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Manufacturing worker perceptions of using wearable inertial sensors for multiple work shifts

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ABSTRACT

Wearable inertial sensors may be used to objectively quantify exposure to some physical risk factors associated with musculoskeletal disorders. However, concerns regarding their potential negative effects on user safety and satisfaction remain. This study characterized the self-reported daily discomfort, distraction, and burden associated with wearing inertial sensors on the upper arms, trunk, and dominant wrist of 31 manufacturing workers collected over 15 full work shifts. Results indicated that the workers considered the devices as generally comfortable to wear, not distracting, and not burdensome to use. Exposure to non-neutral postures (discomfort, right arm, beta = 0.02; trunk, beta = −0.01), non-cyclic tasks (distraction, beta = -0.26), and higher body mass indices (discomfort, beta = 0.05; distraction, beta = 0.02) contributed to statistically significant ($p < 0.05$), albeit practically small increases in undesirable ratings. For instance, for each additional percentage of time working with the right arm elevated ≥60°, self-reported discomfort ratings increased 0.02 cm on a standard 10 cm visual analog scale. Female workers reported less discomfort and distraction while wearing the sensors at work than males (discomfort, beta = −0.93; distraction, beta = −0.3). In general, the low ratings of discomfort, distraction, and burden associated with wearing the devices during work suggests that inertial sensors may be suitable for extended use among manufacturing workers.

1. Introduction

The manufacturing sector reported the second highest number of reported cases and the sixth highest incidence rate of nonfatal occupational injuries and illnesses among all U.S. industries in 2019 (USBLS, 2020a). Musculoskeletal disorders (MSDs) accounted for approximately 30% of all lost workdays, the third highest number of reported cases, and the fifth highest incidence rate of all nonfatal occupational injury and illness cases for full-time workers in the United States in 2018 (USBLS, 2020b). Approximately 10% of workers in automotive assembly-based production report MSDs resulting from exposure to physical risk factors such as working in non-neutral postures and moving at high speeds every year (OSHA, 2014).

Accurate and objective quantification of exposure to physical risk factors associated with MSDs is needed for ergonomists to improve occupational safety and health (Mathiassen et al., 2015). Direct measurement methods provide more precise and objective exposure information when compared to self-report and observational approaches (David, 2005; Spielholz et al., 2001; Teschke et al., 2009; Winkel and Mathiassen, 1994). Wearable inertial sensors are electromechanical devices typically comprised of a combination of accelerometers, gyroscopes, and magnetometers that directly measure the linear acceleration, rotational velocity, and heading of an object in space. They represent an extension of the single-axis inclinometers used for decades by ergonomists by measuring the information necessary to determine the three-dimensional orientation of an object in space; although they are often applied in work settings as more accurate inclinometers (Chen et al., 2020) or for activity recognition and energy expenditure estimation purposes (i.e., a physical activity monitor) (Beeler et al., 2018; McNamara et al., 2016; Schall Jr et al., 2016a; Thiese, 2014).

Although several studies have used inertial sensors to directly measure physical exposure information (e.g., kinematics, physiological

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biometrics) in or for the manufacturing sector (Greco et al., 2019; Hansson et al., 2010; Ji and Piovesan, 2020; Kersten and Fethke, 2019; Maman et al., 2017; Schall et al., 2021; Tao et al., 2018; Zhang et al., 2019), the sensors have not been broadly adopted by occupational safety and health practitioners. Safety and health practitioners have reported interest in applying wearable sensors among their workforces for assessing exposure to physical risk factors in the work environment (Reid et al., 2017; Schall et al., 2018). However, practitioners and employees have valid concerns, including safety issues arising as a result of wearing potentially uncomfortable, distracting, and/or burdensome sensors (Jacobs et al., 2019; le Feber et al., 2020; Reid et al., 2017; Schall et al., 2018; Zhang et al., 2019).

One gap in the scientific literature contributing to the lack of adoption of wearable inertial sensors as exposure assessment tools in the manufacturing sector is limited information regarding worker perceptions of using wearable inertial sensors in the workplace, particularly across multiple work shifts. To address this gap, we (i) characterized the self-reported daily discomfort, distraction and burden associated with using wearable inertial sensors among manufacturing workers completing standard production activities over 15 full work shifts, and (ii) evaluated how different personal (e.g., sex, body mass index [BMI]) and work characteristics (e.g., cyclic vs. non-cyclic work categorization; perceptions of stress; exposure to kinematic risk factors) affected their ratings.

2. Methods

2.1. Participant recruitment and data collection

Thirty-six healthy manufacturing workers were enrolled in this study following procedures described in Schall et al. (2021). In short, participants were categorized into “cyclic” or “non-cyclic” work groups (n = 18 per group) based on their predominant work responsibilities. Participants in the “cyclic” group primarily performed repetitive, assembly-based production tasks characterized by cycle times of less than approximately 3 min in duration (consistent with Paulsen et al., [2014]). Participants in the “non-cyclic” group primarily completed non-routinized tasks (e.g., maintenance, stocking workstations). Each participant was between 19 and 65 years of age, and recruited according to Auburn University Institutional Review Board approved procedures. All participants provided written informed consent.

The participants each wore up to four ActiGraph GT9X Links (ActiGraph, Pensacola, Florida, USA) secured to the body using elastic hook-and-loop fastener straps for 15 weekday shifts in a manner similar to previous studies (Schall et al., 2014; Schall Jr et al., 2016c; Schall et al., 2021). One device was secured over the clothes to the anterior torso over the breast bone approximately between the sternal notch and the xyphoid process. Participants could adjust the positioning of the sensor for comfort. Another was secured to the lateral aspect of each upper arm halfway between the lateral epicondyle and the acromion over the clothes or on the skin (based on participant preference). Finally, one device was also worn on the skin around the dominant wrist. Five participants did not wear the wrist sensor due to potential safety concerns (e.g., prospect of working with hands near machinery). Each device was wrapped in hypoallergenic, cohesive bandages to secure the sensor to the elastic hook-and-loop fastener strap and protect the sensor from environmental hazards (e.g., lubricants).

Immediately after the sensors were secured to each participant, a calibration procedure was performed at the beginning of each work shift. It included standing in a neutral posture, performing three trunk bends to approximately 30–60° of trunk flexion, and three lateral arms raises from a neutral posture to approximately 90° relative to gravity. The time that the calibration procedure began was reviewed in MATLAB (2017b, Mathworks, Natick, MA) and used to identify the beginning of data collection. Participants proceeded with their normal work shift after completing the calibration procedure.

During each work shift, each participant was asked to record the number of hours they spent performing their work activities (i.e., tasks and breaks) in a daily work log. The daily work log included 10 cm visual analog scales (VAS). Participants were asked to rate the “stress” experienced for each logged work activity from a score of 0 indicating “no stress” to a score of 10 for “very stressful” immediately following completion of the task on separate VASs. At the end of the work shift, participants recorded their perceived discomfort, distraction, and burden associated with using the full complement of sensors they wore throughout the entire shift. Verbal anchors of “completely comfortable”, “no distraction”, and “no burden” were attributed to a score of 0, while a score of 10 represented the devices being “as uncomfortable as possible”, a “complete distraction”, or “as burdensome as possible”. At the conclusion of each shift, the raw inertial sensor data were downloaded to a computer using ActiLife software (version 6.13.3, ActiGraph, LLC, Pensacola, FL) and exported to comma-separated files.

2.2. Data processing and feature selection

Upper arm elevation, trunk inclination about the sagittal plane (i.e., flexion/extension), and the magnitude of the associated movement speeds (i.e., the absolute value of velocities) for each work shift were summarized following the procedures described in Schall et al. (2021) to be consistent with several field-based studies (Kazmierczak et al., 2005; Kersten and Fethke, 2019; Wahlström et al., 2016; Wahlström et al., 2010). In the current study, three participants were excluded because over 25% of their trunk data were missing due to data collection failure or because they chose to not wear the sensors for safety or personal reasons. One participant in the cyclic group was excluded from the analysis due to changing job titles and primary work activity classification after the 10th shift of data collection. One participant withdrew from the non-cyclic group on the first day of data collection and was excluded.

For the remaining 31 participants, Multiple Imputation (MI) and Expectation-Maximization (EM) algorithms (see Bennett, 2001) were used to impute any missing ratings of stress (1.9% of shifts), discomfort, distraction, and burden (4.9% of shifts), and missing exposure measurements as a result of data collection failures (0.9% for the left arm, 0.4% for right arm, and 5.8% for the trunk). We performed five iterations of MI in accordance with the rate of missing data (Royston and White, 2011). The EM algorithm is a two-step iterative approach that estimates the maximum likelihood parameters by repeating the Expectation (E-step) and Maximization (M-step) steps in parametric models. Feature selection techniques were then used to identify the most informative variables for inclusion in our inferential statistical models using discomfort, distraction, or burden as the response variable. Specifically, ReliefF Attribute Evaluation was carried out in WEKA 3.8.0 to examine the rank importance of predictors and improve prediction accuracy. The ReliefF algorithm is an extension of Relief-based algorithms (RBAs), which are filter-style feature selection algorithms. These algorithms aim to maximize prediction accuracy and computational efficiency that have been applied in many different areas of study for both classification and regression analyses (Urbanowicz et al., 2018). WEKA 3.8.0 is an open-source software written in the Java programming language with a collection of machine learning algorithms for data mining (Frank et al., 2009).

Variables were selected based on their average merit and rank where merit is a measure of the importance and usefulness of a feature and rank is the order of importance or usefulness assigned based on the merit scoring function (Adams et al., 2017). The larger the value of the merit, the higher the rank of the attribute. The average value of merit and average rank from ten iterations was used from ten-fold cross-validation. The feature selection process seeks to eliminate irrelevant or redundant features, reduce the training time required to build a statistical model, and optimize predictive performance (Onan and Korukoğlu, 2017).

A Pearson correlation coefficient matrix was generated for diagnosing occurrences of multicollinearity. Correlation coefficients ≥0.8 were considered as the occurrence of multicollinearity. In total, 27 candidate predictors were considered:

- Age
- Body mass index (BMI)
- Sex
- Time-weighted average stress ratings calculated using the reported task durations and stress ratings from the self-reported logs
- Work category (i.e., cyclic vs. non-cyclic)
- Eight kinematic exposure variables for each arm, which included:
  - o Mean amplitude of the time-series arm elevation waveform over the duration of each shift
  - o Mean amplitude of the time-series movement speed waveform over the duration of each shift
  - o The 90th percentile of the time-series arm elevation waveform over the duration of each shift
  - o The 90th percentile of the time-series movement speed waveform over the duration of each shift
  - o The percentage of time moving at low movement speeds (<5°/s)
  - o The percentage of time moving at high movement speeds (≥90°/s)
  - o The percentage of time with the arm elevated ≥60° degree (left = LA60+; right = RA60+)
  - o The percentage of time with the arm in a neutral posture (<20°) and moving at a low speed (<5°/s) (left = LANLS; right = RANLS)
- Six kinematic exposure variables for the trunk, which included:
  - o Mean amplitude of the time-series trunk flexion/extension waveform over the duration of each shift
  - o Mean amplitude of the time-series movement speed waveform over the duration of each shift
  - o The 90th percentile of the time-series trunk flexion/extension waveform over the duration of each shift (FE90P)
  - o The 90th percentile of the time-series movement speed waveform over the duration of each shift
  - o The percentage of time with the trunk moving <5°/s
  - o The percentage of time with the trunk moving ≥90°/s

Nine variables were identified as predictors for inclusion in our linear models based on the feature selection procedure: age, sex, BMI (kg/m^2), time-weighted average stress ratings, work category (i.e., cyclic vs. non-cyclic), the percentage of time with an arm elevated ≥60° (left = LA60+; right = RA60+), the percentage of time with the right arm in a neutral posture (<20°) and moving at a low speed (<5°/s) (RANLS), and the 90th percentile of trunk flexion/extension (FE90P) (Table 1). These predictors had (i) positive average merit values in all three models; and (ii) were not highly correlated (i.e., ≥0.8) with other predictors. If two candidate predictors had positive average merit values and were correlated, the predictor with the higher average rank value was selected for inclusion in each model.

2.3. Statistical analysis

Three different generalized linear models were applied to investigate the effects of work category (i.e., cyclic vs. non-cyclic), work stress, the kinematic exposure variables, and personal characteristics on the self-reported discomfort, distraction, and burden ratings. We also included the shift on which the sensor wearing experience was provided to evaluate the trend of subjective ratings over the 15 sampled work shifts. It was hypothesized that participants would become more comfortable, less distracted, and less burdened by the sensors as time went on. The generalized structure of these models was as follows:

$$Y_{ij} = \beta_1 X_{ij1} + \beta_2 X_{ij2} + \beta_3 X_{ij3} + \beta_4 X_{ij4} + \beta_5 X_{ij5} + \beta_6 X_{ij6} + \beta_7 X_{ij7} + \beta_8 X_{ij8} \ldots + \beta_k X_{ijk} + \varepsilon_{ij},$$
$$i = 1, \ldots, n;\ j = 1, \ldots, m;\ n = 31,\ m = 15,\ k = 11$$

Where $X_{ij1} = 1$ for all i and j;

$X_{ij2} = t_j$, the shift on which the sensor wearing experience was rated;
$X_{ij3} = 1$ if the ith participant was categorized as a cyclic worker and 0 if non-cyclic;
$X_{ij4} = 1$ if the ith participant was female and 0 if male;
X_{ij5} = the self-reported score of work-related stress;
X_{ij6} = the body mass index (BMI) value of each participant;
X_{ij7} = the age of each participant;
X_{ij8} = the percentage of time with the left arm elevated ≥60° (LA60+);
X_{ij9} = the percentage of time with the right arm elevated ≥60° (RA60+);
X_{ij10} = the percentage of time with the right arm elevated <20° and moving <5°/s (RANLS);
X_{ij11} = the 90th percentile of trunk flexion/extension (FE90P);
We assume that $\varepsilon ij \sim N(0, \sigma^2)$.

Each model was built and processed in SAS software (version 9.4; SAS Institute Inc., Cary, NC, USA) using the PROC MIXED procedure. Residual Maximum Likelihood (REML) estimation was applied to reduce potential bias. Different types of covariance structures were evaluated based on model fitness using Akaike Information Criterion (AIC). A Heterogeneous Autoregressive (ARH(1)) structure was selected for the discomfort rating model (AIC = 1234.1), while Unstructured (UN) was selected for the distraction rating (AIC = 877.0) and burden rating models (AIC = 621.2). 95% two-sided confidence intervals provide an

Table 1
Feature selection results.

Discomfort			Distraction			Burden		
Attribute	Avg. Merit	Avg. Rank	Attribute	Avg. Merit	Avg. Rank	Attribute	Avg. Merit	Avg. Rank
Stress	0.061	1	Stress	0.044	1	Stress	0.070	1
Age	0.038	2	Age	0.032	2	Age	0.034	2
BMI	0.028	3	BMI	0.026	3	BMI	0.027	3
LA60+	0.023	4	LA60+	0.017	4	LA60+	0.019	4
RA60+	0.013	5.1	FE90P	0.008	5.8	Work Category	0.010	6.1
RANLS	0.007	7.7	Work Category	0.007	6.9	RA60+	0.007	6.8
Work Category	0.007	8	RA60+	0.006	7.2	FE90P	0.006	8.7
Sex	0.004	11.1	Sex	0.006	7.6	RANLS	0.004	9.8
FE90P	0.002	14.5	RANLS	0.004	10	Sex	0.003	11.2

Avg. Merit = A measure of the importance and usefulness of a selected feature in the statistical model.
Avg. Rank = The order of importance or usefulness assigned based on the merit scoring function.
LA60+ = Percentage of time with the left arm elevated ≥60°.
RA60+ = Percentage of time with the right arm elevated ≥60°.
RANLS = Percentage of time with the right arm elevated <20° and moving <5°/s.
FE90P = The 90th percentile of trunk flexion/extension.

overview of the dispersion of the beta coefficient for each predictor.

3. Results

Observations from 31 participants were included in the statistical analysis (Table 2). Only one participant (in the non-cyclic group) was left hand dominant.

In general, average self-reported ratings of discomfort (mean = 1.2; SD = 1.6), distraction (mean = 0.9; SD = 1.4), and burden (mean = 0.8; SD = 1.2) were low (Fig. 1). Participants spent an average of 7.6% and 7.1% of their time with the left and right arm, respectively, in a non-neutral posture (≥60°). Participants worked 14.6% of the time with the right arm in a neutral posture and moving at a low speed (<5°/s), and the 90th percentile of trunk flexion/extension was 11.1°. The average self-reported stress level experienced at work was low (mean = 1.5; SD = 1.7).

Results of the generalized linear models provide information regarding the factors associated with perceptions of wearable sensor discomfort, distraction, and burden (Table 3). For the discomfort model, statistically significant factors included the shift (i.e., the first shift of data collection was associated with a statistically significant increase in perceived discomfort, beta = 0.82, $p < 0.05$), BMI (beta = 0.05, $p < 0.01$), sex (beta for female = −0.93, $p < 0.01$), percentage of time with the right arm elevated >60° (beta = 0.02, $p < 0.05$), and the 90th percentile of the flexion/extension of the trunk (beta = −0.01, $p < 0.05$). Significant factors in the distraction model included work category (beta for non-cyclic group = −0.26, $p < 0.01$), BMI (beta = 0.02, $p < 0.01$), age (beta = 0.01, $p < 0.01$), and sex (beta for female = −0.3, $p < 0.05$). Significant factors for the burden model included perceptions of stress (beta = 0.01, $p < 0.05$) and age (beta = 0.01, $p < 0.01$). In general, male participants reported higher mean discomfort than females.

4. Discussion

Industrial workers and occupational safety and health professionals have expressed concerns regarding using wearable inertial sensors in the workplace, including the potential for discomfort, distraction, and burden among users (Jacobs et al., 2019; le Feber et al., 2020; Reid et al., 2017; Zhang et al., 2019). This work (i) characterized the self-reported daily discomfort, distraction and burden associated with using wearable inertial sensors among 31 manufacturing workers completing standard production activities over 15 full work shifts, and (ii) evaluated how different personal (e.g., sex; age; BMI) and work characteristics (e.g., cyclic vs. non-cyclic work categorization; perceptions of stress; exposure to kinematic risk factors) affected those ratings. The results indicated that the manufacturing workers that participated in this study reported the devices as generally comfortable to wear, not distracting, and not burdensome to use. Although the results also indicated that some personal and work characteristics played a statistically significant role in increasing undesirable ratings of wearable sensor use, the increases were practically small and the findings predominantly support the use of wearable inertial sensors in manufacturing environments for multiple full work shifts.

Right upper arm elevation was a physical risk factor that played a statistically significant, albeit small role in increasing worker discomfort. In particular, for each additional percentage of time working with the right arm elevated ≥60°, self-reported discomfort ratings increased 0.02 cm on a standard 10 cm VAS. Frequent raising of the arms may have contributed to reduced blood flow through the arms and increased discomfort unrelated to the use of the wearable devices (Proger and Dexter, 1934; Rossetti et al., 1994). Alternatively, this result may have been a function of the decision to use easy-to-secure fastener straps which were selected because of their adjustability and ease of application. Some participants reported loosened sensor straps, and the elastic armband as irritating at the conclusion of their work shifts. Such potential negative consequences of using fastener straps should be considered by safety and health practitioners when performing exposure assessments with wearable inertial sensors. Alternative methods for securing inertial sensors to the body should also be explored, particularly since motion sensors attached to the skin with adhesive tapes may lead to skin irritation and limit the users' willingness to use them for prolonged periods (Kent et al., 2015). Regardless, the small increase in discomfort may be considered practically irrelevant, particularly when considering the relatively small amount of time that the manufacturing workers spent, on average, with their arms elevated.

In contrast to the upper arms, participants with greater trunk flexion tended to report slightly less discomfort than peers with less trunk flexion. Participants in this study, however, generally maintained relatively neutral trunk postures relative to workers in several other occupations such as nursing, agriculture, and construction (Fethke et al., 2020; Granzow et al., 2018; Lee et al., 2017; Schall Jr et al., 2016b; Schall et al., 2021). As described in Schall et al. (2021), the trunk sensor was susceptible to shifting down the sternum towards the xiphoid process due to the use of the fastener straps. This shifting may have contributed to an underestimation of the amount of trunk flexion measured among the workers. Additionally, it is important to note that the VASs completed by participants were broadly attributed to the experience of wearing all four inertial sensors. We did not ask for ratings specific to each body segment. It is possible that increased trunk flexion may have led to increased ratings of localized trunk discomfort. Also, the scale only referred to discomfort associated with the sensor wearing experience. Feelings of physical discomfort related to particular work activities were not evaluated. Future studies may consider separate questions to compare the different sensor rating levels among body segments, or use structured interviews among participants to collect more detailed feedback.

Another interesting finding related to discomfort in this study was that manufacturing workers reported greater discomfort on the first shift of data collection relative to the remaining 14 shifts of participation. However, the reports of discomfort were relatively low even on the first day. A possible explanation was that the workers were not accustomed to wearing any devices at work and needed time to adapt. A decreasing trend was observed for discomfort ratings over the 15 shifts suggesting that the workers became more comfortable as time passed. The results suggest that, in real practice, wearable inertial sensors may be comfortably worn in manufacturing environments for extended durations.

Although less commonly studied than discomfort, distraction and/or burden caused by wearable sensors is of concern as they can lead to safety-related incidents (Canina et al., 2006; Leng et al., 2015; Liu et al., 2015). Workers who primarily performed cyclic work tasks reported greater distraction than those who primarily performed non-cyclic work tasks. We previously characterized and compared the kinematics of the cyclic and non-cyclic workers (Schall et al., 2021). Significant differences were observed for the movement speeds where the arms of cyclic workers moved faster, on average, than the non-cyclic workers. This

Table 2
Participant information by work group and sex.

	CYCLIC			NON-CYCLIC		
	N	Mean	SD	N	Mean	SD
Male	6			11[a]		
Age (years)		29.0	6.9		40.2	12.6
Height (cm)		183.7	6.9		179.4	5.2
BMI (kg/m^2)		32.1	10.7		29.6	4.2
Shift duration (hours)		8.3	0.5		8.1	0.7
Female	9			5		
Age (years)		47.0	10.0		47.6	12.4
Height (cm)		164.5	5.9		163.6	6.9
BMI (kg/m^2)		31.1	6.3		33.3	7.8
Shift duration (hours)		8.5	1.2		9.0	1.0

[a] Only one male participant in the non-cyclic group was left hand dominant.

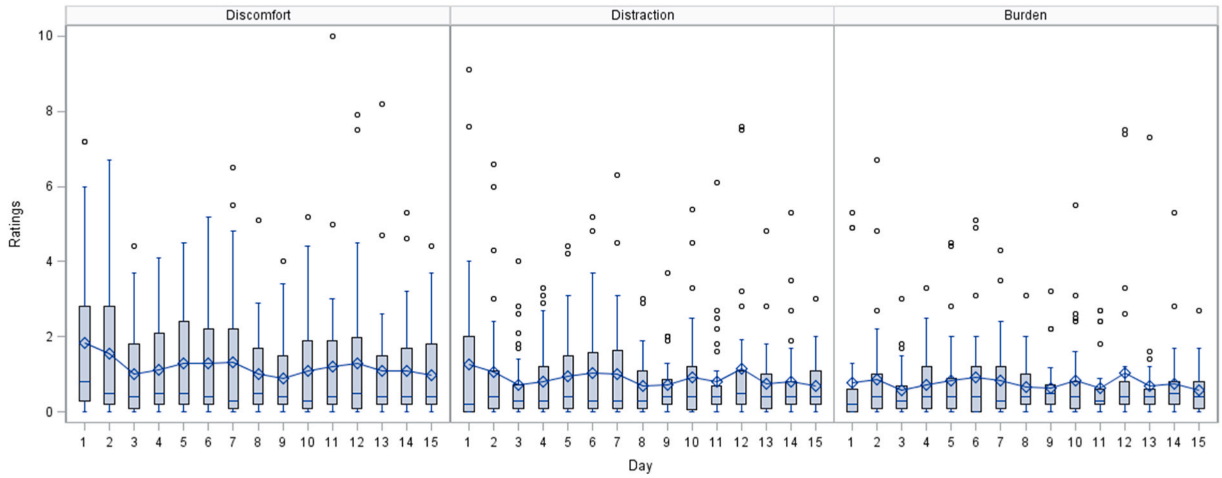

Fig. 1. Boxplots of sensor ratings over 15 full work shifts. A rating of 0 indicated no discomfort, distraction, or burden, while a rating of 10 indicated maximum discomfort, distraction, or burden for that work shift. The length of each box represents the interquartile range (the distance between the 25th and 75th percentiles). The diamond within each box indicates the group mean. The horizontal line in each box indicates the group median. The vertical lines (i.e., whiskers) issuing from each box extend to the most extreme point that is less than or equal to 1.5 times the interquartile range. "Outlier" or extreme values within a group are plotted as circles beyond the whiskers of the each box. The connected line across the 15 boxplots indicates the trend of the group mean from shift to shift.

Table 3
Results of the generalized linear models.

	Discomfort					Distraction					Burden				
Effect	Estimate	Std. Error	*p*	95% CI Lower	95% CI Upper	Estimate	Std. Error	*p*	95% CI Lower	95% CI Upper	Estimate	Std. Error	*p*	95% CI Lower	95% CI Upper
Intercept	−1.04	0.68	0.14	−2.44	0.37	−0.27	0.26	0.31	−0.81	0.26	−0.14	0.22	0.52	−0.59	0.31
Stress	0.02	0.03	0.41	−0.03	0.07	0.01	0.01	0.16	−0.01	0.03	0.01	0.01	**<0.05**	0.00	0.03
Non-Cyclic	−0.02	0.24	0.94	−0.51	0.48	−0.26	0.09	**<0.05**	−0.43	−0.08	−0.08	0.07	0.31	−0.23	0.07
Cyclic	0	.	.	.	.	0	.	.	.	.	0	.	.	.	.
Shift 1	0.82	0.42	**<0.05**	0.00	1.65	0.55	0.37	0.15	−0.21	1.31	0.2	0.25	0.44	−0.32	0.71
Shift 2	0.55	0.4	0.17	−0.23	1.32	0.35	0.3	’	−0.27	0.97	0.26	0.26	0.32	−0.27	0.80
Shift 3	−0.02	0.26	0.94	−0.53	0.49	0.01	0.15	0.94	−0.30	0.33	−0.03	0.12	0.82	−0.28	0.22
Shift 4	0.13	0.26	0.6	−0.37	0.64	0.09	0.15	0.56	−0.22	0.40	0.13	0.15	0.41	−0.19	0.44
Shift 5	0.3	0.27	0.28	−0.24	0.83	0.26	0.17	0.13	−0.08	0.60	0.25	0.19	0.21	−0.15	0.65
Shift 6	0.32	0.29	0.27	−0.25	0.88	0.32	0.21	0.14	−0.12	0.76	0.33	0.21	0.14	−0.11	0.77
Shift 7	0.32	0.34	0.35	−0.35	0.98	0.3	0.23	0.2	−0.17	0.77	0.24	0.17	0.18	−0.12	0.60
Shift 8	0.04	0.25	0.86	−0.44	0.52	−0.02	0.13	0.9	−0.28	0.25	0.07	0.14	0.62	−0.22	0.36
Shift 9	−0.09	0.21	0.65	−0.50	0.31	0.02	0.11	0.83	−0.21	0.26	0.04	0.12	0.72	−0.21	0.30
Shift 10	0.1	0.24	0.69	−0.38	0.57	0.21	0.2	0.29	−0.19	0.62	0.24	0.19	0.22	−0.15	0.63
Shift 11	0.25	0.3	0.41	−0.34	0.84	0.1	0.19	0.6	−0.29	0.49	0.06	0.14	0.68	−0.23	0.34
Shift 12	0.29	0.28	0.31	−0.27	0.84	0.44	0.3	0.16	−0.19	1.06	0.44	0.29	0.15	−0.17	1.04
Shift 13	0.1	0.19	0.61	−0.28	0.48	0.04	0.12	0.75	−0.21	0.30	0.09	0.2	0.65	−0.32	0.51
Shift 14	0.1	0.12	0.39	−0.13	0.34	0.12	0.13	0.38	−0.15	0.38	0.14	0.13	0.28	−0.12	0.41
Shift 15	0	.	.	.	.	0	.	.	.	.	0	.	.	.	.
BMI	0.05	0.02	**<0.01**	0.02	0.08	0.02	0.01	**<0.01**	0.01	0.03	0.01	0	0.06	0.00	0.02
Age	0.02	0.01	0.12	−0.01	0.04	0.01	0	**<0.01**	0.01	0.02	0.01	0	**<0.01**	0.00	0.02
Female	−0.93	0.26	**<0.01**	−1.47	−0.39	−0.3	0.1	**<0.05**	−0.49	−0.10	−0.06	0.08	0.45	−0.23	0.11
Male	0	.	.	.	.	0	.	.	.	.	0	.	.	.	.
LA60+	0.01	0.01	0.44	−0.01	0.03	0	0	0.56	0.00	0.01	0	0	0.24	0.00	0.01
RA60+	0.02	0.01	**<0.05**	0.00	0.04	0	0	0.79	−0.01	0.01	0	0	0.55	−0.01	0.00
FE90P	−0.01	0	**<0.05**	−0.01	0.00	0	0	0.16	0.00	0.00	0	0	0.45	0.00	0.00
RANLS	0	0.01	0.78	−0.02	0.01	0	0	0.53	0.00	0.01	0	0	0.09	0.00	0.01

Estimate = An estimate of the slope for each effect in the model (i.e., beta coefficient).
Std. Error = Standard error of the estimate.
p = *p*-value corresponding to the t-statistic.
95% CI Lower = 95 percent confidence interval lower bound.
95% CI Upper = 95 percent confidence interval upper bound.
LA60+ = percentage of time with the left arm elevated $\geq 60°$.
RA60+ = percentage of time with the right arm elevated $\geq 60°$.
FE90P = the 90th percentile of trunk flexion/extension.
RANLS = percentage of time with the right arm elevated $<20°$ and moving $<5°/s$.

difference in exposure could partially explain why the cyclic workers considered wearing the sensors as more distracting.

Workers who reported higher levels of stress also reported higher burden ratings than those who reported lower levels of stress. Previous studies have indicated that shift workers that report high psychological demand and low job control are more likely to consider their jobs as physically demanding (Buja et al., 2013; Perrucci et al., 2007; Raeisi et al., 2014). It may be that workers who consider their job to be stressful are more likely to consider any additional activities they need to perform while working as burdensome, such as participating in wearing sensors at work. Further research is needed to investigate the relationship between stress experienced at work and the burden of completing additional tasks.

Another interesting finding of this study was the effect that several personal characteristics had on perceptions of discomfort, distraction, and burden. BMI, for instance, was observed to be associated with increases in perceived discomfort and distraction. One possible explanation for these results was that participants with a higher BMI may have had more difficulty finding a comfortable level of adjustment for the straps used to secure the devices around their upper arms. Circumference of the upper arms has been associated with discomfort as a result of pressure from the elastic securing the device that can lead to itchiness, skin irritation and rashes, and/or bruising (McNamara et al., 2016). Another explanation may be that overweight individuals may experience higher sweat levels than individuals with a healthy BMI (Nakayoshi et al., 2015). Wet straps may contribute to feelings of discomfort. Unfortunately, perspiration levels were not measured in this study. Future studies may include observation of perspiration and its potential negative effects on the perceived usability of wearable devices (McNamara et al., 2016).

Although the effect was small (beta = 0.04), age was another significant predictor for sensor-related distraction and burden with younger workers reporting less distraction and burden than older workers. Seniors (aged 60 years or over) have been observed to have challenges adopting to technologies to which they are unaccustomed, such as wearable computer systems (Tedesco et al., 2017). Additional research, therefore, may focus on senior workers use of wearable computing systems in an effort to reduce potential distraction and burden to help improve adoption intention.

The relatively strong sex differences (relative to some other factors such as kinematic exposures) revealed in this study appear consistent with previous research findings suggesting that device preferences may differ based on sex and situation (Beeler et al., 2018; Huberty et al., 2015). The discomfort associated with the use of wearable sensors may be related to the manner by which it is secured to an individual. Specifically, women may be more tolerant to some sensor designs such as sensor bands worn around the chest, as they may be perceived as more socially acceptable to wear, and they are more accustomed to wearing undergarments around the chest relative to men (Ertin et al., 2011). In our study, some participants asked researchers to disguise their sensors by securing them under articles of clothing. Future research may explore the effects of disguising sensors on ratings of sensor wear experience. Occupational safety and health professionals should consider sex differences when contemplating using wearable inertial sensors in the workplace.

The simplicity of the scales included in this study is an important limitation. Discomfort, distraction, burden, and stress may each be considered complex, multifaceted terms. Knight and Baber (2005), for example, suggested six dimensions (emotion, attachment, harm, perceived change, movement, and anxiety) that may affect a user's perception of comfort when using wearables. Given the broad scope of data collection in this study, it was not possible to have participants complete several multidimensional scales. Thus, our findings must be interpreted with caution (i.e., it is unknown which dimensions our ratings are attributed to or if they are consistent within and between participants). Future work may investigate the dimensions of each factor in more detail. It is also important to note that the recruitment procedures used in this study may have affected our results. Employees of the manufacturing facility needed to volunteer as candidates for potential inclusion in the study before they were randomly selected. Thus, participants may be considered early adopters of the technology and, therefore, more receptive to using them in the work environment relative to those that did not volunteer. Along these lines, one participant (of the total 36 that enrolled) withdrew from the study during the first shift of data collection. Although the participant did not provide an assessment of the discomfort, distraction, and burden associated with using the sensors during that time, he was clearly uncomfortable, distracted, and/or burdened by the sensors and/or the experience of participating to a sufficient level to decide to withdraw from participating further.

As indicated in the methods, several participants did not wear one or multiple sensors for some work shifts due to personal health and/or safety concerns. For example, one participant chose not to wear the trunk sensor for several days after missing work due to an illness. Several participants did not wear the wrist and/or trunk sensor because they anticipated working near machinery. Although unfortunate, these scenarios were anticipated and are not expected to have greatly affected the general trend of our results. This study benefitted from a relatively large number of participants when considering the number of shifts collected per worker. However, the decision to not wear the sensors during some work shifts is very important to note. Similarly, undesirable ratings, particularly data points exceeding the upper quartile of the collected data as depicted in Fig. 1, indicate that discomfort, distraction, and burden can present as an important issue even if "typical" ratings are low. Stated reasons from participants for these high ratings were limited to those previously described (e.g., anticipation of working near machinery; loose sensor straps; irritating elastic connections; perceptions of socially unacceptable behavior). Ultimately, we suggest that occupational safety and health practitioners considering using wearable inertial sensors among manufacturing workers carefully factor this variability into the generally small effects that different personal (e.g., sex; age; BMI) and work (e.g., work categorization; perceptions of stress; exposure to kinematic risk factors) characteristics had in this study.

5. Conclusion

Wearable inertial sensors may be generally considered comfortable to wear and not distracting and/or burdensome for extended use (i.e., multiple full shifts) among manufacturing workers. Although spending more working time with the right (typically dominant) arm in non-neutral postures and increased worker BMIs contributed to statistically significantly higher average discomfort ratings, the reports of discomfort remained practically small. Similarly, cyclic work activities and higher BMIs were related to statistically significant, albeit small increases in distraction. Increases in age and perceived stress levels led to similar findings for burden ratings. Personal characteristics, work characteristics, and variability in perceptions of discomfort, distraction, and burden should remain a forethought when considering using wearable inertial sensors to collect physical exposure information in the manufacturing sector.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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