0.872 (0.13)	0.869 (0.15)	0.870 (0.09)	0.143 (0.17)
4	Ankle	Hip	Wrist	Torso		0.875 (0.13)	0.868 (0.15)	0.871 (0.09)	0.141 (0.17)
	Ankle	Hip		Torso	HR	0.850 (0.15)	0.875 (0.13)	0.862 (0.09)	0.142 (0.16)
		Hip	Wrist	Torso	HR	0.877 (0.12)	0.863 (0.15)	0.870 (0.08)	0.144 (0.15)
	Ankle		Wrist	Torso	HR	0.872 (0.12)	0.864 (0.15)	0.868 (0.08)	0.146 (0.16)
	Ankle	Hip	Wrist		HR	-	-	-	-
3			Wrist	Torso	HR	0.877 (0.12)	0.864 (0.15)	0.870 (0.08)	0.141 (0.15)
	Ankle			Torso	HR	0.844 (0.15)	0.874 (0.13)	0.859 (0.09)	0.141 (0.16)
	Ankle	Hip		Torso		0.850 (0.15)	0.875 (0.13)	0.862 (0.09)	0.142 (0.16)
		Hip	Wrist	Torso		0.877 (0.12)	0.863 (0.15)	0.870 (0.08)	0.143 (0.16)
		Hip		Torso	HR	0.859 (0.15)	0.874 (0.14)	0.866 (0.10)	0.143 (0.16)
	Ankle		Wrist	Torso		0.873 (0.12)	0.863 (0.15)	0.868 (0.08)	0.145 (0.16)
	Ankle	Hip			HR	-	-	-	-
	Ankle	Hip	Wrist			-	-	-	-
	Ankle		Wrist		HR	-	-	-	-
		Hip	Wrist		HR	-	-	-	-
2			Wrist	Torso		0.877 (0.12)	0.864 (0.15)	0.870 (0.08)	0.141 (0.15)
	Ankle			Torso		0.844 (0.15)	0.874 (0.13)	0.859 (0.09)	0.141 (0.16)
		Hip		Torso		0.859 (0.15)	0.875 (0.14)	0.867 (0.10)	0.143 (0.16)
				Torso	HR	0.842 (0.15)	0.859 (0.14)	0.850 (0.10)	0.144 (0.16)
	Ankle	Hip				-	-	-	-
	Ankle				HR	-	-	-	-
	Ankle		Wrist			-	-	-	-
		Hip	Wrist			-	-	-	-
		Hip			HR	-	-	-	-
			Wrist		HR	-	-	-	-
1				**Torso**		**0.842 (0.15)**	**0.859 (0.14)**	**0.850 (0.10)**	**0.144 (0.16)**
	Ankle					-	-	-	-
		Hip				-	-	-	-
			Wrist			-	-	-	-
					HR	-	-	-	-

A first step in understanding fatigue is to examine how frequently a feature is selected all of the 105 two-participants-out cross validation bagging model test sets. We limited our analysis here to two cases: a) when all five sensors are utilized; and b) when only the torso sensor is used. The results for these analyses are shown in Figure 6, respectively.

From both figures, one can see that all three categories of features (i.e. statistical, biomechanical, and individual features) are selected in our models. For the five-sensor case, one biomechanical feature (mean back rotational position) and five statistical features appeared in more than 65% of the models. All other remaining features appeared in less than 10% of the models. On the other hand, age becomes a much more predictive factor if we only rely on the torso sensor. In that case, back rotational position is still selected in 100% of the models. Once a list of predictive/important features is established, we then investigate how those features vary as the participant transition from the non-fatigued to fatigued states.



(a) using all five of the sensors



(b) using the torso sensor only

Figure 6. Important features visualization in the materials handling task using the Bagging model

From the fatigue identification results, one can conclude that the type of fatigue is localized at the back. This conclusion is supported by: a) the prediction performance is almost unchanged (and high) when only the features from the torso sensor are used for prediction; and b) the mean back rotational position was selected as an important feature in 100% of the models. This was the only feature that was selected in 100% of the models. Our results are consistent with findings in the ergonomics literature, which suggest that manual material handling may lead to a higher prevalence of back injuries.

Based on the case studies, this study makes three main contributions. First, we demonstrated the capability of using a unified modeling approach for managing physical fatigue in different occupational tasks/settings. The case studies show the ability to detect, identify, and diagnose fatigue in multiple occupationally-relevant settings. The ability to identify/diagnose fatigue through the use of wearable sensors has not been shown prior in the literature. Second, the insights from the fatigue identification phase of our framework can be used to inform sensor placement and selection. We demonstrated that the prediction performance using one sensor is equivalent to that of using all sensors for our two case studies. Third, we showed that the importance of different types of features (statistical summaries of the sensors' profiles, biomechanical features, and individual characteristics of workers) varies with different manufacturing tasks. Thus, researchers and practitioners should consider this finding when developing models for detecting/managing fatigue in other production settings.

In our estimation, the proposed framework and the case study findings have significant implications for both production management practice and research. From a practical perspective, we have shown that changes in a worker's physical performance can be detected and modeled using wearable sensors. Utilizing the principles behind the technology adoption model, we have shown that fatigue associated specialized jobs can be detected using one sensor (without a loss in prediction performance). The emphasis on fatigue identification and diagnosis through visual analytical approaches allows practitioners to identify the risks, which are to be tackled through an appropriate intervention strategy. In essence, our framework can provide near real-time insights into the well-being of shop-floor workers and their associated productivity levels. This information can be incorporated into the safety and productivity components of the SQDCM (safety, quality, delivery, cost, and morale) lean production effectiveness dashboard.

From a productions research perspective, our framework attempts to bridge the gaps between predictive and prescriptive analytics in the context of human performance modeling. The sequential nature of our framework attempts to overcome the "black box" nature of machine learning algorithms. We have shown that the sequential application of predictive models when combined with visual analytic tools can provide insights for prescriptive interventions.

Furthermore, this study demonstrates that futuristic production environments can capture in real-time the well-being of their workers in addition to the data typically captured on the equipment. This can allow for more dynamic operational interventions (e.g., work-rest scheduling models). Our findings have significant implications for manufacturing occupations, as they are likely to encourage the management to invest in data-driven manufacturing to develop better plans to prevent fatal and non-fatal occupational injury. The fatigue detection phase of the proposed framework can be used for work scheduling practice as well, since the scheduling approaches should incorporate the fatigue status of the workers.

Measured changes in walking allow for detection of fatigue along a continuous time series

The mean trajectory of four different motion templates from the training sets is presented in Figure 7. The distinction between the fatigued and non-fatigued states is shown in the separate profiles with the shaded region representing the standard deviation. There is a distinct decrease in the step length after inducing fatigue.

In addition, the mean profiles of velocity magnitude, acceleration magnitude and jerk magnitude show a decrease in step duration. The other comparable quantity is the peak value of these four mean trajectories. The graphical representation shows a decrease in the maximum step height and velocity magnitude after fatigue. The graphs also show that differences between the profile of mean trajectories for other kinematical variables (i.e. acceleration magnitude, and jerk magnitude between fatigued and non-fatigued states are not as visually clear as the position and velocity magnitude trajectories. The combination of all templates for the classification algorithm was found to have the highest accuracy (90%) for correctly detection of the fatigued state as it was assumed. The acceleration template has the second highest accuracy (89%), which can be attributed to the accurate direct segmentation results and the fact that it was the directly collected, rather than calculated, measure since the kinematic computations can be a source of error and uncertainty. The next highest performing templates were position trajectory and velocity magnitude both with an accuracy of (86%). In addition, the templates containing angular properties show a meaningful change in the leg posture in the sagittal plane.

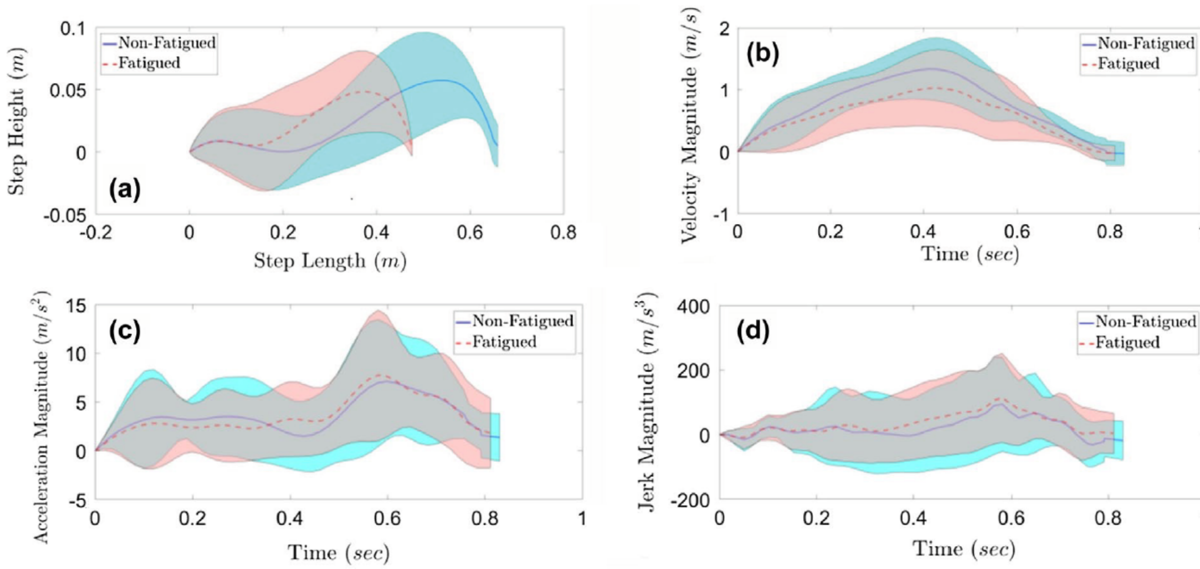


Figure 7. Temporal and spatial characteristics of gait following fatigue

For time series analysis, the data was first divided into sets and then analyzed using an agglomerative non-parametric approach for multiple changepoint analysis of multivariate data. The time series of the step duration, stride length, and stride height were included. The changepoints were identified and compared to the subjective ratings of fatigue (see Figure 8 for examples). Participants fell into two main clusters in which the trajectory-based features (i.e., stride length and stride height) acted in the same manner. The clusters differed in the pattern of stride duration relative to the trajectory-based features.

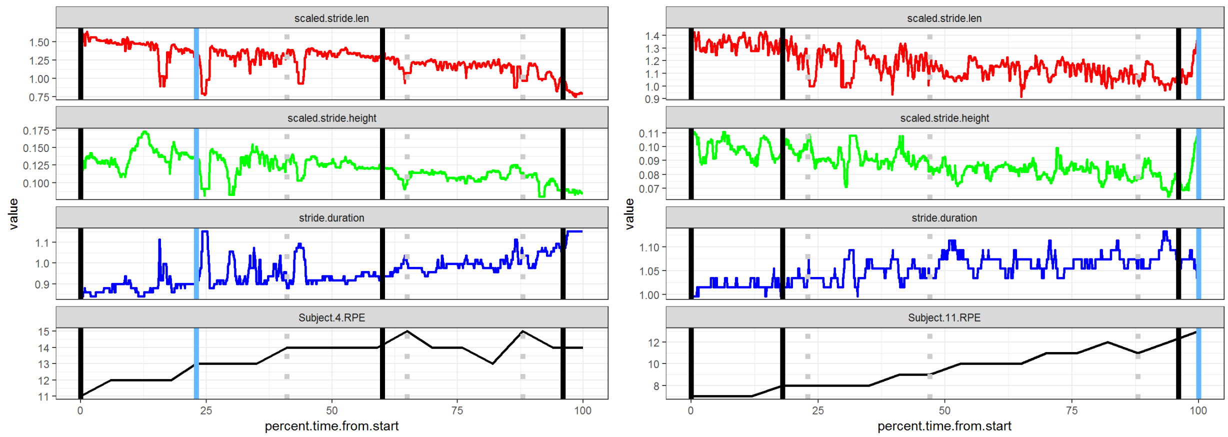


Figure 8. Example gait parameter profiles and identified changepoints for two participants

The current literature on time series analysis and changepoint detection is very limited in the field of ergonomics and human activity monitoring, mainly focused on activity recognition and segmentation from movement measures through spatiotemporal alignment, or movement estimation by monitoring physiological measures, e.g. cardiovascular and respiratory time series. Calzavara, et al. (2018) recently developed an analytic model for rest allowance estimation to avoid fatigue accumulation in the operators of manual material handling activities using the pattern of fatigue and recovery functions. Heart rate as a measure of energy expenditure was used as an indicator of whole-body fatigue, however, no measure was considered for physical movement monitoring and their model requires a person-specific hyperparameter determination leading to model uncertainty and limited generalizability.

Evidence Suggests That Postural Variation, Chemical Supplements and Rest Breaks are Effective Physical Fatigue Interventions

The search terms for the literature review are shown in Table 7. The search terms initially resulted in a total of 2,398 unique studies. These studies represent the union set of studies identified from our first and second searches. Upon applying our inclusion and exclusion criteria, 23 studies have been identified as the most relevant studies to be included in this systematic review. Among the 23 studies, 14 interventions were identified, and each intervention was categorized as either individual- or workplace-focused based on whether the intervention has changed the main process of the work.

Table 7. Search terms used to find literature related to fatigue interventions

Field	Terms
Interventions	intervention, countermeasure, coping, treatment, program
Health outcomes	fatigue
Workplace	workplace, work, worker, operation*, occupation*, manufactur*, construction, mining, nurs*

Several important findings should be highlighted. First, most of the intervention studies (17 out of 23) are published since 2010. Four of the six studies that were published prior to 2010 involved the use of mats/shoe-insoles (3 studies) and a back belt (1 study). From observing the chronological order of the studies, one can also observe the role of technologies in recent intervention studies.

For example, the three studies within posture variation are all published within the last five years since they require the ability to analyze postures through the use of motion capture systems or wearable sensors. The technologies and the ability to process their data in near real-time are somewhat recent events.

The second observation combines information captured in the “Reference” and “Population and Sample Size” columns. Fifteen of the 23 studies were RCTs, and the remaining were CCTs. It should also be noted that 18 of the 23 studies included crossover designs and one study as potential crossover design (not specified in text). Among the 15 RCTs, 10 were crossover studies with random allocation of equipment order. Additionally, six out of the eight CCTs had balanced or systematically varied crossover designs for the experimental tasks or participants’ sex.

The third observation pertains to the participants recruited in these studies. From the 23 studies, 10 studies included subjects from both sexes, five studies included only male participants, two studies included only female participants, and the remaining two did not report the sex distribution. In addition to the sex, the average age distribution of the studies are as follows: 14 studies had an average age of participants in the 20s, five studies had the average age of participants in the 30s, two studies in the 40s, one study in the 50s, and one did not specify the average. From these participants’ information, one could see that most of the studies used a convenience sample of college-aged students that do not typically correspond to the demographics seen in the workplace. This is a potentially limiting factor in the published literature.

The fourth observation pertains to the targeted types of work. Prolonged standing work, repeated lifting or lowering (stooped labor and dynamic lifting belong to this category) and repetitive assembly (pick and place belong to this category) tasks were mentioned four times among the selected literature, respectively. Prolonged sitting has been investigated in three studies. Hand-grip or endurance test and visual work were studied twice. Other individual studies covered overhead work, blowing pipe and outdoor tasks. Among these studies, three of them involve multiple work tasks. Corresponding to these work tasks, the locations of fatigue included the head (facial muscles and eyes), upper extremities (shoulders, arms), lumbar (erector spine, lumbar paraspinal muscles), lower extremities (feet, ankles) and overall fatigue.

Fifth, the choice of outcome measures used by the experimenters was almost uniformly distributed. Eight studies used only objective measures, and eight studies elected to only use subjective measures. The remaining seven studies utilized both objective and subjective measures in their experiment. The most common utilized outcome measures included: electromyography (EMG), maximum voluntary strength (MVS), and subjective ratings of fatigue.

The sixth, and final, observation relates to the location where the experiment is conducted. From our review, 14 studies were performed in a laboratory setting, and the remaining nine were performed in the field. Note that field studies tended to have larger sample sizes.

Three interventions had strong evidence, two of which are individual-focused interventions (chemical supplements and posture variation). Second, no interventions in the literature were found to have a moderate quality of evidence. The implication of the second observation is the remaining 11 interventions had either limited- to minimal-evidence. The ratings for these 11 interventions is based on: a) individual studies were found to be of low quality using the PEDro score; and/or b) the intervention of interest has only been examined in one study.

Two high-quality RCTs prevented overall/visual fatigue through the intake of chemical supplements. Suh, et al. (2012) showed that administration of high-dose intravenous vitamin C reduced fatigue significantly compared to placebo in office workers, especially with the subjects who have lower baseline levels of vitamin C. Ozawa, et al. (2015) found a dietary supplement containing bilberry extract improved several objective and subjective parameters of eye fatigue induced by video display terminal loads. Bilberry extract contains antioxidants and may have acted on eyes and eye muscles.

Three RCTs with high methodological quality concluded that changing between standing and working postures during prolonged sitting or having a footrest at 10% of body height while prolonged standing show positive effects in reducing fatigue. The location of fatigue investigated in those studies included whole body and lumbar regions. As the modern workplace environment becomes increasingly dependent on computer use, office workers' postural allocations are reliant on prolonged sitting or standing. Thorp, et al. (2014) conducted two 5-day x 8-hour/day experimental conditions in an equal, randomized order among overweight/obese office workers, who performed their usual occupational tasks either in a seated work posture or interchanging between a standing and seated work posture every 30 minutes using an electric, height-adjustable workstation. Through self-administered questionnaires, participants' total fatigue score was significantly lower in the stand-sit condition.

Son, et al. (2018) applied a footrest at 10% of body height condition during a two-hour prolonged standing task that caused the lowest muscle fatigue and placed the lowest load on the lumbar region, with the lowest pain development, comparing with 5% or 15%of body height. Compared with sitting in a standard office chair, Tanoue, et al. (2016) introduced a dynamic sitting balance chair. Healthy adults performed a 30-minute Kraepelin test under these two conditions, and lumbar fatigue was significantly lower in the seated postures that encourage pelvic movements. The "combination of postures" lowers the static load on postural muscles, compared to sustained sitting or standing postures. Physiologically, frequent alternating between postures reduces muscle fatigue via sustained activation of low threshold motor units while prolonged postures cause low-level static muscle loading (Hagg, 1991). In summary, posture variations show strong evidence in lowest muscle fatigue development for office work that has prolonged work postures. Diverse real-world settings are needed to confirm the generalizability of this intervention.

Two RCTs with high methodological quality provide rest breaks to workers and showed consistent results. The location of fatigue investigated using this intervention included whole body and lumbar regions. For repetitive lifting and lowering, Faucett, et al. (2007) provided an additional five-minute rest break to every working hour in which there was no other scheduled break for workers in two trials of stoop labor tasks. In this condition, fatigue scores did not show significant changes in the strawberry harvest trial (ntotal = 66, predominately male participants), but were less severe in the budding and tying of young citrus trees (ntotal = 32, predominately female participants). The study results suggest that alternative patterns of rest breaks, including brief rest breaks early in the work shift, may reduce workers' fatigue over the course of the day. Similar interventions are likely to benefit workers in other strenuous jobs including construction and manufacturing. Mailey, et al. (2017) found that short, frequent breaks (stand/move for one to two minutes every half hour) significantly reduced fatigue interference compared to longer, planned breaks for inactive females with full-time sedentary occupations from sitting each workday for eight weeks.

Project Extensions and Planned Future Work

Approximately 3.9 million Americans are employed as hand laborers and material movers [Bureau of Labor Statistics (BLS), 2017a)], with ~1 million employed in warehouses and distribution centers (WDCs) (Wright, 2016). With the rapid increase in e-commerce, supporting hand laborer jobs are expected to increase by 7% over the next 10 years (BLS, 2017a). Across WDCs, the recordable injury rate is 5.0 per 100 FTE workers, compared to an average 2.9 for all industries (BLS, 2017b), placing a large *burden* on the employees and their employers. This incidence rate translates to 63,790 non-fatal injury cases requiring days away from work by laborers and freight, stock, and material movers, accounting for 6% of all cases (BLS, 2017b). Moreover, a recent study found the risk of suffering a musculoskeletal disorder (MSD) for an order picker to be 75% higher than the average employee (Schneider & Irastorza, 2010). Injuries to the arm/shoulder account for ~18% of all workers' compensation claim loss amounts across industries (highest percentage), often resulting from strains and overexertion (BLS, 2017b; EHSvToday, 2001; National Council on Compensation Insurance, 2014).

While automation has increased productivity and output at WDCs, many tasks in warehouse facilities cannot be fully automated, and remain manual, due to variations in the size and shape of objects and packaging requirements (Kopytoff, 2012). Approximately half of workers in the warehousing and storage industry are hand laborers and hand pickers (Wright, 2016). These jobs are characterized by repetitive lifting and carrying over the course of shifts exceeding eight hours and/or lasting overnight. Workers in a person-to-parts fulfillment center may pick 200-250 items/hour (Kopytoff, 2012) and walk ~6 miles/day (Fiveash, 2016).

To minimize the inefficiency of walking to the parts (~ 50% of a picker's time (R. De Koster, Le-Duc, & Roodbergen, 2007)), WDCs are quickly transitioning to parts-to-person systems in which workers stand at a fixed workstation to pick from and place into bins located in front of them. The percentage of WDCs using such a system more than doubled over the past two years, increasing from 5% in 2015 to 12% in 2017 (Michel, 2017). These systems concentrate the physical load on the upper extremity, with high repetitions (picking ~500 items per hour (M. De Koster, 2012)) and fewer periods of built-in recovery while walking.

Physically demanding work (characterized by forceful exertions, prolonged duration, repetitiveness, or their interactions) places high biomechanical and physiological stresses on the shoulder muscle and passive tissues, which can result in fatigue in the absence of adequate rest/recovery (Kumar, 2001). Physical fatigue can lead to decreased muscle capacity, which in turn results in a decline in work efficiency and an increased injury risk (Kumar, 2001; Rose, Neumann, Hägg &診enttä, 2014; van Rijn, Huisstede, Koes & Burdorf, 2010; Visser & van Dieën, 2006). For example, those with shoulder disorders were 3x more likely to have had jobs involving repetitive shoulder movements (up to 36 movements/min) (Frost, et al., 2002). Thus, considering important fatigue parameters (e.g., length of time-on-task between breaks, work pace, task variability, and timing of rest breaks) through job design can reduce the subsequent risk of injuries.

At the work organization level, fatigue is often addressed through work-rest scheduling or job rotation. Currently ergonomics practice lacks adequate physical fatigue assessment and work-rest/job rotation scheduling tools, as existing models of fatigue and recovery are limited in their practical application (Rose, Beauchemin & Neumann, 2018; Rose, et al., 2014). Due to the limitations of the existing approaches and the physically demanding nature of WDC work, there is a need for greater understanding of fatigue accumulation and the recovery process during relevant tasks. The proposed project extension aims to address many of these limitations by evaluating fatigue accumulation during and recovery following a dynamic, order picking, upper extremity task. The information on fatigue accumulation and recovery processes will be incorporated into improved models that can support job design and work-rest scheduling, which can reduce the incidence of fatigue and ultimately minimize the likelihood of shoulder injuries. These models will be made freely available to practitioners via a tool (project output), translating research to practice (r2P) and enabling them to develop cost-effective controls for their workers.

Translation of Findings

Application of this work can facilitate the implementation of fatigue monitoring to allow for identification of indicators of behavior change prior to adverse effects. This will allow for intervention to support recovery from fatigue. In addition, the review of current fatigue interventions from the literature highlights the paucity of evidence-based interventions and the need for further research into the effect of controls on fatigue development and recovery It is important that those in both the research and practice communities are made aware of the new findings from this work.

Thus, over the course of the project, research completed during this project has resulted in conference presentations, conference proceedings papers, and journal publications that contribute to the scientific knowledge base on the modeling of fatigue development using wearable sensors. Six journal papers have been published, two manuscripts are under review, and one manuscript is in preparation for submission this month. It is expected that these remaining three manuscripts will be published in 2019. To promote the project and build buy-in from industry, the PI and Co-I have also been interacting with industry representatives and other researchers on the relevance and application of the project. Going forward, the investigators will continue to engage with industry leaders for the implementation of the methods and recommendations.

Journal Publications

1) Sedighi Maman, Z., Yazdi, M.A.A., Cavuoto, L.A., & Megahed, F.M. (2017) Using wearables to model physical fatigue at the workplace: A data-driven approach to detect the occurrence of fatigue, estimate its severity and determine suitable location(s) for sensor placement. *Applied Ergonomics, 65,* 515-529.

2) Cavuoto, L.A. & Megahed, F.M. (2017) Understanding fatigue and the implications for worker safety. *Professional Safety,* December 2017.

3) Lu, L., Megahed, F. M., Sesek, R. F., & Cavuoto, L. A. (2017). A survey of the prevalence of fatigue, its precursors and individual coping mechanisms among US manufacturing workers. *Applied Ergonomics, 65,* 139-151.

4) Baghdadi, A., Megahed, F. M., Esfahani, E. T., & Cavuoto, L. A. (2018). A machine learning approach to detect changes in gait parameters following a fatiguing occupational task. *Ergonomics,* 1-14.

5) Baghdadi, A., Cavuoto, L. A., & Crassidis, J. L. (2018). Hip and Trunk Kinematics Estimation in Gait Through Kalman Filter Using IMU Data at the Ankle. *IEEE Sensors Journal, 18*(10), 4253-4260.

6) Schall Jr, M. C., Sesek, R. F., & Cavuoto, L. A. (2018). Barriers to the Adoption of Wearable Sensors in the Workplace: A Survey of Occupational Safety and Health Professionals. *Human factors*, *60*(3), 351-362.

Journal Manuscripts Submitted or to be Submitted

7) Maman, Z.S., Chen, Y.-J., Baghadi, A., Lombardo, S., Cavuoto, L.A., Megahed, F.M., "A Data Analytic Framework for Physical Fatigue Management using Wearable Sensors", under review

8) Lu, L., Megahed, F.M., Cavuoto, L.A., "Workplace Interventions to Reduce Physical Fatigue: A Systematic Review Grading Research Quality and Levels of Evidence for Intervention Efficacy", under review

9) Baghdadi, A., Cavuoto, L.A., Esfahani, E.T., Jones-Farmer, L.A., Rigdon, S.E., Megahed, F.M., "Estimating the Onset of Physical Fatigue at the Workplace: A Statistical Perspective on Using Wearables to Detect Changes in Gait Trajectory Parameters" to be submitted

Conference Proceedings Papers

10) Baghdadi, A., Maman, Z. S., Lu, L., Cavuoto, L. A., & Megahed, F. M. (2017, September). Effects of task type, task duration, and age on body kinematics and subjective fatigue. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 61, No. 1, pp. 1040-1040). Sage CA: Los Angeles, CA: SAGE Publications.

11) Nardolillo, A. M., Baghdadi, A., & Cavuoto, L. A. (2017, September). Heart rate variability during a simulated assembly task; influence of age and gender. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 61, No. 1, pp. 1853-1857). Sage CA: Los Angeles, CA: SAGE Publications.

12) Maman, Z. S., Baghdadi, A., Megahed, F., & Cavuoto, L. (2016, August). Monitoring and change point estimation of normal (in-control) and fatigued (out-of-control) state in workers. In ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. V003T11A011-V003T11A011). American Society of Mechanical Engineers.

Conference and Invited Presentations

13) Maman, Z.S., Chen, Y.-J., Baghadi, A., Lombardo, S., Cavuoto, L.A., Megahed, F.M. (2018) "A Data Analytic Framework for Physical Fatigue Management using Wearable Sensors", INFORMS Annual Meeting, Phoenix, AZ.

14) Cavuoto, L.A., Megahed, F.M. (2018) "Recommending Workplace Interventions for Physical Fatigue", Safety 2018, San Antonio, TX.

15) Zahra Sedighi Maman, Ying-Ju Chen, Amir Baghdadi, Seamus Lombardo, Lora Cavuoto, and Fadel Megahed, A Data Analytic Framework for Physical Fatigue Management Using Wearable Sensors. 2018 Joint Research Conference on Statistics in Quality, Industry, and Technology. June 11-14, 2018. Santa Fe, New Mexico.

16) Cavuoto, L.A., Schall, M., & Sesek, R. (2018) Understanding the potential uses and barriers to the adoption of wearable technology in the workplace. Presented at the 2018 Applied Ergonomics Conference. Atlanta, GA.

17) Cavuoto, L.A. (2017) Industrial and Systems Engineering Department, Rochester Institute of Technology.

18) Lu, L., Cavuoto, L.A., & Megahed, F.M. (2017) Review for workplace interventions of physical fatigue. Presented at INFORMS. Houston, TX. Oct. 22-25.

19) Maman, Z.S., Cavuoto, L.A., & Megahed, F.M. (2017) Comparing machine learning models on data from wearable sensors to model physical fatigue occurrence. Presented at INFORMS. Houston, TX. Oct 22-25.

20) Cavuoto, L.A. & Megahed, F.M. (2017) A data-driven approach to predicting physical fatigue. Presented at Safety 2017 (American Society of Safety Engineers Annual Meeting). Denver, CO

21) Cavuoto, L.A. (2017) Understanding the Implications of Fatigue and Changing Demographics in the Workplace, Western New York Safety Conference, Niagara Falls, NY.

22) Cavuoto, L.A. (2017) A More Tired and More Obese Workforce: Implications for Injury Risk, ErgoX a conference by the Human Factors and Ergonomics Society, Tampa, FL.

23) Cavuoto, L.A. (2017) Industrial and Systems Engineering Department, Auburn University.

24) Cavuoto, L.A. (2017) Lecture on Fatigue in Manufacturing, Department of Environmental and Occupational Health, Texas A&M University.

25) Cavuoto, L.A. (2016) National Safety Council Blue Ribbon Panel on Fatigue, Chicago, IL.

26) Sedighi Maman, Z., Yazdi, M.A.A., Cavuoto, L.A., & Megahed, F.M. (2016) A data-driven approach to model fatigue at the workplace. Presented at the INFORMS Annual Meeting. Nashville, TN.

27) Cavuoto, L.A. (2016) Research and business defining market need and research questions. Presented as part of a symposium at PREMUS 2016. Toronto, Ontario, Canada

28) Cavuoto, L.A. & Megahed, F.M. (2016) Understanding fatigue and the implications for worker safety. Presented at Safety 2016 (American Society of Safety Engineers Annual Meeting). Atlanta, GA.

29)Cavuoto, L.A. (2016) Managing Fatigue in the Workplace, Keynote Address, 4th Annual Centre for Research in Occupational Safety and Health (CROSH) Conference, Sudbury, ON.

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