FINAL PROGRESS REPORT

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ABSTRACT

Introduction. Work-related musculoskeletal disorders (MSDs) are prevalent and disabling health conditions that result in substantial health care costs and lost productivity. Manufacturing workers report a high prevalence of MSDs resulting from repeated exposure to physical risk factors in their work environment. One contributing factor for the repeated adverse exposure is insufficient control of these risk factors due to the routine use of imprecise and potentially biased self-report and/or observation-based exposure assessment tools. Direct measurement technologies such as ambulatory inertial sensors (AISs) provide more precise and unbiased information for estimating occupational exposure to physical risk factors compared to self-report or observation-based exposure assessment methods.

Methods. This study was executed in three phases. Each phase addressed barriers preventing the adoption of AISs in manufacturing environments. In the first phase, wearable AISs were deployed among a stratified sample of manufacturing workers performing cyclic and noncyclic work tasks over 15 complete working days for each participant to gather information regarding kinematic exposure variability. The information was used to evaluate the precision of exposure measurements from AISs and estimate the number of workdays that must be sampled depending on worker group categorization (i.e., cyclic vs. non-cyclic). In the second phase, a workplace occupational health and safety "dashboard" was developed, evaluated, and implemented that summarized direct measurements obtained from the wearable sensors to inform operational decision-making. The third phase evaluated the AIS-driven dashboard's effects on exposure to physical risk factors and safety behaviors, considering stakeholder perceptions of organizational and group-level safety climate.

Results. Statistically significantly higher upper arm and trunk movement speeds among manufacturing workers performing predominantly cyclic tasks were measured compared to those performing non-cyclic tasks despite similar postures. Greater exposure variability was measured both between and within workers in the non-cyclic group. Bootstrap analyses of the kinematic exposure metrics indicated that nine days of data collection would be sufficient to obtain stable estimates of the kinematic metrics associated with work-related MSDs in previous epidemiological investigations. The AISs were identified as being comfortable to wear, not distracting, and not burdensome for the participating manufacturing workers to use. The occupational health and safety dashboard developed in this study received a "marginal" rating from evaluators. Mixed results were measured when evaluating the effects of using the AIS-driven dashboard on exposure to physical risk factors and safety behaviors. Both work groups spent approximately six to eight percent more time in neutral postures compared to the pre-intervention phase. The trunk flexion/extension movement speeds among the cyclic participants improved post-intervention, whereas the movement speeds among the non-cyclic participants generally worsened.

Conclusion. The results of this study suggest that AISs can be successfully used to quantify and compare occupational exposures to kinematic risk factors (e.g., non-neutral postures and high movement speeds) among manufacturing workers over extended durations without substantial discomfort, distraction, or burden. Additional studies exploring the use of AISs and software systems that leverage summaries of key performance indicators for guiding the prioritization of work design improvements are warranted.

SECTION 1

Significant Findings

- Substantially higher upper arm and trunk movement speeds were measured among manufacturing workers performing predominantly cyclic tasks relative to workers performing non-cyclic tasks despite similar postures.
- Greater exposure variability was measured both between and within workers in the non-cyclic group.
- Nine work shifts of data collection or less (depending on the exposure metric of interest) were determined to be adequate to obtain stable kinematic measurements of the upper arms and trunk.
- The AISs were generally rated as being comfortable to wear, not distracting, and not burdensome by the participating manufacturing workers.
- Small increases in undesirable ratings of (dis)comfort, distraction, and burden were associated with some kinematic measures and personal characteristics.
- The dashboard developed in this study received a "marginal" rating from evaluators.
- Cyclic and non-cyclic workers spent approximately 6-8 % more time in neutral postures when measured in the post-intervention phase following the use of the AIS-driven dashboard.
- The trunk flexion/extension movement speeds among the cyclic participants improved post-intervention, whereas the movement speeds among the non-cyclic participants generally worsened.
- Additional studies exploring the use of AISs and software systems that leverage summaries of key performance indicators for guiding the prioritization of work design improvements are warranted.

Translation of Findings

- Computationally efficient, non-proprietary complementary filters were developed and evaluated. The complementary filters were comparable (<1° peak displacement difference) to more complex Kalman filters. The filters are available as open-source code for others at: https://github.com/how-chen/imu-inclination
- The participating manufacturing facility used the information collected with the AISs and summarized in the dashboard to prioritize opportunities for operational improvements that benefit worker health.
- A training objective of this K01 award was to develop new knowledge, skills, and abilities regarding workplace safety climate and leadership. A review was published by the PI and a co-mentor that provides practical guidance for group-level supervisors, occupational safety and health managers, and organizational leaders responsible for promoting health and safety among teleworkers during and after the Coronavirus pandemic.

Research Outcomes / Impact

Ambulatory inertial sensors are often marketed as capable of measuring human motion in three dimensions in field environments, an important technological advancement compared to other direct measurement devices. However, technical limitations such as reduced measurement accuracy in the presence of ferromagnetic disturbances and concerns regarding their practicality in some work environments are known to be a barrier to their broad adoption among occupational health and safety professionals. Our team has continued to develop a robust, open-source library of sensor fusion algorithms for converting raw data streams into established summary measures of worker posture and movement throughout the performance of this project. Furthermore, we have developed new knowledge about manufacturing workers' perceptions and the best practices for using wearable AISs over multiple work shifts. We anticipate that the findings of this study will directly benefit the manufacturing industry and improve the science and practice of kinematic assessment in future research across a broad range of occupational settings.

SECTION 2: SCIENTIFIC REPORT

Note: Much of the content of this report was adapted from the resultant publications identified at the end of the report. It is recommended that readers review the publications for additional information.

Background and Specific Aims

Work-related musculoskeletal disorders (MSDs) are among the most common and burdensome of all health conditions affecting Americans. Accounting for approximately one-third of all nonfatal occupational injuries and illnesses across US industries each year (USBLS, 2020), MSDs are estimated to cost the nation over $800 billion annually and are the second most common cause of disability worldwide (Horton, 2012; USBJI, 2014; Vos et al., 2013). Occupational safety and health (OSH) personnel employed in industries that commonly report a high incidence of MSDs, such as manufacturing, are often responsible for evaluating and modifying workspaces to prevent these conditions through workplace ergonomics programs (Rivilis et al., 2008; Van Eerd et al., 2015). An essential aspect of a successful workplace ergonomics program is the systematic characterization and monitoring of exposure to physical risk factors associated with MSDs, such as extremes of posture (Punnett & Wegman, 2004; Zalk, 2001). While self-report and observation-based exposure assessment methods are routinely used by OSH personnel to identify, characterize, and monitor exposures to physical risk factors, these methods are widely considered to be less precise and more prone to bias than direct measurement methods (David, 2005; Dempsey, McGorry, & Maynard, 2005; Prince et al., 2008; Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001; Teschke et al., 2009; Winkel & Mathiassen, 1994). Bias and imprecision in exposure estimates may lead to misclassification errors that attenuate true exposure-outcome relationships, as well as contribute to the inappropriate selection of interventions intended to reduce exposures (N. B. Fethke, Gerr, Anton, Cavanaugh, & Quickel, 2012; Svend Erik Mathiassen, Möller, & Forsman, 2003; S. E. Mathiassen, Wahlstrom, & Forsman, 2012).

Ambulatory inertial sensors (AISs) are innovative, objective, and valid direct measurement technologies that have emerged as an alternative to self-report or observation-based methods for measurement of exposure to physical risk factors in occupational settings (Schall Jr, Fethke, Chen, & Gerr, 2015; Schall Jr, Fethke, Chen, Oyama, & Douphrate, 2016). Despite their small size, decreasing costs, and growing use among the general public, most OSH personnel employed in industry do not currently deploy AISs among employees to promote workplace safety and health (Schall Jr, Sesek, & Cavuoto, 2018). Potential explanations for the limited use of AISs in industry include (i) an incomplete understanding of how long data must be sampled for a given work task to obtain adequate precision of the exposure estimate, (ii) the lack of a user-centered system capable of summarizing information gathered from the sensors for efficient use, and (iii) the unknown effects of using AISs on exposure to physical risk factors and safety behaviors in a manufacturing environment.

To address these research gaps and other methodological limitations of the existing literature, we conducted a repeated-measures, field-based exposure assessment study addressing the following specific aims:

Aim 1: Deploy AISs among a stratified sample of 36 production workers performing cyclic and noncyclic work tasks to estimate the number of workdays that must be sampled to obtain stable exposure estimates of several common physical risk factors.

Aim 2: Develop, implement, and evaluate an OSH "dashboard" designed to present summarized exposure information to help prevent MSDs and promote healthier workplace behaviors.

Aim 3: Evaluate the effects of implementing AISs and the OSH dashboard on exposure to physical risk factors and workplace safety behaviors as well as determine how those effects vary depending on stakeholder perception of safety climate.

Procedures and Methodology

Study design and setting

We conducted a repeated-measures, field-based exposure assessment intervention study among a random sample of production workers at a Fortune 1000 manufacturing facility in Auburn, AL. The manufacturing facility employed approximately 450 workers across three eight-hour work shifts. Before any data collection, the research team toured the manufacturing facility and reviewed its production processes with the facility safety director. The research team and safety director agreed that employees could be broadly categorized into one of two work groups: those predominantly completing ‘cyclic’ and ‘noncyclic’ work tasks. Consistent with Paulsen et al. (2014), cyclic work tasks were defined as those completed following standard production procedures and characterized by cycle times of less than approximately three minutes. Study activities began in September 2018.

Description of the Intervention

We developed and implemented an OSH “dashboard” designed to present summarized exposure information to prioritize opportunities for work redesign, help prevent MSDs, and promote healthier workplace behaviors. The OSH dashboard was developed following an iterative design process that involved regular interactions with OSH personnel and safety committee members at the collaborating work facility and spanned approximately two years. The development process began by introducing a pilot dashboard to demonstrate potential functionality. At the same time, kinematic data were collected from facility employees as described in Schall Jr, Zhang, Chen, Gallagher, and Fethke (2021). As kinematic data was collected, it was implemented into the dashboard and provided to the facility to facilitate the job assessments completed for approximately one year prior to system evaluation. The pilot version of the dashboard was improved and tailored to meet the needs of the collaborating production facility based on feedback from the OSH personnel and safety committee members. The revisions primarily focused on identifying meaningful measures and methods to present the collected data. For example, the pilot version of the dashboard had limited data analysis functionality. Most data were presented in a tabular form. A charting option plotted a time series of mean exposure for each collection day was included, but it had limited summary parameters. Additional details on the development process and final design of the dashboard are included in the Results section. The facility continued its usual OSH protection and workplace health promotion activities during the study.

Eligibility and enrollment of study participants

Study participants were recruited and enrolled following Auburn University Institutional Review Board (IRB) approved study procedures for each aim of the study as follows:

Aim 1. The manufacturing facility employees were made aware of the study via the distribution of recruitment letters (i.e., flyers), face-to-face meetings, and word-of-mouth. Employees interested in being considered candidates for potential inclusion in Aim 1 of the study volunteered by informing the facility safety director. The research team then randomly selected from the pool of interested candidates that were separated into the two categories of work groups by the facility safety director to achieve an equal sample in each group. Participant exclusion criteria included any self-reported: (i) history of physician-diagnosed muscle or bone diseases in the low back, neck/shoulder, or upper extremity (ii) “chronic” (i.e., constantly recurring); low back, neck/shoulder, or upper extremity pain during the previous 14 days; or (iii) history of a physician-diagnosed neurodegenerative disorder that may affect movement (e.g., Parkinson’s Disease, multiple sclerosis).

Thirty-six participants (18 cyclic and 18 non-cyclic workers) were enrolled in Aim 1. One participant in the non-cyclic study group withdrew from participation during the first day of data collection, and no data collected from that participant were analyzed. Data were collected for 15 consecutive weekday shifts from the remaining 35 participants. One of the 35 participants switched job titles following the 10th shift of participation. No data from this participant's five shifts following the job title change were included in the analyses. Each participant provided written informed consent before any data was collected. Thus, 520 work shifts were collected during the pre-intervention phase of the study.

Aim 2. Members of the research team attended safety committee meetings at the manufacturing facility to gather information related to the intervention. The research team provided information on the purpose of the study to all safety committee members using an IRB-approved information letter. This information letter served as a Waiver of Documentation of Consent for attendance at the meetings and to inform attendees that information relevant to the project may be collected during the meetings.

The research team invited safety committee members to complete the three safety climate and behavior surveys used in Aims 1 and 3. Interested safety committee members met with a research team member at the manufacturing facility and reviewed the eligibility criteria. Eligible safety committee members provided written informed consent before participating. Four safety committee members met the study inclusion criteria and enrolled in the study's safety climate and behavior survey component.

A total of 43 human factors professionals were recruited via email and information letter to participate in the OSH dashboard evaluations. If an individual responded with interest in participating, the research team sent an electronic invitation to the evaluation using the Qualtrics survey engine. Participants were provided a waiver of documentation of consent via the electronic survey information letter. Nineteen human factors professionals registered on a functional demonstration version of the web application. Ten of those 19 proceeded to complete a SUS evaluation using the Qualtrics survey engine, and seven also provided comments regarding the dashboard as part of a heuristic evaluation. This sample size has been identified as sufficient for usability studies (Lewis, 1994; Turner, Lewis, & Nielsen, 2006).

Aim 3. Similar to Aim 1, manufacturing facility employees were made aware of the study via the distribution of recruitment letters (i.e., flyers), face-to-face meetings, and word-of-mouth. Employees interested in being considered candidates for potential inclusion in Aim 3 of the study volunteered by informing the facility safety director. The research team then randomly selected from the pool of interested candidates that were separated into the two categories of work groups by the facility safety director to achieve an equal sample in each group. Participant exclusion criteria included any self-reported: (i) history of physician-diagnosed muscle or bone diseases in the low back, neck/shoulder, or upper extremity (ii) “chronic” (i.e., constantly recurring); low back, neck/shoulder, or upper extremity pain during the previous 14 days; or (iii) history of a physician-diagnosed neurodegenerative disorder that may affect movement (e.g., Parkinson’s Disease, multiple sclerosis).

Twenty-two participants (6 cyclic and 16 non-cyclic workers) enrolled in Aim 3 of the study. Thirteen of the 22 participants in Aim 3 were also enrolled in Aim 1. Data were collected for ten consecutive weekday shifts from all participants in Aim 3 (i.e., ten shifts were determined adequate to obtain stable kinematic measurements of the upper arms and trunk in Aim 1). Thus, 220 work shifts were collected during the post-intervention phase.

Data collection instruments and procedures, data quality, and statistical analyses by the study aim

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Aim 1

Data Collection Instruments and Procedures

Four ActiGraph GT9X Link (ActiGraph, Pensacola, Florida, USA) AISs were secured to each participant with elastic hook-and-loop fastener straps and hypoallergenic cohesive bandages each work shift (Fig. 1). The AISs were worn on (i) the anterior trunk over the sternum approximately between the sternal notch and the xiphoid process (depending on the anatomy and comfort of each participant) over an item of each participant’s clothes; (ii) on each upper arm

approximately one-half the distance between the lateral epicondyle and the acromion (either on the skin or over a participant's clothes depending on comfort); and (iii) on the dominant wrist (on the skin). Each AIS measured linear acceleration (±16 g), angular velocity (±2000 deg/sec), and magnetic field strength (±4800 µT) at a sampling rate of 100 Hz using a tri-axial accelerometer, gyroscope, and magnetometer.
A calibration procedure was performed immediately following the placement of all AISs at the beginning of each work shift. The calibration procedure involved asking participants to briefly stand in a neutral posture and perform three bends between approximately 30-60° of trunk flexion followed by three lateral arms raises from a neutral posture to approximately 90° relative to gravity. A research team member noted the time that the calibration procedure began. These calibration periods were reviewed in MATLAB and used to identify the beginning of data collection. Participants proceeded with their regular work shift after completing the calibration procedure.

The raw data from each AIS were downloaded to a computer using ActiLife software (version 6.13.3, ActiGraph, LLC, Pensacola, FL) after each shift. The raw AIS data were then exported to comma-separated files for offline processing. Inclination measurements of the upper arms and trunk were calculated using a computationally efficient first-order complementary filter that combined accelerometer and gyroscope measurements (Chen, Schall Jr, & Fethke, 2020; Chen, Schall, & Fethke, 2018). No magnetometer data were used. The trunk inclination measurements (flexion/extension and lateral bending) were calibrated to register an inclination of 0◦ (i.e., aligned with gravity) when in the neutral calibration posture to compensate for differences in subject anatomy. Upper arm inclination (i.e., elevation) measurements were also relative to gravity; however, they were not aligned to a neutral posture. After calculating the inclination measurements, the data were downsampled to 20 Hz using MATLAB's resample function to improve computational post-processing speed. Movement speeds (i.e., the absolute value of velocities) of the arms and trunk were calculated using the derivative of the arm and trunk posture waveforms with respect to time.

During each shift, participants logged in a pre-printed diary the times when work tasks were performed. The research team used information from the diaries to classify the work tasks into one of six categories. Participants in the cyclic group predominantly performed assembly or operating machinery tasks. Tasks categorized as maintenance or set-up were predominantly performed by participants in the non-cyclic group. "Other" tasks that did not meet the primary task categories identified for each group were routinely performed by participants in both groups. All participants (cyclic and non-cyclic) were also asked to report their work breaks. 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 each work task on separate VASs. Participants were asked to rate the "force" exerted for each logged work activity from a score of 0 indicating "no force" to a score of 10 for "max force" immediately following completion of each work task on separate VASs. At the end of each 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. In contrast, a score of 10 represented the devices being "as uncomfortable as possible," a "complete distraction," or "as burdensome as possible."

In addition to the direct exposure measurements and daily logs, participants completed three short surveys regarding their perceptions of their employer's safety climate and personal safety behaviors. Specifically, 16 items assessed organizational safety climate using the organizational multi-level safety climate sub-scale (Zohar & Luria, 2005). This scale's items reflect top management's commitment to safety (Zohar & Luria, 2010). Sixteen items assessed group safety climate using the group multi-level safety climate sub-scale (Zohar & Luria, 2005). This scale's items examine the priority of safety versus competing goals (Zohar & Luria, 2010). The Items were accompanied by a 5-point Likert rating scale ranging from Completely Agree (5) to Completely Disagree (1), and they were aggregated to produce a single score of managerial commitment (Zohar & Luria, 2010). The safety behaviors survey addressed task safety behavior and contextual safety behavior in 10 items (Cigularov, Chen, & Rosecrance, 2010). The surveys were completed on paper on the first day of participation after providing informed consent and before proceeding to their work.

Metrics

Kinematic Measures

Several common posture, movement speed, and rest/recovery exposure metrics were calculated using full-shift inclination and movement speed measurements consistent with previous research (Barbieri, Srinivasan, Mathiassen, Nogueira, & Oliveira, 2015; Jackson, Srinivasan, & Mathiassen, 2020; Kazmierczak, Mathiassen, Forsman, & Winkel, 2005; Kersten & Fethke, 2019; Wahlström et al., 2010). For the upper arms, exposure metrics included the mean amplitude and the 10th, 50th, and 90th percentiles of the posture and movement speed time-series waveforms. The percentage of time in neutral (<20°) and "extreme" (≥60°) upper arm posture angles, as well as the percentage of time moving in low (<5°/s) and high movement speeds (≥90°/s), were calculated. 'Posture variation,' or the exposure range, was expressed as the difference between the 90th and 10th percentiles of posture; a similar measure was calculated for movement speed (Ciccarelli, Straker, Mathiassen, & Pollock, 2014; Svend Erik Mathiassen, 2006; S. E. Mathiassen et al., 2012; Wahlström et al., 2010). Rest/recovery exposure metrics included the percentage of time in a neutral posture for ≥ 3s, time moving at a low speed for ≥ 3s, and time in a neutral posture and moving at a low speed. Identical variables were used to describe trunk motion in the flexion/extension and lateral bending planes, except that a neutral posture was defined as the range from -20° (extension or left lateral bending) to 20° (flexion or right lateral bending).

In a portion of Aim 1 analyses, we examined within-shift 'exposure variability' by (i) parsing each full-shift recording into non-overlapping 1-min windows, (ii) calculating the mean amplitude and 90th – 10th percentile range of both posture and movement speed within each 1-min window, and then (iii) calculating the standard deviation (SD) of the 1-min means (i.e., SD_{means}) and the SD of the 1-min 90th – 10th percentile ranges (i.e., SD_{ranges}) across the duration of the recording for both posture and movement speed. Conceptually, for any participant, SDmeans quantifies the between-minute dispersion of the average posture and average movement speed, while SDranges quantifies the between-minute dispersion of the within-minute posture variation and movement speed variation (Barbieri et al., 2015; Jackson et al., 2020). We also calculated the mean power frequency (MPF) as an index of repetitiveness (Douphrate, Fethke, Nonnenmann, Rosecrance, & Reynolds, 2012; G-Å Hansson, Balogh, Ohlsson, Rylander, & Skerfving, 1996; Radwin & Lin, 1993). The posture data was parsed into consecutive, non-overlapping sections of 4096 samples (4096 samples ÷ 20 Hz = 204.8 s) in duration to calculate the power spectra. The last section of the recording, if unequal to 4096 samples, was discarded from the analysis. A Hanning window was then applied to each section to reduce spectral leakage. A Fast Fourier Transform was used to derive the power spectrum separately for each non-overlapping section. The MPF was calculated for each section to produce a time series of MPF estimates. The overall averaged MPF was computed by averaging the spectra from each section between 0.033 Hz and 5 Hz.

Information from the diaries completed during each shift was used to generate a second dataset containing time-weighted averages of each posture, movement speed, and rest/recovery metric by predominant task category. Only one time-weighted value for each task category per participant per shift was calculated for each exposure metric; however, not every participant performed every task associated with their group status (i.e., cyclic or non-cyclic) during each shift.

In addition to the posture, movement speed, and rest/recovery metrics, energy expenditure at work expressed as metabolic equivalents (METs) was calculated using the gyroscope and accelerometer approach (i.e., Algorithm 2, ENMO and GVM (°/s, 1-s epochs) described by Hibbing, Lamunion, Kaplan, and Crouter (2018) for the AIS worn on the dominant wrist of each participant for each work day. A MET is the amount of oxygen consumed while sitting at rest, equal to 3.5 ml O2 per kg body weight x min.

Safety Climate and Safety Behaviors

Item responses for each respective safety climate and safety behavior survey were aggregated consistently with the methods described in Zohar and Luria (2010) and Cigularov et al. (2010).

Data Quality

Of the 520 work shifts measured across the 35 participants who completed Aim 1, 515 left arm, 517 right arm, and 477 trunk files were included in the final analysis. Instrumentation failures and data collection issues (e.g., participants removing/not wearing a sensor) led to the loss of the files not included in the analysis. Fourteen of the 43 removed trunk files were considered outliers (conservatively defined as measurements more than 1.5 times the interquartile range below the first quantile or more than 1.5 times the interquartile range above the third quantile for the 50^{th} percentile of posture across each respective participant's 15 shifts). The location of the trunk sensor on the anterior sternum also led to occasional transient artifacts (e.g., the sensor being contacted). Of the 477 trunk data files included in the analysis, 72 (15%) required the replacement of transient artifacts with the mean posture of the entire recording duration. On average, 99.49% of the original data from these 72 full trunk files was retained for analysis.

Statistical Analyses

Mixed-effect Analysis of Variance

The mean and SD of each posture, movement, and rest/recovery exposure metric across participants were calculated by work group (i.e., cyclic vs. non-cyclic). Potential violations of the normality assumption for mixed-effect analysis of variance (ANOVA) were reviewed by examining distributions of the studentized conditional residuals for each exposure metric. Although the normality assumption was violated for some exposure metrics, particularly where skewing may be anticipated (e.g., percentage of time in an extreme posture), no transformations were applied to maintain consistency with previous studies (e.g., Kersten and Fethke, 2019) and because ANOVA models are generally regarded as being robust to violations of normality in the absence of bias (Blanca, Alarcón, Arnau, Bono, & Bendayan, 2017). For each full-shift exposure metric, a hierarchical mixed-effects linear model was used to test the fixed effect of work category (cyclic vs. non-cyclic) on the mean values of the exposure summary metrics. The model had the following general form:

$$y_{ijk} = \mu + \alpha_i + \beta_{j(i)} + \varepsilon_{k(ij)} \quad (1)$$

where y_{ijk} is the full-shift exposure metric value associated with the k^{th} shift on the jth subject within the i^{th} group, μ is the overall mean exposure metric value across all shifts, α_i is the fixed effect of group i, $\beta_{j(i)}$ is the random effect of subject j within group i, and the residual term, $\varepsilon_{k(ij)}$, is the random effect of shift k within both group i and subject j. Both random effects were assumed normally distributed, and observations from different participants were assumed independent. Non-independence of observations from the same participant (i.e., observations from different shifts) was modeled using the first-order autoregressive (AR(1)) covariance structure. The AR(1) structure was selected based on examining model fit using the Akaike Information Criterion. The dataset was unbalanced due to unequal numbers of shifts among the participants in each group. Therefore, the restricted maximum likelihood (REML) approach was used to fit the models. An alpha value of 0.05 was used to assess the statistical significance of the fixed effect of group.

Variance components associated with the random effects of subject (nested within group) and shift (nested within group and subject) were also calculated (Rappaport, Weaver, Taylor, Kupper, & Susi, 1999; Searle, Casella, & McCulloch, 2009). Model outputs included estimates of the variance between subjects (S^2_{BS}, i.e., the variance of $\beta_{j(i)}$) and the variance between shifts within subject (S^2_{WS}, i.e., the variance of $\varepsilon_{k(ij)}$), as well as the Wald 95% confidence intervals around the estimated variances. For each posture, movement speed, and rest/recovery exposure metric and separately for the cyclic and non-cyclic groups, the ratio of S^2_{WS} to S^2_{BS} was calculated as a measure of exposure homogeneity ($\lambda = S^2_{WS}/S^2_{BS}$)(Burdorf, 1992; Houba, Heederik, & Kromhout, 1997).

Finally, SD_{means} and SD_{ranges} for both posture and movement speed were summarized using means and SDs across participants by work group. Although no formal inferential statistical procedures were applied, the results were used to make a qualitative assessment regarding differences in the within-shift exposure variability between the cyclic and non-cyclic work groups. Likewise, the task-based measures were used to add context to and assist in the interpretation of the observed differences in the full-shift exposure metrics between the cyclic and non-cyclic groups (i.e., it was not our objective to compare task-level exposures statistically).

All statistical procedures were performed using SAS (version 9.4, SAS Institute Inc., Cary, NC). The PROC MEANS procedure was used to calculate all presented means and SDs. The PROC MIXED procedure was used to test the fixed effect of group for statistical significance and to estimate variance components and associated confidence intervals.

Bootstrap Resampling

Nonparametric bootstrap resampling (i.e., random sampling with replacement) was used to examine the effect of the number of days of observation (i.e., data collection) on the precision of a selection of exposure metrics for each work group and upper arm (Figure 1) (Nathan B Fethke, Anton, Cavanaugh, Gerr, & Cook, 2007; Hoozemans, Burdorf, Van Der Beek, Frings-Dresen, & Mathiassen, 2001). Exposure metrics were selected based on their association with work-related MSDs in epidemiological studies and common use in the occupational health and safety literature (Arvidsson, Dahlqvist, Enquist, & Nordander, 2021; Balogh et al., 2019; Coenen, Douwes, van den Heuvel, & Bosch, 2016; Kazmierczak et al., 2005; Kersten & Fethke, 2019; Svend Erik Mathiassen, 2006; Palm et al., 2018). They included:

- The 90th percentile of upper arm elevation (RA90P/LA90P).
- The percentage of work time spent with the upper arm elevated in an “extreme” posture > 60° (RAEXP/LAEXP).
- The difference between upper arm elevation's 10th and 90th percentiles (RA1090P/LA1090P).
- The 50th percentile movement velocity (RA50V/LA50V).
- The difference between the 90th and 10th percentiles of the magnitude of upper arm movement velocity (RA1090V/LA1090V).

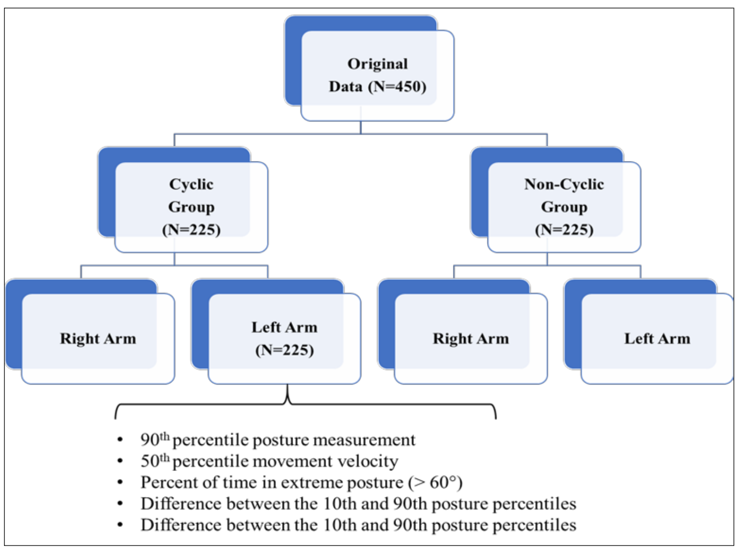

Figure 1. Illustration of Bootstrap Procedure for Each Group and Body Location

Each unit of observation, a work day, was randomly selected out of 15 days of observations. When adding each unit of observation, 15 observations from 15 workers would be added to the bootstrap sample. The resampled data set was randomly generated with replacement from the parent sample per work group (e.g., N = 15, 30, …, or 225). Each observation had 1/N probability of being selected into the resampled data set. The resampling process was carried out repetitively for 10,000 iterations. The statistic ɵ was recalculated in each iteration based on the number of resampled observations chosen from the parent sample. For each iteration, statistic ɵ hat was calculated. The distribution of the resampled statistics (ɵ hat) is the bootstrap distribution (Blank, Seiter, & Bruce, 2001). An illustration of the bootstrap process is provided in Figure 2.

Bootstrap sample	***Randomly selected observation day(s)***	***Randomly selected value from each sample***	***Iterations***	***Bootstrap Distribution***
N = 15	Day 3 (Day=1)	36.6, 34.8, 34.3 … (N=15)	10,000	Bias Corrected Confidence Intervals (BCa)
N = 30	Day 5, Day 8 (Day=2)	37.1, 34.2, 37.7… (N=30)		
N = 45	Day 1, Day 9, Day 5 (Day=3)	35.8, 34.2, 33.9 … (N=45)		
→	→	→	→	→
N = 225	Day 7, Day 11, Day 2, Day 3, … (Day=15)	38.2, 39.7, 35.7, …(N=225)		

Figure 2. Illustration of Bootstrap Procedure of RA1090P for Cyclic Workers (15 participants from Day 1 to Day 15, total sample size = 225 observations)

We used 95% Bias Corrected and Accelerated (BCa) Confidence Intervals to evaluate the precision of the bootstrap distribution of ɵ hat. Specifically, the bias-corrected term of BCa adjusted the possible bias in the bootstrap estimate of the mean while comparing it with the mean from the sample of observations (B Efron & Tibshirani, 1986; Hoozemans et al., 2001). The acceleration term of the BCa took into consideration the changing standard error parameter depending on the true population and accounted for the skewness in the sampling distribution (Albright, 2019; Tibshirani, 1984). The BCa method corrected for bias and skewness of the bootstrap distribution estimator (Bradley Efron, 1987; Bradley Efron & Tibshirani, 1994; Jung, Lee, Gupta, & Cho, 2019).

In this analysis, data were collected from 15 participants in each work group. Each participant had 15 days of repeated measurements. Part of the repeated measurements over 15 days were correlated based on an analysis of Pearson Correlation Coefficients. Since a vital assumption of bootstrapping is the independence of resampled observations (Nathan B Fethke et al., 2007; Ju, 2015), non-overlapping blocks were created to account for the within-subject correlation given repeated measurements of the same subjects over 15 days (Carlstein, 1986; Ju, 2015; Lahiri, 1999) (see Figure 3). The block bootstrap derived estimates of the bootstrap distribution by blocking observations from the same subject into each block (James, Witten, Hastie, & Tibshirani, 2013). The bootstrap procedure was programmed and processed in R programming software (Team, 2015). We used a conservative criterion to determine a sufficient sample size of less than a 10% increase in the confidence interval widths. An improvement of <10% was equivalent to an improvement in the precision for RAEXP and LAEXP of less than 0.1% of the time. For RA90P, LA90P, RA1090P, and LA1090P, the improvement of precision estimates was less than 1°. For RA50V, LA50V, RA1090V, and LA1090V, the improvement of precision was <0.5°/s.

Bootstrap Procedure Sample Size	***Block based on participant***	***Block Length***	***# of blocks***
N=15 (1 day of observation)	Participant X: $\boxed{x_1}$ Participant Y: $\boxed{y_1}$	1	15
N=30 (2 days of observation)	Participant X: $\boxed{x_1, x_2}$ Participant Y: $\boxed{y_1, y_2}$	2	15
N=45 (3 days of observation)	Participant X: $\boxed{x_1, x_2, x_3}$ Participant Y: $\boxed{y_1, y_2, y_3}$	3	15
……	……	……	……
N=225 (15 days of observation)	Participant X: $\boxed{x_1, x_1, \ldots\ldots x_{15}}$ Participant Y: $\boxed{y_1, y_1, \ldots\ldots y_{15}}$	15	15

Figure 3. Illustration of Created Non-overlapping Blocks (in red) for each participant in every bootstrap analysis.

Linear Models to Assess (Dis)comfort, Distraction, and Burden

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). Three participants were excluded because over 25% of trunk data were missing due to data collection failure or choosing not to 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.

We performed five iterations of MI per the missing data rate (Royston & White, 2011). The EM algorithm is a two-step iterative approach that estimates the maximum likelihood parameters by repeating 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). RBAs are filter-style feature selection algorithms aiming to maximize prediction accuracy and computational efficiency that have been applied in many different areas of study for classification and regression analyses (Urbanowicz, Meeker, La Cava, Olson, & Moore, 2018). WEKA 3.8.0 is 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, Meekins, & Beling, 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 & 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 were calculated using the reported task durations and stress ratings from the self-reported shift logs
- Work category (i.e., cyclic vs. non-cyclic)
- Eight kinematic exposure variables for each arm, which included:
    - Mean amplitude of the time-series arm elevation waveform over the duration of each shift
    - Mean amplitude of the time-series movement speed waveform over the duration of each shift
    - The 90th percentile of the time-series arm elevation waveform over the duration of each shift
    - The 90th percentile of the time-series movement speed waveform over the duration of each shift
    - The percentage of time moving at low movement speeds (< 5°/s)
    - The percentage of time moving at high movement speeds (≥ 90°/s)
    - The percentage of time with the arm elevated ≥ 60° degree
    - The percentage of time with the arm in a neutral posture (< 20°) and moving at a low speed (< 5°/s)
- Six kinematic exposure variables for the trunk, which included:
    - Mean amplitude of the time-series trunk flexion/extension waveform over the duration of each shift
    - Mean amplitude of the time-series movement speed waveform over the duration of each shift

- The 90th percentile of the time-series trunk flexion/extension waveform over the duration of each shift
- The 90th percentile of the time-series movement speed waveform over the duration of each shift
- The percentage of time with the trunk moving < 5 °/s
- 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). These predictors had (i) positive average merit value in all three models; and (ii) no occurrence of multicollinearity 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.

Three generalized linear models were applied to investigate the effect of work category (i.e., cyclic vs. non-cyclic), work stress, kinematic exposure variables, and personal characteristics on self-reported discomfort, distraction, and burden ratings. The generalized structure of these models was as follows:

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

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 i^{th} participant was categorized as a cyclic worker and 0 if non-cyclic;
X_{ij4} = 1 if the i^{th} 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;
$X_{ij8} \ldots X_{ijk}$ = posture and movement speed variables, including LA60+; RA60+; RANLS; 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 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 overview of the dispersion of the beta coefficient for each predictor.

Aim2

Data Collection Instruments and Procedures

Evaluation of the OSH dashboard followed a concurrent triangulation mixed-methods design.

Heuristic and System Usability Scale Evaluations

Heuristic and system usability scale (SUS) evaluations were conducted to assess the functionality of the OSH dashboard. Heuristic evaluation is a qualitative assessment method in which experts judge an interface's compliance with usability principles (Nielsen, 1994; Nielsen & Molich, 1990). The SUS is a 10-item, Likert-scale survey (with responses ranging from "strongly disagree" to "strongly agree") used to gather an individual's assessment of a system's usability. We analyzed following the recommendations of Brooke (1996, 2013). Specifically, the SUS yielded a composite score between 0 and

100, with products scoring > 85 generally considered highly usable (i.e., among the top 10 percent of products) (Brooke, 2013; Orfanou, Tselios, & Katsanos, 2015).

The SUS is reliable and highly correlated with other usability scales (Bangor, Kortum, & Miller, 2009; Bangor, Kortum, & Miller, 2008). Thus, priority was given to the quantitative SUS results in our analysis. While the SUS provides a single score indicating the overall perceived usability of a system, previous research has indicated that its ten items load on two primary factors – 1) the "learnability" of a system and 2) the overall "usability" of a system (Brooke, 2013; Lewis & Sauro, 2009). These two factors were, therefore, considered 'themes' (Creswell, Plano Clark, Gutmann, & Hanson, 2003). The audio recordings and transcriptions of the safety committee meetings and the qualitative heuristic analysis results were integrated during the interpretation phase.

Aim 3

Data Collection Instruments and Procedures

Identical data collection instruments and procedures were used in Aim 3 as in Aim 1, except for the following:

- Participants were asked to rate the "fatigue" experienced for each logged work activity from a score of 0, indicating "Not at all tired," to a score of 10 for "Very tired" immediately following completion of each work task on separate VASs.
- Participants did not record their perceived discomfort, distraction, and burden associated with using the full complement of sensors they wore throughout the shift.

Metrics

Identical metrics were used in Aim 3 as in Aim 1 except for the following:

- We did not examine within-shift exposure variability measures, or report mean power frequency (MPF) information since the work groups were identified to be sufficiently different in Aim 1.

<u>Data Quality</u>

Of the 220 work shifts measured across the 22 participants, 212 left arm, 212 right arm, and 192 trunk files were included in the final analysis. Instrumentation failures and data collection issues (e.g., participants removing/not wearing a sensor) led to the loss of the files not included in the analysis. Fourteen of the 28 removed trunk files were considered outliers (conservatively defined as measurements more than 1.5 times the interquartile range below the first quantile or more than 1.5 times the interquartile range above the third quantile for the 50th percentile of posture across each respective participant's ten shifts). The location of the trunk sensor on the anterior sternum also led to occasional transient artifacts (i.e., the sensor being contacted). Of the 192 trunk data files included in the analysis, 14 (7%) required the replacement of transient artifacts with the mean posture of the entire recording duration. On average, 99.95% of the original data from these 14 full trunk posture files was retained for processing and analysis.

Statistical Analyses

<u>Differences between Pairs of Measurements</u>

The mean and SD of each posture, movement, and rest/recovery exposure metric across participants were calculated by work group (i.e., cyclic vs. non-cyclic). Potential violations of the normality assumption for examining differences between the Aim 1 and Aim 3 data were examined using the Shapiro-Wilk test. Because the normality assumption was violated for some exposure metrics, non-parametric statistics were used to evaluate differences between the Aim 1 (n=35) and Aim 3 (n=22) data. Specifically, the Wilcoxon-Mann-Whitney test was used to evaluate differences for data that may be considered independently sampled. An estimate of the effect size for each difference was produced following the procedures described in Pallant (2011).

Statistical tests of paired differences were completed for the sub-sample of participants that enrolled in both Aim 1 and Aim 3 of the study and that maintained the same work category (i.e., cyclic vs. non-cyclic) across both data collection periods (n=10). Potential violations of the normality assumption for examining differences were again examined using the Shapiro-Wilk test. Paired t-tests were used to evaluate differences between the Aim 1 and Aim 3 sub-sample data if the data were normally distributed. The Wilcoxon signed-rank test was used to conduct a paired difference test for data considered not normally distributed. The Wilcoxon signed-rank test was also used to compare results of the Likert-scale organizational safety, group safety, and safety behavior survey responses. All statistical procedures were performed using SAS (version 9.4, SAS Institute Inc., Cary, NC).

Mediation Analyses

We completed mediation analyses using the data from the sub-sample of participants that enrolled in both Aim 1 and Aim 3 of the study and that maintained the same work category (i.e., cyclic vs. non-cyclic) across both data collection periods (n=10). This analysis evaluated the effect of the baseline exposure to using AISs on perceived organizational safety climate (considered the mediator) and exposure to select kinematic risk factors and safety behaviors (considered the outcomes) (MacKinnon, 1994). Figure 4 illustrates the proposed causal path diagram. Consistent with the linear models to assess (dis)comfort, distraction, and burden, the kinematic risk factor exposure metrics were selected based on their association with work-related MSDs in epidemiological studies and common use in the occupational health and safety literature (Arvidsson et al., 2021; Balogh et al., 2019; Coenen et al., 2016; Kazmierczak et al., 2005; Kersten & Fethke, 2019; Svend Erik Mathiassen, 2006; Palm et al., 2018). Specifically, we examined the percentage of work time spent with each upper arm elevated in an “extreme” posture > 60° (RAEXP/LAEXP); the 50th percentile movement velocity (RA50V/LA50V); and the difference between the 90th and 10th percentiles of trunk flexion / extension (FE9010P). The safety behaviors included task safety behaviors and contextual safety behaviors (Cigularov et al., 2010). Each model was constructed and processed in SAS software (version 9.4; SAS Institute Inc., Cary, NC, USA) using the PROC CALIS procedure.

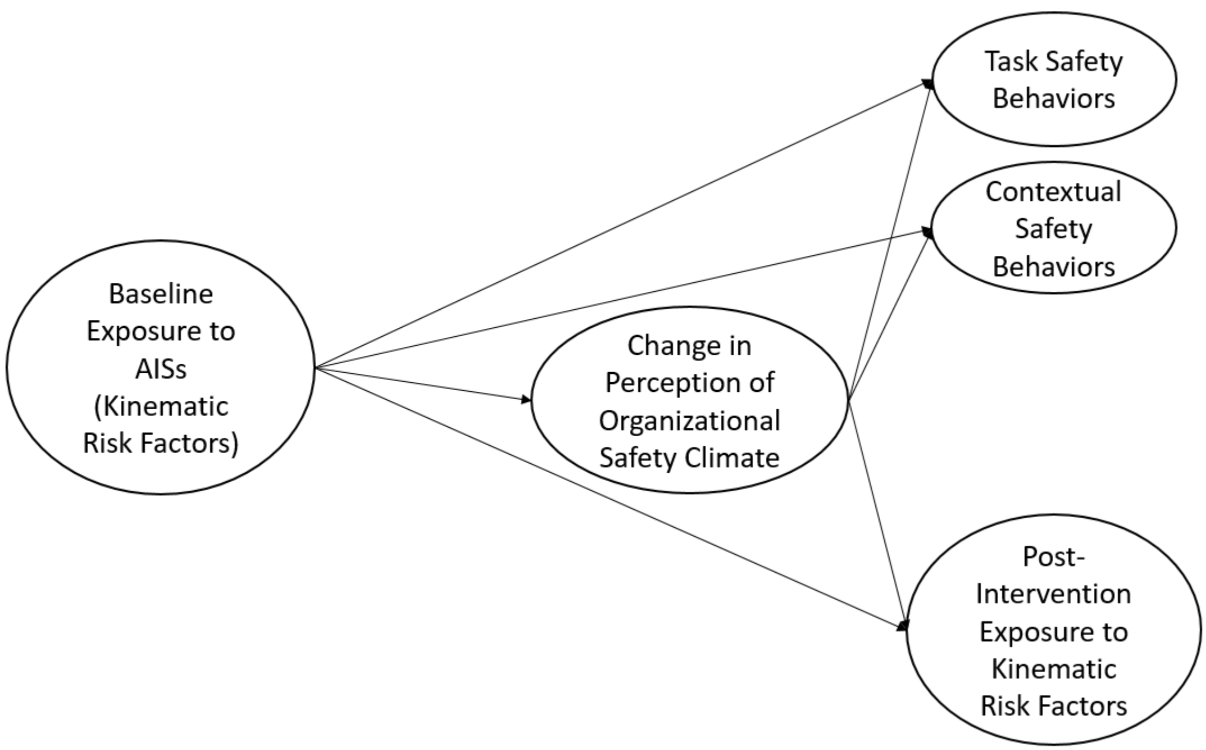

Figure 4. Illustration of the proposed causal pathway.

Notable Data Delivery Challenges and Barriers

- Variability in production practices and participant location in the manufacturing facility delayed the overall rate at which participant data collection occurred. Although the intent was to collect data from four to five participants simultaneously each weekday for Aims 1 and 3, the team typically collected from three to four participants. Logistical challenges contributing to the reduced number of participants collected simultaneously included the physical distance between participants throughout the facility while needing to begin collection at the start of a shift; challenges associated with immediately enrolling a new participant as another completes the study; shifting collection from one shift to another; production variability such as unexpected cancellation of some production areas due to parts not available from supplier; and others. Overall, these delays extended Aim 1 and Aim 3 data collection by approximately three months from the proposed six months. Additional graduate students were recruited and trained to help resolve this issue.
- Consistent with the Just-In-Time response to the summary statement document, only those individuals enrolled for the exposure assessment data collection (Aims 1 and 3) and the evaluation of the OSH dashboard (Aim 2) were recruited to complete the safety behavior scale and questions regarding perceptions of organizational and group-level safety climate.
- The partnering manufacturing site underwent several changes to the facility management team that affected the project. For example, the site safety director retired on 3.8.2019, and a new site safety director was not hired until 4.15.19. The plant manager changed in January 2019, and many area managers also changed roles throughout the project. The original site safety director informed the PI that he did not anticipate any project changes and to keep moving forward as originally planned. Although this was the case for Aim 1 activities, Aim 2 activities encountered unexpected delays due to the changes. In particular, safety committee meetings were administratively placed on hold until the new safety director was hired. Although the new safety director was interested in resuming the safety committee meetings, he felt it prudent to wait to resume the meetings until he understood the plant dynamics better. The stated intent was to resume the meetings after a planned annual plant shutdown in early July 2019. However, as other responsibilities took precedence and given some shifts in supervisor priorities, the safety director continued to delay the safety committee meetings and implementation of the Aim 2 dashboard until 11.14.19. Despite these challenges, the research team maintained open communication with the facility. While the safety committee meetings were delayed, the project and dashboard development continued to the greatest extent possible.
- When the safety committee was reconvened, participation in safety committee meetings was poor. The poor participation may have resulted from challenges the new safety director experienced gaining support from management. Shortly after efforts to convene meetings, the Coronavirus disease of 2019 (COVID-19) pandemic began. The pandemic forced the facility administration to halt safety committee meetings again for social-distancing purposes. As a result of the combined delays, the development of the OSH dashboard may have suffered and may not be indicative of a proper participatory ergonomics approach as intended. No safety committee members participated in the heuristic and usability evaluations of the dashboard as intended in Aim 2 due to the meetings not being held in person due to COVID-19.
- Discussions with a co-mentor indicated that it would not be possible to draw any meaningful inferences regarding comparisons between employment groups (production employee vs. other [management and OSH personnel]) for the organizational, group-level, and safety behavior surveys as a function of the distribution of participants and responsibilities throughout the plant.

Results

Note: Tables referred to in-text are located at the end of the "Results" section.

Participants and demographic/personal health characteristics

Participant age, height, body mass index, and shift duration by work group and sex for the pre and post-intervention phases of the study are provided in Table 1. Notably, a substantial proportion of participants who provided written informed consent were lost to follow-up because of either voluntary or involuntary termination of employment or a lack of continued interest in participating in post-intervention data collection.

Tables 2a (pre-intervention phase) and 2b (post-intervention phase) provide information about the number of time-weighted average task-based exposure estimates calculated, along with means and SDs of the total task durations, during a shift for the primary task categories.

Aim 1

Effect of Group (Cyclic vs. Non-Cyclic) on Full-Shift Exposure Metrics

Means and SDs for each upper arm posture, movement speed, and rest/recovery exposure metric across the full work shifts by work group are provided in Tables 3 (for the left arm) and 4 (for the right arm). The cyclic and non-cyclic groups were measured at 2.91 METs and 2.34 METs, respectively ($F_{1,29}$ = 18.13; p <0.01). The fixed effect of group (cyclic vs. non-cyclic) was not statistically significant for any posture-based exposure metric. For example, both groups spent approximately 31-33 % time with the arms in a neutral posture, 7-8 % time with their arms in an extreme posture, and 18-21 % time with the arms in a neutral posture for substantial periods (≥ 3s). In contrast, the fixed effect of group was statistically significant for every exposure metric based solely on movement speed. For example, workers in the cyclic group moved approximately 10°/s faster at peak speeds (i.e., the 90th percentile left arm [39.14° vs. 29.80°; $F_{1,33}$ = 12.36; p <0.01] and right arm [41.78° vs. 31.68°; $F_{1,33}$ = 17.81; p <0.01] movement speeds), spent 13-14% less time moving at low speeds (left arm: [42.98° vs. 56.40°; $F_{1,33}$ = 25.96; p <0.01]; right arm: [40.50° vs. 54.35°; $F_{1,33}$ = 30.86; p <0.01]), and spent approximately half the percentage of time at low speed for ≥ 3s as the non-cyclic participants (left arm: [14.95° vs. 32.42°; $F_{1,33}$ = 35.85; p <0.01]; right arm: [13.89° vs. 29.18°; $F_{1,33}$ = 30.16; p <0.01]).

Measured differences between the groups in upper arm exposure metrics based on movement speed appeared to be a consequence of exposures while operating machinery and performing assembly tasks (Tables 5 and 6). While posture metrics were similar across the tasks regardless of group status, operating machinery and assembly work (performed mostly by those in the cyclic group) generally involved approximately 10-17 % less time spent at low speeds than maintenance and set-up activities (performed mostly by those in the non-cyclic group). The "other" activities performed by the cyclic workers also involved approximately 10-12 % less time spent at low speeds than the non-cyclic workers. However, "other" activities comprised a substantially smaller proportion of the shift among those in the cyclic group than those in the non-cyclic group (see Section 2.4). Movement speeds during breaks were also similar between the groups (e.g., 3-5% difference in the proportion of time spent working at low speeds).

Means and SDs for each trunk posture, movement speed, and rest/recovery exposure metric across the full work shifts by work group are provided in Tables 7 (for flexion/extension) and 8 (for lateral bending). Similar to the upper arms, posture-based exposure summary metrics were generally similar between the two work groups. However, the effect of group was statistically significant in two cases: 1) for flexion/extension, posture variation (i.e., 90th -10th percentile) was greater among those in the non-cyclic group than among those in the cyclic group (35.56° vs. 28.86°; $F_{1,33}$ = 4.56; p = 0.04); and 2) for lateral bending, the percentage of time with neutral posture for ≥ 3s was greater among those in the non-cyclic group than among those in the cyclic group (76.67% vs. 72.38%; $F_{1,33}$ = 4.57; p = 0.04).

Several statistically significant differences were identified for movement speed metrics of the trunk. For example, non-cyclic workers spent a greater percentage of time working at low speeds (60.03% vs. 53.15%; $F_{1,33} = 7.16$; $p = 0.01$) and almost twice the percentage of time working at low speeds for three seconds or more (24.53% vs. 13.53%; $F_{1,33} = 12.98$; $p < 0.01$) relative to the cyclic workers for movements in the sagittal plane (i.e., flexion/extension).

Similar to the upper arms, differences in work activities (i.e., operating machinery and assembly activities completed primarily by the cyclic participants vs. maintenance and set-up activities completed primarily by the non-cyclic participants) contributed to the differences (Tables 9 and 10). Non-cyclic work tasks generally required a greater percentage of time moving at low speeds (56-59% vs. 47-53%) and almost twice the time spent working at low speeds for three seconds or more (19-22% vs. 10-11%) for movements in the sagittal plane (i.e., flexion/extension) than cyclic work tasks.

Variance Components and Exposure Homogeneity

For the upper arms (both left and right) and regardless of group status, the between-subjects variance component (S^2_{BS}) exceeded the within-subject (i.e., between-shifts) variance component (S^2_{WS}) for most posture, movement speed, and rest/recovery metrics (Tables 3 and 4). As the lone exception, among participants in the cyclic group, S^2_{WS} exceeded S^2_{BS} for the percentage of time with low movement speed for ≥ 3s.

However, a more complex pattern of variance component estimates was observed for the trunk than for the upper arms. Most notably, S^2_{WS} exceeded S^2_{BS} for the majority of posture-based metrics. In contrast, S^2_{BS} exceeded S^2_{WS} for most metrics based on movement speed (Tables 7 and 8), particularly those in the non-cyclic group.

Patterns of differences between the cyclic and non-cyclic groups for exposure homogeneity ($\lambda = S^2_{WS} / S^2_{BS}$) can also be observed in Figure 5. In general, the median values of λ across both posture-based metrics and metrics based on movement speed were greater for those in the cyclic group than those in the non-cyclic group. The lone exception occurred for posture-based metrics of the left arm (i.e., median λ of the cyclic group < median λ of the non-cyclic group), which was the non-dominant arm among all participants except for one. Also, for both trunk flexion/extension and lateral bending and the cyclic and non-cyclic groups, the median values of λ were >1.0 for posture-based metrics (implying homogeneous exposures) but ≤1.0 for metrics based on movement speed (implying heterogeneous exposures).

Within-Shift Exposure Variability and Repetitiveness

Table 11 provides the means and SDs of SD_{means} and SD_{ranges}. Results suggest greater between-minute variability in both the average exposure levels and the within-minute exposure variation among those in the non-cyclic group compared to those in the cyclic group. The magnitude of the differences in mean SD_{means} and mean SD_{ranges} between the groups was generally greater for posture than for movement speed. Cyclic workers were also measured to have a higher mean MPF (Left arm = 0.40 ± 0.19 Hz; Right arm = 0.41 ± 0.18 Hz; Trunk flexion/extension = 0.33 ± 0.18 Hz) when compared with the non-cyclic workers (Left arm = 0.34 ± 0.12 Hz; Right arm = 0.34 ± 0.12 Hz; Trunk flexion/extension = 0.31 ± 0.15 Hz) (Left arm $F_{1,33} = 5.01$; $p = 0.03$; Right arm $F_{1,33} = 11.29$; $p < 0.01$; Trunk flexion/extension $F_{1,33} = 1.07$; $p = 0.31$).

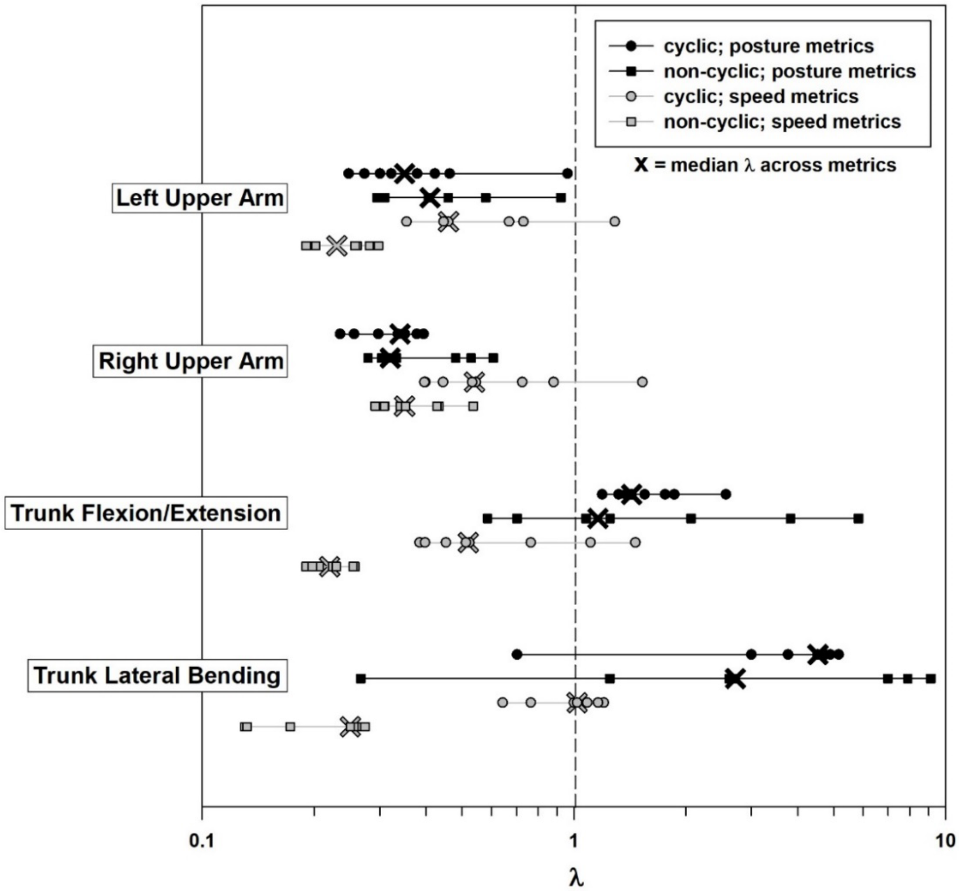

Figure 5. Exposure homogeneity ($\lambda = S^2_{WS} / S^2_{BS}$) by sensor location for the cyclic and non-cyclic work groups.

Bootstrap Resampling

In general, the range between the 5th and 95th percentiles of the BCa Confidence Intervals decreased for all exposure metrics as the number of days of observation increased. As sample duration increased cumulatively, the precision of estimated exposure measurements also increased gradually. For example, comparing the bootstrap analysis using one day of observation (N=15) with analysis using fifteen days of observations (N=225), the result of RA90P for cyclic workers showed that the range between the 5th and 95th percentile reduced from (50.20, 58.70) to (51.08, 53.79). The precision of RA90P measurement increased as the sampling duration increased from one day to fifteen days of observations. Additional details are provided in Table 12.

Detailed information on the necessary numbers of observation days required for each exposure measurement variable is summarized in Figure 6. For the cyclic group of workers, eight days of data collection were identified as sufficient to capture the 90th percentile of posture, 50th percentile of movement velocity, and the percentage of time spent in extreme posture (> 60°) for both upper arms. The results also indicated that seven days of data collection would be sufficient to evaluate cyclic workers' exposure variation of the upper arms. For the non-cyclic group of workers, nine days was identified as the maximum number of data collection days needed to reach a sufficient sample size for posture and velocity measurements and exposure variation of the upper arms. The percentage of time spent in an extreme posture (>60°) for the left arm required more observation days than the right arm for both cyclic and non-cyclic work groups. Preliminary explorations of the data for the trunk led to similar conclusions.

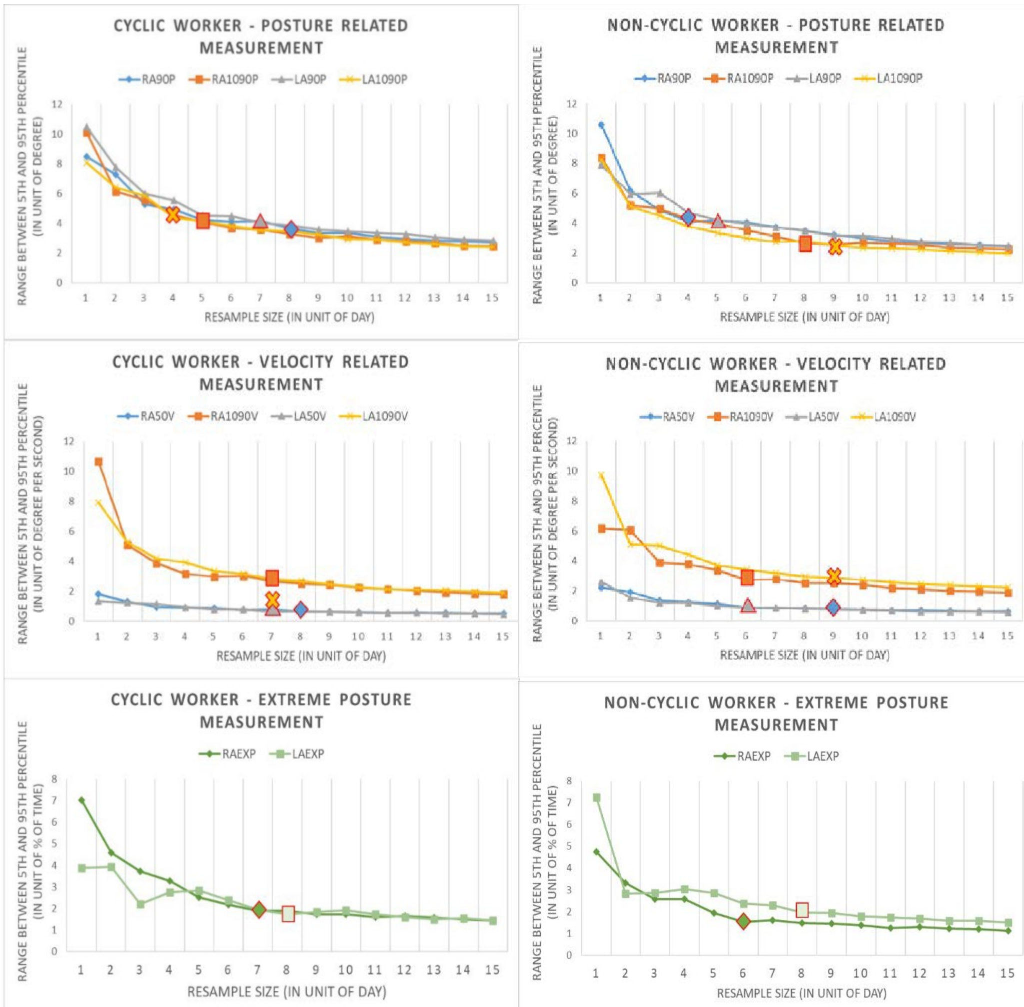

Figure 6. Result of Bootstrap analysis based on the precision of the estimated exposure measurement.

<u>Ratings of (Dis)comfort, Distraction, and Burden</u>

Observations from 31 participants were included in the statistical analysis of (dis)comfort, distraction, and burden. 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. 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 13). 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.

Aim 2

The OSH Dashboard Design

Pre-processed kinematic data (e.g., from Aim 1) was uploaded in bulk or by a single record into a relational PostgreSQL database. Figure 7 provides the database schema. Each box shows a different app. The tables inside each box are the associated models to that app. The arcs show the relational dependencies between the tables. Five main apps were created: User Profile, Video and Quiz, Django Auth, Django Admin, and Safety. The following sections explain the apps' functionality and associated data models:

User Profile App

This app enables user entity definition and management. This app's most critical data models are the User table and Company table, which have a one-to-many relationship (i.e., each user entity has only one affiliated company, and each company can be assigned to several users).

1. **Company Table**: A data model is designed to create a company entity with three attributes to store the company name, address, and phone number.
2. **User Table**: The user table has a few identifying attributes such as email address, First Name, Last Name, Password, and a foreign key from the company table, representing the relationship between the users and the company entities. The boolean attributes are used to represent the status of the users. Based on these boolean attributes, different features are provided for users. These boolean attributes are:
    - is_active: Designates whether this user account should be considered active. This flag will be set to False rather than forcing the deletion of accounts.
    - is_employee: This flag designates whether our administrator verifies the user as an employee of the company to which the user is linked.
    - is_manager: This flag designates whether our administrator verifies the user as a manager to the company to which the user is linked.
    - is_staff: Designates whether this user can access the admin site.
    - is_superuser: Designates whether this user has all permissions without explicitly assigning them.
3. **Departments Table**: A company may have several departments. Therefore, a one-to-many relationship is defined to enable company-department dependencies, where departments have a foreign key from the company model.
4. **Jobs Table**: The jobs table is defined to create multiple jobs associated with a department via a one-to-many relationship (i.e., one department may have several jobs with foreign key cross-reference to the department).
5. **Video**: Many training videos are made for each job that the company manager or staff can upload. The videos are stored and accessed using a video model. Four attributes are used for each video: name, description, file, and a foreign key column with reference to the job table.

Safety App

This app handles worker exposure information.

1. **Database**: The database table is defined to store data collected using wearable sensors. This table has a foreign key reference to the company and department tables. Additional to the foreign key fields are several other explanatory attributes such as JobID, Employee, and Date, which show the job, employee, and the date the data has been collected, respectively. Other attributes are defined to collect the data coming from the sensors. The fields definitions included the following variables:

- LA: Left Arm Elevation: The angle between the left upper arm vector and the vertical line (i.e., gravity). The upper arm vector is the line from the shoulder joint's center to the elbow joint's center.
- RA: Right Arm Elevation: The angle between the right upper arm vector and the vertical line (i.e., gravity). The upper arm vector is the line from the shoulder joint's center to the elbow joint's center.

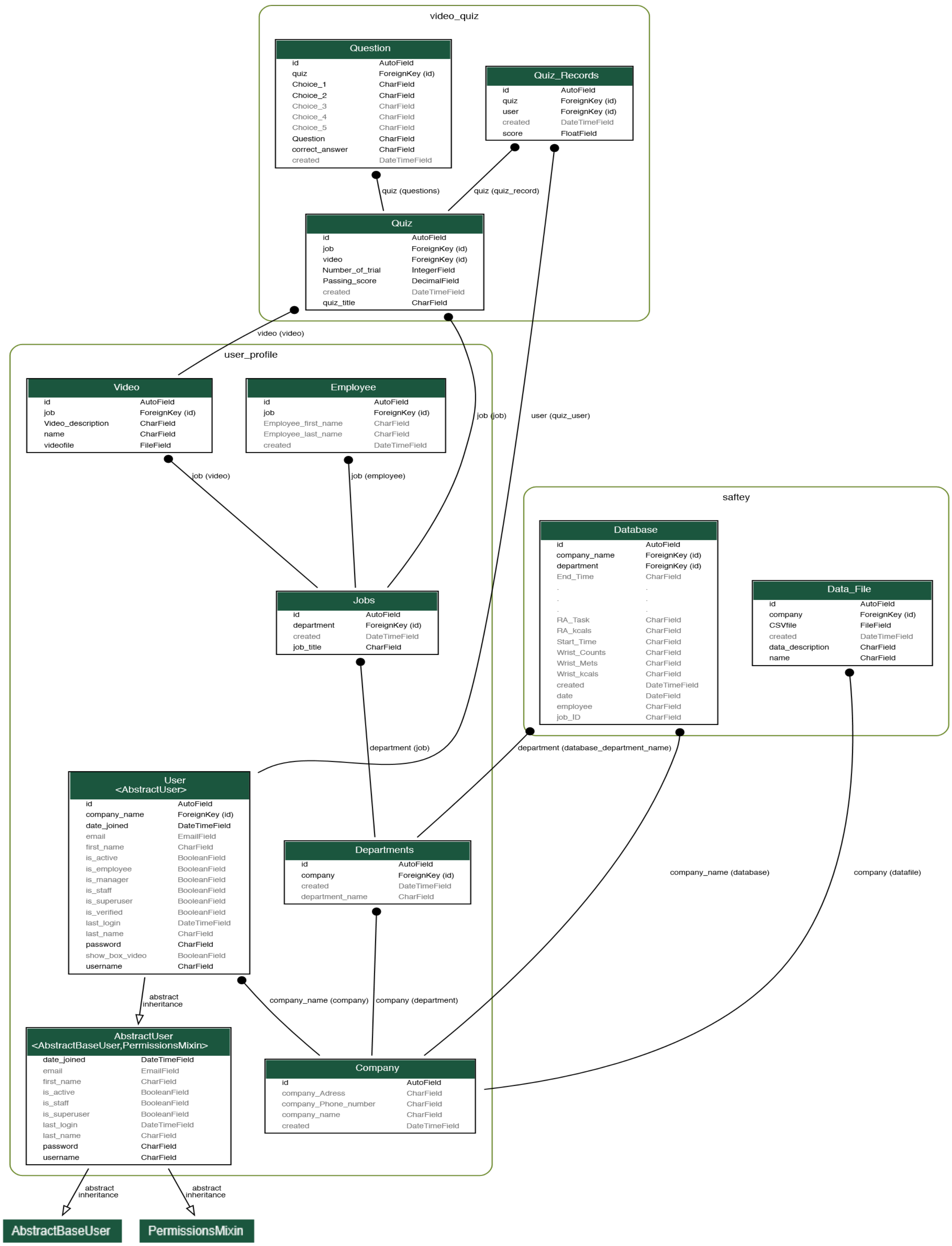

Figure 7. The OSH Dashboard Database Schema

- FE: Flexion/Extension: The action of bending the upper body forward in the sagittal plane toward the horizontal axis (i.e., the ground) from standing in a relaxed, neutral position. Extension is the action of leaning the upper body backward from standing in a relaxed, neutral position. Positive values denote trunk flexion. Negative values denote trunk extension.
- LB: Lateral Bending: The action of bending the upper body to the left and/or the right in the coronal plane toward the horizontal axis (i.e., the ground) from standing in a relaxed, neutral position. Positive values denote right lateral bending. Negative values denote left lateral bending.
- Mets: Metabolic Equivalent of Task: A measure used to express the intensity of physical activities. A MET is the ratio of a person's working metabolic rate relative to their resting metabolic rate. 1 MET is typically defined as the energy it takes to sit quietly. Light-intensity activities are typically considered tasks that burn less than 3.0 METs. Moderate-intensity are typically considered tasks that burn 3.0 to 6.0 METs. Vigorous-intensity activities are typically considered tasks that burn more than 6.0 METs.
- Mean_Posture: Average amount of angular displacement (in degrees) throughout the data collection period selected (i.e., full shift, a particular task, etc.).
- 10_Percentile_Posture: 10% of the data collection period is spent at or below this angle for the data collection period selected (i.e., full shift, a particular task, etc.).
- 90_Percentile_Posture: 90% of the data collection period is spent at or below this angle for the data collection period selected (i.e., full shift, a particular task, etc.).
- Percent_Time_in_Neutral_Posture: Percentage of time throughout the data collection period selected (i.e., full shift, a particular task, etc.) that the selected body segment does not exceed predefined thresholds. For the left and right upper arms, neutral postures are defined as less than 20° of upper arm elevation. For the trunk, neutral postures are defined as any posture between -20° and 20° of flexion/extension or lateral bending.
- Percent_Time_in_Extreme_Posture: Percentage of time throughout the data collection period selected (i.e., full shift, a particular task, etc.) that the selected body segment exceeds predefined thresholds. For the left and right upper arms, extreme postures are defined as more than 60° of upper arm elevation. For the trunk, extreme postures were defined as any posture exceeding -60° or 60° of flexion/extension or lateral bending.
- Mean_Velocity: Average velocity (in degrees per second) throughout the data collection period selected (i.e., full shift, a particular task, etc.).
- 10_Percentile_Velocity: 10% of the data collection period is spent at or below this velocity for the data collection period selected (i.e., full shift, a particular task, etc.).
- 90_Percentile_Velocity: 90% of the data collection period is spent at or below this velocity for the data collection period selected (i.e., full shift, a particular task, etc.).
- Percent_Time_with_Low_Velocity: Percentage of time throughout the data collection period selected (i.e., full shift, a particular task, etc.) that the selected body segment moves at a velocity of <5° per second.
- Percent_Time_with_High_Velocity: Percentage of time throughout the data collection period selected (i.e., full shift, a particular task, etc.) that the selected body segment moves at a velocity ≥ 90° per second.

2. **Data_file Table** Data points can be manually entered one-by-one or in bulk using a CSV file into the database table. If the latter option is chosen, it requires either the user or the administrator to upload a data file to the server. The data file can be stored in the server using the Data_file model. The difference between the Database Table and Data_file table is that the Database stores collected data from wearable sensors in a table. In contrast, the Data_file table stores a file containing data records. The Data_file table has a foreign key reference to the company table. This file field contains the directory address of the stored CSV file, a character attribute for the file name, and a character field for the file description. This table is designed to keep track of users' files uploaded to the server for backup purposes and potential errors.

Quiz App

The quiz app enables managers and administrators to make interactive quizzes for employees based on a training video. This app contains three tables: the Quiz table, Question Table, and Quiz_Records table. These tables include:

1. **Quiz App**: This table is designed to enable the users to create a quiz entity. Each entity has a foreign key reference to a job, a foreign key reference to a training video, an integer field showing the number of allowed attempts, a decimal field showing the passing score, and a character field showing the quiz title.
2. **Question App**: This table stores the questions associated with each quiz. Each quiz may have several questions. Therefore, a one-to-many relationship is defined to address this dependency. The Question Table has a foreign key reference to the Quiz table, a few character fields for the choices, a character field for the question description, and a field for the correct answer to the question, which needs to be specified by the quiz creator.
3. **Quiz_Records App**: The quiz_records table is used to save the user's performance record. This table has two foreign key columns referring to the Quiz and User tables and a character field that stores the quiz score.

Basic Views and Visualizations

The backend view functions are written in Python (Django). This function queries a database based on the user status and other criteria and passes the achieved context data to the frontend HTML page, which the users can view. Besides HTML for some pages, JavaScript facilitates some capabilities, such as interactive graphs. Some of the most crucial view functions are presented hereunder.

Home View

Most data visualizations are included on the dashboard's home page (Figure 8). Three drop-down menus are provided, enabling filtering data based on Department, Task, and Job title. Three visualizations are presented in a slider for the filtered data. The first graph shows a time series plot of collected data. Up to three variables can be selected in a drop-down menu and shown on the graph. The second graph is also a time series plot of the data; however, in this visualization, only one variable of interest can be shown at a time. This graph provides more image manipulation features relative to the first. Lastly, we provide a box plot of the selected variables by the user (Figure 9). Up to 10 variables can be selected in the drop-down. For each variable, a box plot for that specific variable will be plotted. Multiple descriptive statistics are shown to the user by hovering over each boxplot.

Help View

The help view is a simple view function that links the users to the help page. Some brief explanations of the services are provided on this page.

Single Data Point Upload View

This view allows the authenticated users with a valid Manager status to upload a new data row to the database. A form with the required field is provided that can be filled by the user. Once the form is filled with the proper inputs, then the form can be submitted. The user then will be redirected to another page with a success message.

Bulk Data Upload View

This view allows the authenticated users with a valid Manager status to upload a comma-delimited file to the database following a specific format. Upon uploading, the user will be redirected to another page that shows the newly added data points color-coded according to the data type, either new data with a unique ID or a modified data row with an existing ID.

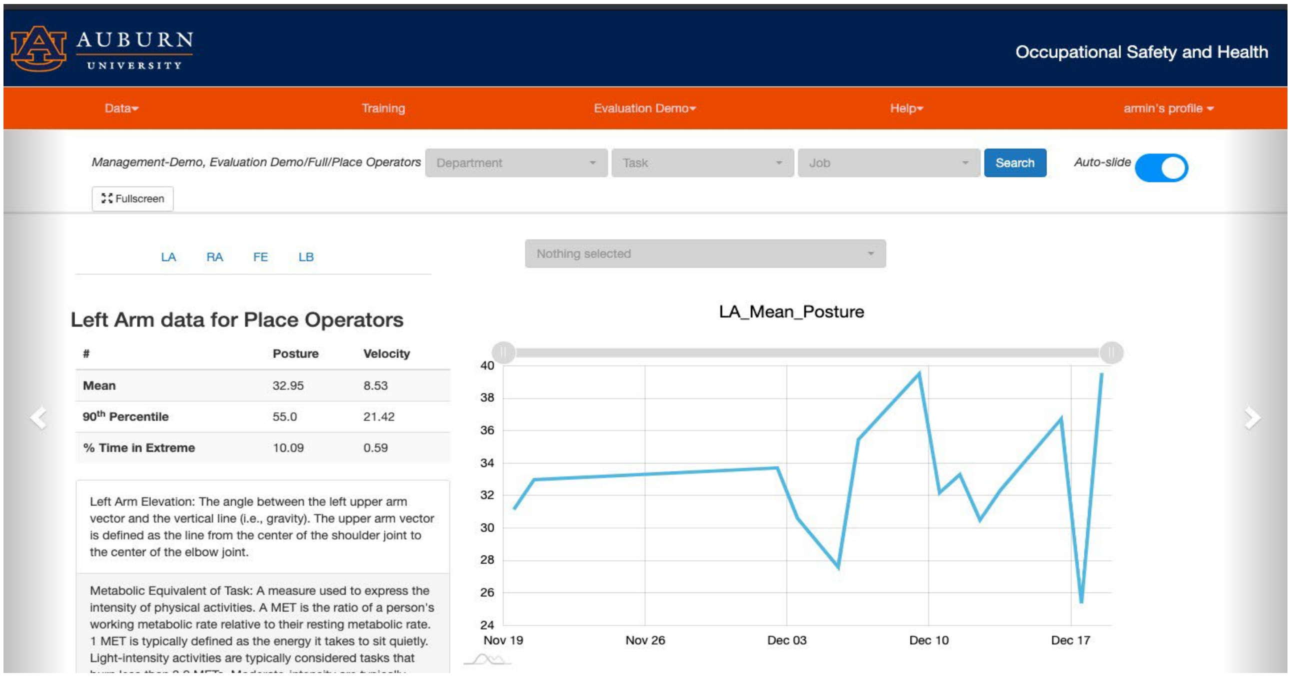

Figure 8. Home screen, time-series graph.

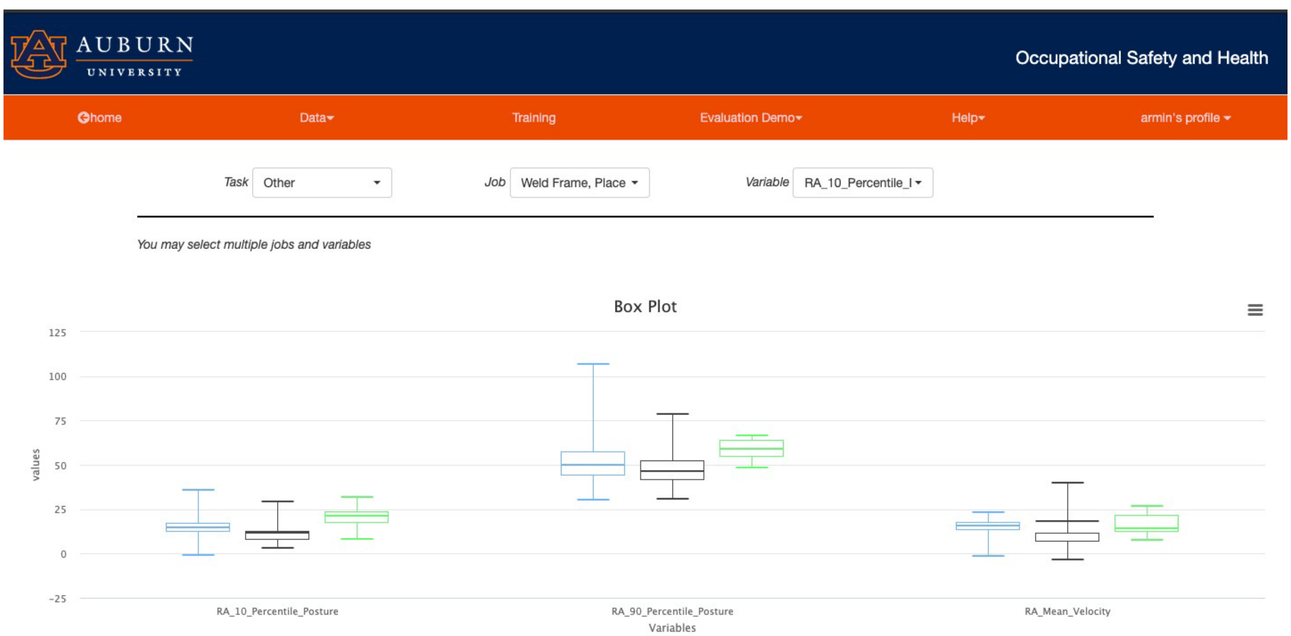

Figure 9. Box plots.

Box Plot Charts View

This view function enables the authenticated users to preview a box plot for multiple jobs on the same plot. This way, they will be able to compare multiple variables for different jobs next to one another. This view function first makes sure that the user is authenticated. It then filters the data based on the user's selected tasks, jobs, and variables and plots the chart box. The users are provided descriptive statistics when they hover their cursor over the box plots.

User Profile View

Further information about each user, such as name and email address, can be viewed and edited by the user here.

Company Profile View

Further information on each company, such as company name and address, can be viewed and edited by the user with a manager status through this function.

Sign Up View

This view function provides a sign-up form that the users can fill. Once all the fields are filled with appropriate inputs, the form is submitted, and the user will be saved with their corresponding information, such as first name, last name, email address, and password.

Login View

This function checks the user credentials; if they match an existing user, they will be flagged as authenticated users. Security aspects are essential features to ensure the privacy of workers. Several authentication and authorization layers were implemented to ensure accredited access to specific actions according to the user’s role and granted permissions. Moreover, an independent view was designed from the one visible to the regular users, which is only visible to the site administrators. In this view, the users can edit, add, or delete the collected data, control the other users' authentication, and so on. Another requirement of the system specification is the possibility of deploying the system on a local server. A local server may be suitable for enterprises with highly restrictive policies about storing data on a cloud network. The analytical part of the system can be deployed on local private servers.

Evaluation of the OSH Dashboard

The ten survey respondents (mean age = 39.2 years; SD = 14.1) assigned a mean SUS score of 60 (SD = 15.2) to the dashboard, indicating a "marginal" rating (Bangor et al., 2008). Detailed scores for each participant and questions of the SUS are provided in Figure 10. A total of 59 comments were provided by seven of the survey respondents via the heuristic evaluations. Of the seven evaluators, participant 3 provided all negative comments, while participant 9 provided predominantly positive comments (Figure 11).

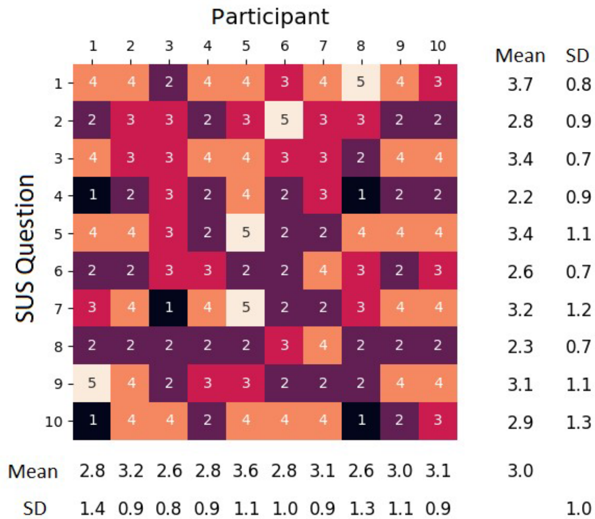

Figure 10. System Usability Scale (SUS) calculations by question and participant.

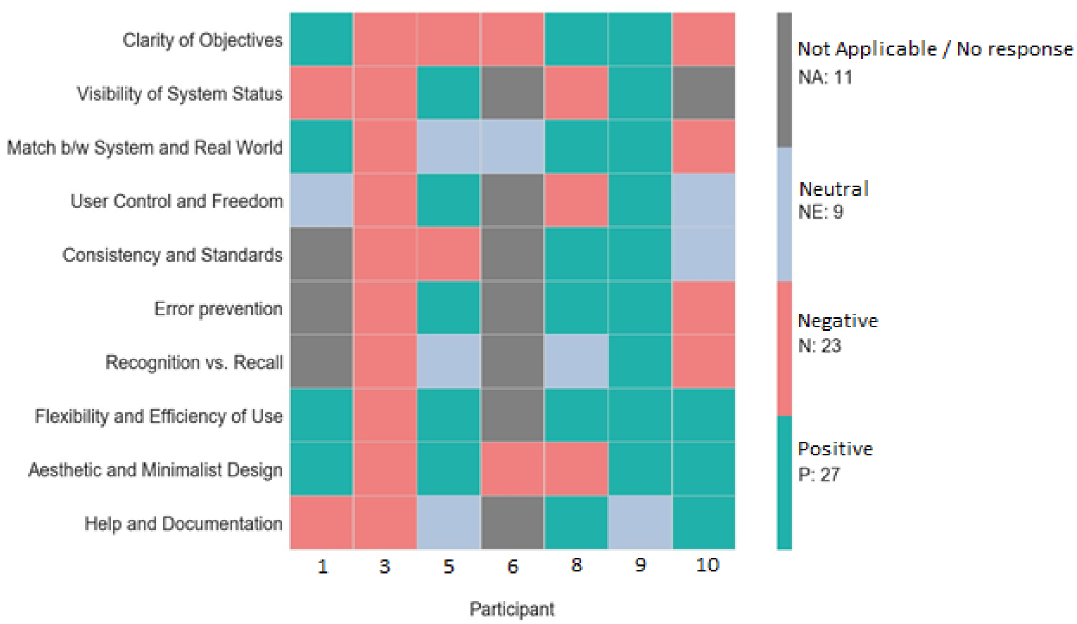

Figure 11. Characterization of comments for the seven participants that completed the heuristic evaluation.

Aim 3

Differences between Pairs of Measurements - Kinematic Risk Factors for the Upper Arms

Means and SDs for each upper arm posture, movement speed, and rest/recovery exposure metric across all participants (n=35 pre and n=22 post-intervention) for all full work shifts by work group (i.e., cyclic vs. non-cyclic) and intervention phase (i.e., pre vs. post) are provided in Tables 14 (left arm) and 16 (right arm). Corresponding statistics are provided for the sub-sample of participants that enrolled in both data collection phases and maintained the same work category (i.e., cyclic vs. non-cyclic) in Tables 15 (left arm) and 17 (right arm).

For the left arm, statistically significant improvements were measured for 11 of the 14 posture-based exposure metrics during the post-intervention phase relative to the pre-intervention phase when examining all participants. For example, the cyclic and non-cyclic work groups experienced an increase of approximately 5% time with the left arm in a neutral posture. Although the only statistically significant result to be maintained for the sub-sample of repeat cyclic workers was the 10th percentile arm posture (14.78° vs. 13.02°; $t(25)=2.10$; $p=0.05$), all seven posture-based exposure metrics were statistically significant for the repeat non-cyclic workers for the left arm. On average, the repeat noncyclic participants spent approximately 8 % more time with the left arm in a neutral posture during the post-intervention data collection phase. Their mean exposure was reduced by approximately 4.7°.

For the right arm, the non-cyclic workers experienced statistically significant improvements for six of seven posture-based exposure metrics during the post-intervention phase relative to the pre-intervention phase. Like the left arm, the non-cyclic work group experienced an increase of approximately 5% time with the right arm in a neutral posture. Interestingly, statistically significant improvements were observed for four of seven and all seven of the posture-based exposure metrics for the sub-sample of repeat cyclic and non-cyclic workers, respectively. Both groups spent approximately 6-8% more time in a neutral posture during the post-intervention phase than in the pre-intervention phase.

The upper arm movement speed results were not as consistently beneficial as the posture-based results. For the left and right arms, statistically significant reductions were measured for workers in the cyclic group. However, these results were not maintained when considering the sub-sample of repeat participants. The cyclic workers generally saw relative improvements in their upper arm movement speeds in the post-intervention phase. In contrast, statistically significant undesirable findings were measured for workers in the non-cyclic group during the post-intervention phase relative to the pre-intervention phase. For example, the mean upper arm movement speed increased by approximately 2°/s for both the left and right arms. Some undesirable results were also observed for the sub-sample of repeat participants. For instance, the mean upper arm movement speed of the non-cyclic workers increased by 0.79°/s for the right arm (11.94°/s vs. 12.73°/s; $t(58)=5.12$; $p<0.01$).

The rest/recovery metrics generally followed the same patterns as the posture and movement speed results. That is, posture-based metrics such as % time with the arm in a neutral posture for ≥ 3s improved, while participants spent a shorter % time moving their arms at a low speed.

Differences between Pairs of Measurements - Kinematic Risk Factors for the Trunk

Means and SDs for each trunk posture, movement speed, and rest/recovery exposure metric across all participants (n=35 pre and n=22 post-intervention) for all available full work shifts by work group (i.e., cyclic vs. non-cyclic) and intervention phase (i.e., pre vs. post) are provided in Tables 18 (flexion/extension) and 20 (lateral bending). Corresponding statistics are provided for the sub-sample of participants (n=3 cyclic and n=7 non-cyclic) that maintained the same work group category (i.e., cyclic vs. non-cyclic) across both data collection periods in Tables 19 (flexion/extension) and 21 (lateral bending).

Many statistically significant findings were measured for both the flexion/extension posture and movement speed-based exposure metrics during the post-intervention phase relative to the pre-intervention phase when examining all participants and the reduced data set of repeat participants. When examining all participants, the cyclic and non-cyclic work groups experienced an increase of approximately 6-7% time with the trunk in a neutral posture (> -20° to <20°). The repeat cyclic participants experienced an increase of 18.64 % time with the trunk in a neutral posture (67.57% vs. 86.21%; $S=-113.5$, $p<0.01$), whereas the repeat non-cyclic participants experienced an increase of 4.33 % time (80.82% vs. 85.15%; $S=-348.0$, $p<0.01$). The trunk flexion/extension movement speeds among the cyclic participants improved post-intervention, whereas the movement speeds among the non-cyclic participants were generally undesirable.

The rest/recovery metrics followed the same patterns as the posture and movement speed results. The repeat cyclic participants experienced a statistically significant increase of 15.16 % time with the trunk in a neutral posture and moving at a low speed (34.64% vs. 49.80%; t(25)=, *p*<0.01).

<u>Differences between Pairs of Measurements - Physical Activity</u>

The cyclic group MET estimate decreased by 0.46 METs post-intervention relative to the pre-intervention phase. The non-cyclic group MET estimate increased 0.15 METs post-intervention relative to the pre-intervention phase. Activities of 2 to 4 METs (light walking, doing household chores, etc.) are considered "light," suggesting that a change of 0.5 METs or less may be considered minimal to negligible for both groups.

<u>Differences between Pairs of Measurements - Perceptions of Workplace Safety Climate and Safety Behaviors</u>

Means, SDs, and the percentage of possible points available in each scale for the Workplace Organizational-Level Safety Climate, Workplace Group-Level Safety Climate, and Workplace Safety Behavior scales are provided in Tables 22, 23, and 24, respectively. A statistically significant difference in the aggregate score for the Organizational-Level Safety Climate survey was measured for the sub-sample of participants (n=10) that enrolled in the pre and post-intervention phases of the study and that maintained the same work category (i.e., cyclic vs. non-cyclic) across both data collection periods (S = -18.5; *p* = 0.03). This reduction appears to have been driven by statistically significant reductions in perceptions of top management's consideration of a person's safety behavior when moving/promoting people (Q8; *p* = 0.02), investment of time and money in safety training for workers (Q10; *p* = 0.03), use of available information to improve existing safety rules (Q11; *p* = 0.02) and holding regular safety-awareness events (Q15; *p* = 0.03).

<u>Mediation Analyses</u>

The mediation analyses indicated that introducing the AISs and OSH dashboard did not positively affect the perceived safety climate (Figure 12). Changes in perception of organizational safety climate were strongly related to task and contextual safety behaviors.

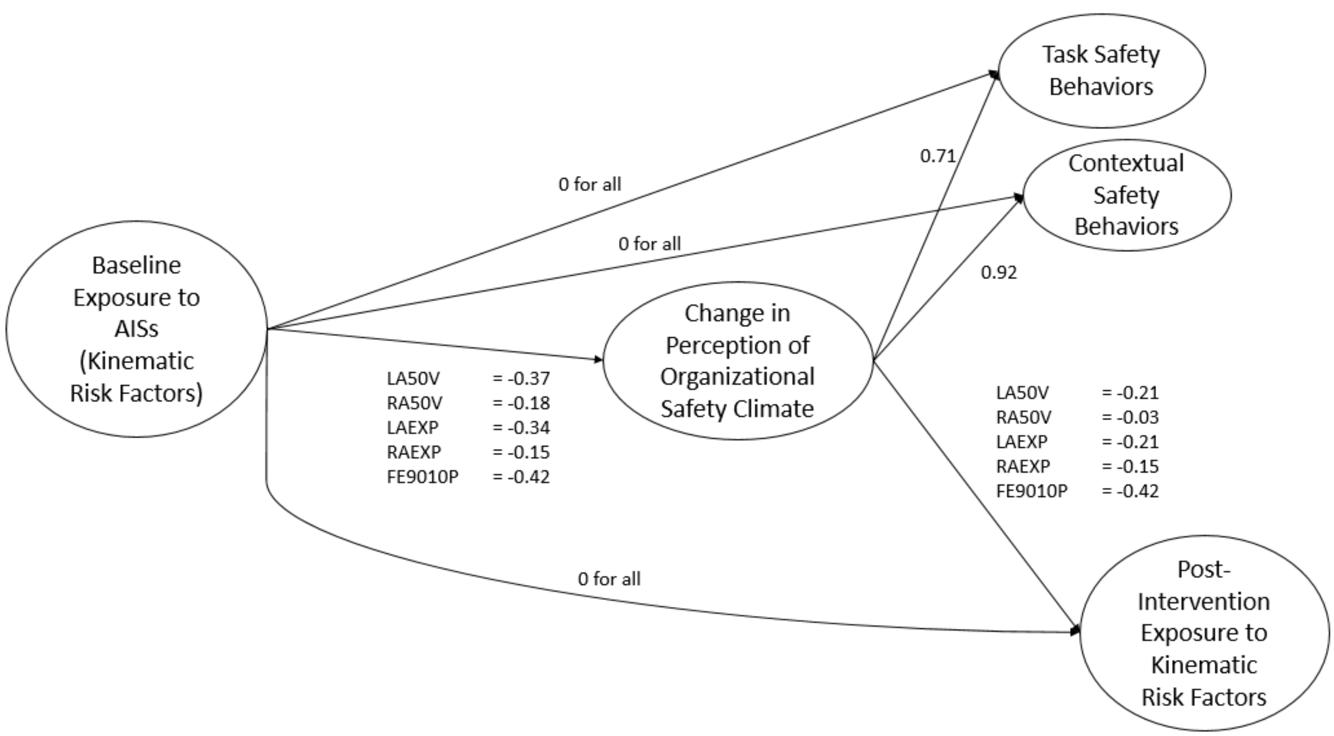

Figure 12. Resulting path coefficients.

Table 1. Participant age, height, body mass index, and shift duration by work group and sex (pre-intervention n=35; post-intervention n=22).

	Cyclic						Non-cyclic					
	Pre			Post			Pre			Post		
	n	Mean	SD	n	Mean	SD	n	Mean	SD	n	Mean	SD
Male	6			2			12[a]			10[b]		
Age (years)		29.0	6.9		37.0	7.1		40.0	12.1		36.0	10.5
Height (cm)		183.7	6.9		181.6	16.2		179.5	5.0		181.4	7.6
Body mass index (kg/m^2)		32.1	10.7		44.0	2.4		30.2	4.6		27.0	3.8
Shift Duration (hours)		8.3	0.5		7.9	0.3		8.1	0.7		8.3	0.5
Female	12			4			5			6		
Age (years)		44.3	13.1		43.0	8.8		47.6	12.4		41.2	11.6
Height (cm)		164.9	6.1		166.4	6.7		163.6	6.9		163.4	3.8
Body mass index (kg/m^2)		31.1	6.1		31.1	4.0		33.3	7.8		33.4	7.9
Shift Duration (hours)		8.5	1.1		8.6	0.7		9.0	1.0		8.9	0.4

[a] All participants in the pre-intervention phase were right-hand dominant except for one male in the non-cyclic group.
[b] All participants in the post-intervention phase were right-hand dominant except for two males in the non-cyclic group.

Table 2a. Primary task categories by work group. The number (n) of time-weighted average exposure estimates included in the task-based dataset and the means ± SDs of the total task durations by sensor location for the pre-intervention phase.

Task category	Sensor location (n; duration)
Cyclic	
Assembly: tasks associated with machine-paced production (e.g. constructing part from sub-components; packaging parts).	Trunk (n=175; 7.2 ± 1.7 hours per day) Arms (n=188; 7.2 ± 1.7 hours per day)
Operating machinery: tasks associated with running a machine (e.g. loading parts into machining cell; operating crane lift).	Trunk (n=63; 5.7 ± 2.0 hours per day) Arms (Left n=72; Right n=71; 5.9 ± 1.9 hours per day)
Other: productive, work-related task (e.g., working on computer; walking between work cells; meetings).	Trunk (n=76; 1.5 ± 1.5 hours per day) Arms (n=81; 1.5 ± 1.5 hours per day)
Break: non-productive pause of the above work categories (e.g. meal break).	Trunk (n=239; 0.8 ± 0.3 hours per day) Arms (n=261; 0.8 ± 0.3 hours per day)
Non-cyclic	
Maintenance: tasks associated with cleaning or clearing work equipment and/or space (e.g., washing a machine; fixing equipment that had broken down).	Trunk (n=126; 3.0 ± 2.3 hours per day) Arms (Left n=133; Right n=134; 3.0 ± 2.3 hours per day)
Set-up: tasks associated with preparing a workstation for work activities (e.g., moving pallets; coordinating production line change; restocking).	Trunk (n=141; 4.5 ± 3.2 hours per day) Arms (Left n=148; Right n=149; 4.5 ± 3.1 hours per day)
Other: productive, work-related task (e.g., working on computer; walking between work cells; meetings).	Trunk (n=171; 4.2 ± 2.3 hours per day) Arms (Left n=185; Right n=186; 4.2 ± 2.3 hours per day)
Break: non-productive pause of the above work categories (e.g. meal break).	Trunk (n=188; 1.0 ± 0.7 hours per day) Arms (n=202; 1.1 ± 0.7 hours per day)

Table 2b. Primary task categories by work group. The number (n) of time-weighted average exposure estimates included in the task-based dataset and the means ± SDs of the total task durations by sensor location for the post-intervention phase.

Task category	Sensor location (n; mean ± SD duration)
Cyclic	
Assembly: tasks associated with machine-paced production (e.g. constructing part from sub-components; packaging parts).	Trunk (n=14; 6.7 ± 1.7 hours per day) Arms (n=14; 6.7 ± 1.7 hours per day)
Operating machinery: tasks associated with running a machine (e.g. loading parts into machining cell; operating crane lift).	Trunk (n=24; 7.7 ± 1.2 hours per day) Arms (n=28; 7.7 ± 1.1 hours per day)
Other: productive, work-related task (e.g., working on computer; walking between work cells; meetings).	Trunk (n=3; 2.2 ± 1.3 hours per day) Arms (n=3; 2.2 ± 1.3 hours per day)
Break: non-productive pause of the above work categories (e.g. meal break).	Trunk (n=42; 0.8 ± 0.2 hours per day) Arms (n=45; 0.8 ± 0.2 hours per day)
Non-cyclic	
Maintenance: tasks associated with cleaning or clearing work equipment and/or space (e.g., washing a machine; fixing equipment that had broken down).	Trunk (n=61; 4.7 ± 2.6 hours per day) Arms (n=69; 4.7 ± 2.7 hours per day)
Set-up: tasks associated with preparing a workstation for work activities (e.g., moving pallets; coordinating production line change; restocking).	Trunk (n=86; 4.4 ± 2.9 hours per day) Arms (n=93; 4.4 ± 2.8 hours per day)
Other: productive, work-related task (e.g., working on computer; walking between work cells; meetings).	Trunk (n=49; 2.1 ± 2.3 hours per day) Arms (n=57; 2.1 ± 2.1 hours per day)
Break: non-productive pause of the above work categories (e.g. meal break).	Trunk (n=138; 0.9 ± 0.5 hours per day) Arms (n=154; 0.9 ± 0.5 hours per day)

Table 3. Full-shift left arm elevation exposure metrics across all data collection days and results of variance components analyses.

Exposure Metric	Fixed effect of group					Random effects of between-subjects and between-shifts within subject									
	Cyclic		Non-cyclic			Cyclic					Non-cyclic				
	Mean	SD	Mean	SD	*p*	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ
Posture															
Mean (°)	30.43	7.14	31.29	6.32	0.67	37.90	(20.94 - 88.45)	14.35	(11.91 - 17.64)	0.38	32.14	(17.65 - 75.93)	9.47	(7.96 - 11.45)	0.29
10th Percentile (°)	13.91	5.48	13.88	4.59	1.00	23.88	(13.25 - 55.27)	7.19	(5.98 - 8.82)	0.30	16.79	(9.22 - 39.69)	5.21	(4.38 - 6.30)	0.31
50th Percentile (°)	26.20	7.62	27.02	6.74	0.70	45.06	(24.95 - 104.72)	14.54	(12.04 - 17.92)	0.32	36.32	(19.95 - 85.82)	11.00	(9.25 - 13.29)	0.30
90th Percentile (°)	53.18	10.64	54.20	9.16	0.73	79.10	(43.64 - 185.27)	36.61	(30.57 - 44.66)	0.46	54.86	(29.86 - 132.13)	31.74	(26.69 - 38.37)	0.58
90th-10th Percentile (°)	39.27	8.91	40.32	7.21	0.67	57.27	(31.76 - 132.67)	24.22	(20.39 - 29.25)	0.42	27.80	(14.95 - 68.71)	25.64	(21.56 - 31.01)	0.92
Neutral (<20°) (%time)	32.85	18.75	31.32	15.60	0.76	290.79	(162.12 - 666.65)	71.87	(60.30 - 87.13)	0.25	180.14	(98.67 - 428.14)	73.10	(61.51 - 88.33)	0.41
Extreme (≥60°) (%time)	7.41	5.68	7.90	5.53	0.75	16.70	(8.94 - 41.64)	16.05	(13.27 - 19.83)	0.96	22.50	(12.31 - 53.65)	9.12	(7.66 - 11.04)	0.41
Movement speed															
Mean (°/s)	14.92	3.64	10.83	3.26	**<0.01**	9.58	(5.19 - 23.29)	4.28	(3.39 - 5.58)	0.45	9.28	(5.10 - 21.86)	1.89	(1.58 - 2.30)	0.20
10th Percentile (°/s)	0.49	0.28	0.22	0.12	**<0.01**	0.05	(0.03 - 0.12)	0.03	(0.03 - 0.04)	0.72	0.01	(0.01 - 0.03)	0.00	(0.00 - 0.00)	0.37
50th Percentile (°/s)	7.16	2.62	3.88	2.18	**<0.01**	4.84	(2.63 - 11.68)	2.21	(1.77 - 2.83)	0.46	3.96	(2.18 - 9.35)	1.01	(0.85 - 1.23)	0.26
90th Percentile (°/s)	39.14	9.14	29.80	8.33	**<0.01**	60.57	(32.86 - 146.86)	27.30	(21.70 - 35.38)	0.45	61.18	(33.67 - 144.03)	11.63	(9.72 - 14.18)	0.19
90th-10th Percentile (°/s)	38.64	8.93	29.59	8.23	**<0.01**	57.83	(31.37 - 140.30)	26.23	(20.86 - 33.99)	0.45	59.73	(32.87 - 140.63)	11.37	(9.50 - 13.86)	0.19
Low speed (<5°/s) (%time)	42.98	7.43	56.40	9.99	**<0.01**	32.77	(17.46 - 82.54)	23.92	(19.21 - 30.62)	0.73	82.65	(45.36 - 195.61)	21.57	(18.05 - 26.23)	0.26
High speed (≥90°/s) (%time)	1.64	0.93	0.95	0.63	**<0.01**	0.70	(0.38 - 1.65)	0.25	(0.20 - 0.32)	0.36	0.35	(0.19 - 0.82)	0.07	(0.06 - 0.08)	0.20
Rest/Recovery															
Neutral for ≥ 3s (%time)	20.42	16.57	21.48	13.64	0.81	221.72	(123.40 - 510.03)	60.56	(50.70 - 73.61)	0.27	132.46	(72.48 - 315.49)	60.80	(51.16 - 73.45)	0.46
Low speed for ≥ 3s (%time)	14.95	6.19	32.42	12.27	**<0.01**	17.14	(8.81 - 46.83)	22.12	(17.86 - 28.12)	1.29	122.75	(67.28 - 291.31)	34.58	(28.90 - 42.13)	0.28
Neutral and low speed (%time)	15.03	8.95	16.83	9.04	0.48	55.72	(30.57 - 132.05)	26.21	(21.57 - 32.53)	0.47	58.82	(32.22 - 139.77)	26.16	(22.01 - 31.61)	0.44

Table 4. Full-shift right arm elevation exposure metrics across all data collection days and results of variance components analyses.

Exposure Metric	Fixed effect of group					Random effects of between-subjects and between-shifts within subject									
	Cyclic		Non-cyclic			Cyclic					Non-cyclic				
	Mean	SD	Mean	SD	*p*	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ
Posture															
Mean (°)	30.40	6.53	30.96	5.55	0.75	35.37	(19.74 - 80.87)	9.07	(7.65 - 10.93)	0.26	24.08	(13.24 - 56.85)	7.98	(6.72 - 9.64)	0.33
10th Percentile (°)	13.70	5.18	13.62	4.80	0.97	21.55	(11.99 - 49.59)	6.39	(5.38 - 7.71)	0.30	18.45	(10.02 - 44.63)	5.58	(5.28 - 5.90)	0.30
50th Percentile (°)	26.38	7.01	26.78	6.30	0.83	41.48	(23.16 - 94.78)	9.73	(8.20 - 11.74)	0.23	31.75	(17.47 - 74.74)	9.62	(8.09 - 11.62)	0.30
90th Percentile (°)	52.83	10.09	53.50	9.03	0.80	78.73	(43.74 - 181.82)	26.39	(22.13 - 32.00)	0.34	57.34	(31.36 - 136.70)	27.57	(23.22 - 33.28)	0.48
90th-10th Percentile (°)	39.13	9.04	39.88	8.15	0.76	62.03	(34.31 - 144.49)	21.75	(18.00 - 26.82)	0.35	45.03	(24.52 - 108.38)	23.79	(20.00 - 28.77)	0.53
Neutral (<20°) (%time)	32.44	16.08	31.46	15.52	0.84	199.96	(97.61 - 616.00)	69.04	(65.41 - 72.98)	0.35	193.02	(106.32 - 453.45)	58.34	(55.40 - 61.53)	0.30
Extreme (≥60°) (%time)	7.36	5.50	6.94	4.16	0.78	22.76	(12.70 - 52.11)	8.58	(7.22 - 10.35)	0.38	11.16	(6.06 - 26.94)	6.75	(5.68 - 8.16)	0.60
Movement speed															
Mean (°/s)	16.04	3.94	11.51	2.94	**<0.01**	11.51	(6.29 - 27.48)	5.13	(4.17 - 6.46)	0.45	6.65	(3.64 - 15.85)	2.34	(1.96 - 2.85)	0.35
10th Percentile (°/s)	0.55	0.34	0.25	0.14	**<0.01**	0.07	(0.04 - 0.18)	0.05	(0.04 - 0.07)	0.76	0.02	(0.01 - 0.04)	0.01	(0.00 - 0.01)	0.36
50th Percentile (°/s)	8.02	3.04	4.28	2.22	**<0.01**	7.15	(3.92 - 16.93)	2.82	(2.29 - 3.55)	0.39	3.93	(2.15 - 9.31)	1.20	(1.01 - 1.46)	0.31
90th Percentile (°/s)	41.78	9.46	31.68	7.15	**<0.01**	62.10	(33.72 - 150.30)	33.08	(26.86 - 41.76)	0.53	37.21	(20.28 - 89.38)	15.93	(13.33 - 19.39)	0.43
90th-10th Percentile (°/s)	41.24	9.21	31.43	7.04	**<0.01**	58.29	(31.62 - 141.41)	31.74	(25.75 - 40.10)	0.54	35.94	(19.58 - 86.37)	15.60	(13.05 - 18.98)	0.43
Low speed (<5°/s) (%time)	40.50	7.24	54.35	9.71	**<0.01**	29.39	(15.47 - 75.94)	25.94	(20.80 - 33.27)	0.88	75.18	(41.22 - 178.34)	23.24	(19.51 - 28.17)	0.31
High speed (≥90°/s) (%time)	1.87	1.17	1.01	0.50	**<0.01**	1.05	(0.58 - 2.47)	0.42	(0.35 - 0.52)	0.40	0.17	(0.09 - 0.42)	0.09	(0.07 - 0.11)	0.52
Rest/Recovery															
Neutral for ≥ 3s (%time)	18.16	13.43	20.57	13.36	0.57	133.38	(73.43 - 313.74)	52.53	(43.21 - 65.24)	0.39	146.03	(80.22 - 344.96)	40.67	(34.20 - 49.17)	0.28
Low speed for ≥ 3s (%time)	13.89	5.92	29.18	11.94	**<0.01**	14.18	(7.14 - 40.55)	21.68	(17.45 - 27.67)	1.53	114.96	(62.97 - 273.18)	33.50	(27.98 - 40.84)	0.29
Neutral and low speed (%time)	13.72	6.93	15.74	8.44	0.39	31.06	(16.93 - 74.61)	18.64	(15.38 - 23.06)	0.60	54.64	(29.90 - 130.11)	19.63	(16.48 - 23.80)	0.36

Table 5. Left arm elevation exposure metrics across primary work task categories across all data collection days.

Exposure Metric	Work Tasks															
	Assembly		Operate Machinery		Maintenance		Set-up		Other				Break			
	Cyclic		Cyclic		Non-cyclic		Non-cyclic		Cyclic		Non-cyclic		Cyclic		Non-cyclic	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Posture																
Mean (°)	29.51	6.08	32.78	8.85	31.01	6.73	31.74	6.19	29.44	7.14	31.43	7.12	33.02	7.80	33.50	11.53
10th Percentile (°)	13.01	4.79	17.39	5.92	14.60	4.62	14.99	4.72	14.07	5.23	15.15	5.09	16.57	6.36	17.43	9.97
50th Percentile (°)	25.32	6.74	28.90	8.83	26.61	6.80	27.88	6.59	25.43	7.70	27.49	7.42	30.89	8.63	31.99	12.79
90th Percentile (°)	52.82	9.73	53.49	12.95	53.72	12.59	54.17	10.85	50.61	12.19	53.22	11.98	51.99	12.60	51.05	14.80
90th-10th Percentile (°)	39.80	9.00	36.10	8.88	39.12	11.19	39.18	9.23	36.55	11.30	38.07	10.57	35.42	11.54	33.62	10.81
Neutral (<20°) (%time)	35.41	16.89	25.89	20.47	31.68	15.99	28.56	16.31	34.30	21.46	30.30	16.91	25.76	17.64	30.16	23.39
Extreme (≥60°) (%time)	7.05	5.10	8.54	7.33	8.26	6.97	7.91	5.22	6.93	5.99	7.73	6.41	7.37	8.44	8.44	11.78
Movement Speed																
Mean (°/s)	15.26	2.71	16.61	5.56	10.90	3.28	12.26	3.62	12.40	3.15	10.26	3.47	9.35	4.08	7.58	3.51
10th Percentile (°/s)	0.64	0.23	0.83	0.53	0.32	0.28	0.33	0.18	0.56	0.35	0.28	0.19	0.20	0.22	0.17	0.20
50th Percentile (°/s)	7.36	1.82	9.26	4.09	4.32	2.57	5.22	2.41	5.93	2.50	4.00	2.38	2.73	2.53	2.07	2.18
90th Percentile (°/s)	39.84	7.04	41.97	13.54	29.20	7.64	32.68	9.56	31.52	7.74	27.40	8.78	26.75	11.09	21.36	9.34
90th-10th Percentile (°/s)	39.20	6.89	41.15	13.09	28.89	7.47	32.35	9.44	30.96	7.51	27.12	8.63	26.55	10.94	21.20	9.20
Low Speed (<5°/s) (%time)	41.51	6.22	37.99	10.23	55.21	11.95	50.95	10.04	47.27	10.80	57.70	12.86	64.09	12.63	69.21	11.86
High Speed (≥90°/s) (%time)	1.73	0.79	1.77	1.35	0.89	0.53	1.13	0.77	1.10	0.79	0.83	0.49	0.86	0.73	0.59	0.56
Rest/Recovery																
Neutral for ≥ 3s (%time)	21.78	15.44	13.73	14.45	20.92	14.35	18.32	13.50	22.33	20.47	20.72	14.90	18.34	16.72	23.24	21.65
Low Speed for ≥ 3s (%time)	11.43	5.74	12.89	7.77	30.65	15.38	25.22	11.66	18.27	13.64	33.88	16.59	43.25	16.50	50.29	15.81
Neutral and Low Speed (%time)	15.57	7.59	11.64	9.40	17.11	10.58	14.48	8.68	16.45	11.38	16.60	9.79	15.19	13.33	19.60	18.86

Table 6. Right arm elevation exposure metrics across primary work task categories across all data collection days.

Exposure Metric	Work Tasks															
	Assembly		**Operate Machinery**		**Maintenance**		**Set-up**		**Other**				**Break**			
	Cyclic		**Cyclic**		**Non-cyclic**		**Non-cyclic**		**Cyclic**		**Non-cyclic**		**Cyclic**		**Non-cyclic**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Posture																
Mean (°)	29.93	6.46	30.81	7.09	30.64	5.64	30.38	5.35	29.55	6.68	31.37	6.52	33.88	6.81	34.32	9.64
10th Percentile (°)	13.48	5.54	15.06	4.09	14.23	4.76	13.87	4.93	13.41	4.98	15.15	5.60	17.51	7.15	18.15	8.16
50th Percentile (°)	25.70	6.84	27.14	7.15	26.19	6.03	26.68	6.13	25.47	7.32	27.62	7.27	32.90	8.21	33.73	10.90
90th Percentile (°)	52.81	10.42	51.91	12.42	53.67	11.91	51.99	8.73	51.53	12.02	52.53	10.89	50.54	9.60	49.93	11.99
90th-10th Percentile (°)	39.33	10.09	36.85	10.24	39.44	11.93	38.12	8.69	38.12	12.18	37.38	10.64	33.03	10.47	31.78	9.46
Neutral (<20°) (%time)	34.21	16.33	29.96	15.65	32.00	14.84	31.52	16.81	35.30	19.01	29.94	16.80	21.50	16.34	23.55	19.31
Extreme (≥60°) (%time)	7.50	5.67	7.36	5.96	7.54	5.36	6.26	4.10	7.46	6.52	6.84	4.94	6.18	6.36	6.58	8.88
Movement Speed																
Mean (°/s)	16.32	2.60	18.19	6.55	12.13	3.31	12.64	3.04	14.00	4.05	10.89	3.53	9.99	4.99	8.38	3.28
10th Percentile (°/s)	0.73	0.30	0.94	0.65	0.37	0.29	0.38	0.21	0.64	0.39	0.32	0.23	0.22	0.26	0.19	0.20
50th Percentile (°/s)	8.27	1.93	10.49	4.99	4.95	2.77	5.52	2.21	7.02	3.19	4.31	2.49	3.16	3.15	2.46	2.12
90th Percentile (°/s)	42.24	6.52	45.37	15.50	32.82	7.77	33.60	7.70	35.87	10.26	29.16	8.89	28.50	13.53	23.73	8.81
90th-10th Percentile (°/s)	41.52	6.33	44.43	14.94	32.44	7.60	33.22	7.57	35.23	10.03	28.84	8.73	28.27	13.36	23.53	8.69
Low Speed (<5°/s) (%time)	38.78	5.96	35.57	10.14	52.50	12.13	49.38	9.44	43.99	11.60	56.06	12.70	63.02	14.31	66.16	11.91
High Speed (≥90°/s) (%time)	1.89	0.91	2.31	1.98	1.07	0.54	1.08	0.54	1.35	0.96	0.92	0.54	1.02	0.96	0.62	0.43
Rest/Recovery																
Neutral for ≥ 3s (%time)	19.24	13.09	13.61	10.77	19.65	12.60	20.08	14.65	21.43	18.54	19.41	13.81	13.93	13.82	16.42	16.93
Low Speed for ≥ 3s (%time)	10.43	5.81	11.73	6.81	27.41	15.34	22.43	11.01	16.93	13.74	30.75	16.18	42.25	17.58	44.79	15.72
Neutral and Low Speed (%time)	14.48	6.76	11.78	6.83	16.02	8.71	15.03	8.93	15.50	10.21	15.19	9.03	10.71	10.44	13.60	14.09

Table 7. Full-shift trunk flexion/extension exposure metrics across all data collection days and results of variance components analyses.

Exposure Metric	Fixed effect of group					Random effects of between-subjects and between-shifts within subject									
	Cyclic		Non-cyclic			Cyclic					Non-cyclic				
	Mean	SD	Mean	SD	*p*	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ
Posture															
Mean (°)	-6.15	12.07	-5.01	11.63	0.68	66.33	(35.04 - 170.29)	87.49	(72.83 - 107.10)	1.32	66.65	(35.42 - 168.89)	71.69	(59.80 - 87.54)	1.08
10th Percentile (°)	-19.87	14.38	-22.68	13.95	0.44	99.86	(53.20 - 251.65)	118.86	(98.98 - 145.42)	1.19	88.76	(46.54 - 231.54)	110.93	(92.09 - 136.24)	1.25
50th Percentile (°)	-7.31	11.67	-6.00	11.03	0.61	59.46	(31.13 - 155.64)	85.20	(70.84 - 104.46)	1.43	60.40	(32.15 - 152.55)	65.12	(54.39 - 79.39)	1.08
90th Percentile (°)	8.99	12.62	12.88	16.14	0.29	59.16	(30.56 - 159.55)	104.00	(86.29 - 127.82)	1.76	155.74	(84.18 - 380.56)	109.50	(91.47 - 133.47)	0.70
90th-10th Percentile (°)	28.86	9.60	35.56	14.11	**0.04**	26.70	(12.98 - 83.09)	68.53	(55.93 - 85.95)	2.57	129.92	(70.66 - 313.42)	76.09	(63.65 - 92.61)	0.59
Neutral (>-20° to <20°) (%time)	74.89	22.93	73.71	18.06	0.87	192.25	(97.72 - 537.91)	358.29	(296.25 - 442.22)	1.86	108.07	(56.05 - 288.85)	222.97	(186.52 - 271.31)	2.06
Extreme (≥60°) (%time)	0.60	0.77	1.07	2.90	0.21	0.24	(0.13 - 0.61)	0.37	(0.31 - 0.45)	1.54	1.23	(0.55 - 4.78)	7.17	(5.99 - 8.75)	5.82
Movement speed															
Mean (°/s)	8.23	2.26	7.05	1.80	**0.04**	4.10	(2.25 - 9.72)	1.63	(1.32 - 2.05)	0.40	2.71	(1.49 - 6.38)	0.62	(0.52 - 0.76)	0.23
10th Percentile (°/s)	0.55	0.20	0.42	0.20	**0.02**	0.02	(0.01 - 0.06)	0.02	(0.02 - 0.02)	0.77	0.03	(0.02 - 0.08)	0.01	(0.01 - 0.01)	0.21
50th Percentile (°/s)	4.70	1.58	3.53	1.50	**0.01**	2.02	(1.11 - 4.77)	0.77	(0.63 - 0.96)	0.38	1.95	(1.07 - 4.59)	0.38	(0.31 - 0.46)	0.19
90th Percentile (°/s)	19.84	5.20	17.95	3.94	0.11	19.63	(10.67 - 47.41)	10.05	(8.07 - 12.86)	0.51	12.75	(7.01 - 30.12)	3.26	(2.72 - 3.97)	0.26
90th-10th Percentile (°/s)	19.29	5.06	17.52	3.81	0.13	18.46	(10.02 - 44.67)	9.64	(7.73 - 12.37)	0.52	11.88	(6.53 - 28.07)	3.07	(2.56 - 3.75)	0.26
Low speed (<5°/s) (%time)	53.15	8.41	60.03	9.75	**0.01**	53.34	(29.08 - 128.04)	24.10	(19.47 - 30.60)	0.45	79.63	(43.78 - 187.80)	17.81	(14.85 - 21.77)	0.22
High speed (≥90°/s) (%time)	0.19	0.26	0.11	0.12	0.09	0.04	(0.02 - 0.10)	0.04	(0.03 - 0.05)	1.04	0.01	(0.01 - 0.03)	0.00	(0.00 - 0.00)	0.18
Rest/Recovery															
Neutral for ≥ 3s (%time)	55.25	20.49	57.26	16.55	0.52	186.43	(97.79 - 485.96)	256.58	(212.96 - 315.19)	1.38	57.18	(28.04 - 174.30)	218.87	(183.08 - 266.33)	3.83
Low speed for ≥ 3s (%time)	13.53	5.68	24.53	13.43	**<0.01**	13.45	(6.80 - 38.04)	19.75	(15.86 - 25.28)	1.47	154.53	(85.02 - 363.95)	30.50	(25.38 - 37.36)	0.20
Neutral and low speed (%time)	38.70	14.70	41.00	12.55	0.36	126.02	(67.77 - 311.29)	105.57	(87.32 - 130.24)	0.84	35.76	(17.42 - 110.69)	123.67	(103.27 - 150.80)	3.46

a Positive values denote trunk flexion; Negative values denote trunk extension.

Table 8. Full-shift trunk lateral bending exposure metrics across all data collection days and results of variance components analyses.

Exposure Metric	Fixed effect of group					Random effects of between-subjects and between-shifts within subject									
	Cyclic		Non-cyclic			Cyclic					Non-cyclic				
	Mean	SD	Mean	SD	*p*	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ	S^2_{BS}	(95% CI)	S^2_{WS}	(95% CI)	λ
Posture															
Mean (°)	-1.26	4.64	-1.01	4.79	0.73	3.71	(1.71 - 13.21)	18.21	(15.21 - 22.19)	4.91	2.29	(0.95 - 11.02)	20.77	(17.37 - 25.27)	9.06
10th Percentile (°)	-8.41	4.93	-8.30	4.98	0.86	6.09	(3.02 - 18.05)	18.35	(15.29 - 22.44)	3.01	3.13	(1.38 - 12.53)	21.92	(18.34 - 26.68)	7.01
50th Percentile (°)	-1.38	4.73	-1.12	4.91	0.72	4.11	(1.94 - 13.91)	18.64	(15.58 - 22.69)	4.53	2.72	(1.17 - 11.83)	21.57	(18.04 - 26.25)	7.92
90th Percentile (°)	5.95	5.14	6.37	5.37	0.70	5.69	(2.75 - 17.99)	21.35	(17.84 - 26.02)	3.75	7.85	(4.00 - 21.91)	21.37	(17.88 - 26.00)	2.72
90th-10th Percentile (°)	14.37	3.68	14.67	4.00	0.87	8.11	(4.44 - 19.32)	5.72	(4.77 - 6.99)	0.71	12.98	(7.14 - 30.59)	3.46	(2.90 - 4.21)	0.27
Neutral (>-20° to <20°) (%time)	97.66	4.18	97.42	3.27	0.81	2.90	(1.34 - 10.19)	14.89	(12.46 - 18.12)	5.14	4.88	(2.62 - 12.05)	6.10	(5.09 - 7.45)	1.25
Extreme (≥60°) (%time)	0.00	0.01	0.00	0.03	0.27	0.00	(0.00 - 0.00)	0.00	(0.00 - 0.00)	-	0.00	(0.00 - 3.50E+72)	0.00	(0.00 - 0.00)	-
Movement speed															
Mean (°/s)	6.11	1.38	5.56	1.81	0.16	1.04	(0.54 - 2.80)	1.05	(0.81 - 1.43)	1.01	2.93	(1.61 - 6.87)	0.50	(0.42 - 0.61)	0.17
10th Percentile (°/s)	0.30	0.12	0.18	0.09	**<0.01**	0.01	(0.00 - 0.02)	0.01	(0.01 - 0.01)	0.92	0.01	(0.00 - 0.01)	0.00	(0.00 - 0.00)	0.30
50th Percentile (°/s)	3.43	1.02	2.34	1.19	**<0.01**	0.64	(0.34 - 1.62)	0.50	(0.40 - 0.63)	0.77	1.14	(0.63 - 2.70)	0.31	(0.26 - 0.38)	0.28
90th Percentile (°/s)	15.58	3.41	15.65	4.91	0.80	6.01	(3.00 - 17.50)	6.95	(4.97 - 10.43)	1.16	22.16	(12.23 - 51.90)	2.92	(2.43 - 3.57)	0.13
90th-10th Percentile (°/s)	15.27	3.34	15.47	4.86	0.88	5.64	(2.80 - 16.66)	6.76	(4.80 - 10.25)	1.20	21.69	(11.96 - 50.78)	2.84	(2.36 - 3.47)	0.13
Low speed (<5°/s) (%time)	60.68	7.15	66.93	8.98	**<0.01**	33.77	(18.15 - 83.60)	21.68	(17.41 - 27.74)	0.64	66.35	(36.45 - 156.72)	16.97	(14.16 - 20.69)	0.26
High speed (≥90°/s) (%time)	0.01	0.09	0.01	0.02	0.48	0.00	(0.00 - 0.00)	0.01	(0.01 - 0.01)	-	0.00	(0.00 - 0.00)	0.00	(0.00 - 0.00)	-
Rest/Recovery															
Neutral for ≥ 3s (%time)	72.38	12.41	76.67	11.32	**0.04**	26.95	(12.62 - 92.23)	127.49	(106.40 - 155.57)	4.73	36.11	(18.16 - 103.51)	94.40	(78.85 - 115.07)	2.61
Low speed for ≥ 3s (%time)	23.29	8.39	40.37	12.78	**<0.01**	36.03	(18.58 - 97.58)	39.11	(31.19 - 50.51)	1.09	132.52	(72.71 - 313.86)	35.36	(29.44 - 43.28)	0.27
Neutral and low speed (%time)	59.52	7.69	65.48	9.75	**0.02**	35.86	(19.03 - 91.15)	29.41	(23.60 - 37.66)	0.82	77.12	(42.36 - 182.20)	20.98	(17.54 - 25.56)	0.27

a Positive values denote right lateral bending; Negative values denote left lateral bending.

Table 9. Trunk flexion/extension exposure metrics across primary work task categories across all data collection days.

Exposure Metric	Work Tasks															
	Assembly		Operate Machinery		Maintenance		Set-up		Other				Break			
	Cyclic		Cyclic		Non-cyclic		Non-cyclic		Cyclic		Non-cyclic		Cyclic		Non-cyclic	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Posture																
Mean (°)	-5.76	12.06	-5.63	11.73	-2.97	12.49	-4.21	10.92	-5.01	11.47	-4.05	13.76	-15.04	19.49	-9.93	16.11
10th Percentile (°)	-17.80	13.58	-15.86	11.15	-16.77	11.70	-18.00	10.77	-16.26	11.86	-19.77	14.04	-31.55	20.38	-26.84	15.36
50th Percentile (°)	-7.64	11.77	-7.08	11.98	-4.84	12.24	-5.92	11.16	-7.34	10.86	-5.14	13.50	-17.22	21.57	-10.73	17.57
90th Percentile (°)	7.64	12.66	5.52	13.08	12.84	17.15	10.85	14.48	8.94	16.01	12.47	18.08	3.29	20.21	6.28	18.47
90th-10th Percentile (°)	25.44	8.63	21.38	6.99	29.61	13.10	28.85	11.71	25.20	12.10	32.23	13.80	34.84	15.24	33.12	12.87
Neutral (>-20° to <20°) (%time)	76.24	23.75	76.81	26.50	76.64	20.58	77.09	18.87	78.43	25.48	72.32	21.67	52.89	28.25	60.87	24.84
Extreme (≥60°) (%time)	0.58	0.64	0.46	0.72	1.14	3.43	1.13	3.76	0.68	1.40	1.16	3.31	0.60	1.96	0.36	1.17
Movement Speed																
Mean (°/s)	8.13	2.09	9.27	2.71	7.13	1.82	7.81	1.95	8.04	2.32	6.77	2.09	5.99	2.74	5.57	1.97
10th Percentile (°/s)	0.65	0.25	0.75	0.30	0.51	0.27	0.54	0.26	0.63	0.29	0.47	0.26	0.27	0.16	0.33	0.19
50th Percentile (°/s)	4.77	1.46	5.81	2.05	3.85	1.64	4.22	1.66	4.66	1.83	3.61	1.74	2.34	1.54	2.55	1.40
90th Percentile (°/s)	19.33	5.06	21.69	5.47	17.73	3.92	19.35	4.24	18.82	4.98	16.71	4.71	16.23	7.46	14.33	4.89
90th-10th Percentile (°/s)	18.68	4.89	20.94	5.21	17.22	3.72	18.82	4.10	18.20	4.74	16.24	4.50	15.96	7.36	14.00	4.75
Low Speed (<5°/s) (%time)	52.96	8.30	47.18	9.58	58.50	10.99	55.67	10.20	54.07	10.68	61.16	12.51	69.80	11.83	69.36	11.52
High Speed (≥90°/s) (%time)	0.17	0.24	0.23	0.32	0.09	0.08	0.15	0.16	0.26	0.37	0.10	0.10	0.17	0.25	0.08	0.07
Rest/Recovery																
Neutral for ≥ 3s (%time)	57.31	21.42	53.63	22.76	59.30	18.96	59.19	18.04	58.80	21.88	56.72	18.91	41.82	25.35	49.05	22.50
Low Speed for ≥ 3s (%time)	10.52	6.11	9.90	5.92	22.05	15.05	19.19	13.73	14.19	11.51	25.75	17.09	43.30	17.73	37.83	19.40
Neutral and Low Speed (%time)	40.29	15.34	35.10	15.28	41.83	13.87	41.01	13.60	40.80	16.89	40.32	14.44	31.84	21.84	37.80	19.17

a Positive values denote trunk flexion; Negative values denote trunk extension.

Table 10. Trunk lateral bending exposure metrics across primary work task categories across all data collection days.

Exposure Metric	Work Tasks															
	Assembly		Operate Machinery		Maintenance		Set-up		Other				Break			
	Cyclic		Cyclic		Non-cyclic		Non-cyclic		Cyclic		Non-cyclic		Cyclic		Non-cyclic	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Posture																
Mean (°)	-1.61	4.41	-0.36	5.29	-1.27	4.85	-0.88	5.20	-1.63	4.64	-0.90	4.78	-1.04	4.99	-1.46	5.21
10th Percentile (°)	-8.77	4.90	-6.58	4.98	-7.82	5.26	-8.26	5.29	-7.28	4.51	-7.49	4.96	-6.41	5.27	-6.89	5.42
50th Percentile (°)	-1.74	4.49	-0.60	5.45	-1.48	4.94	-1.07	5.27	-1.86	4.77	-0.94	4.85	-1.06	5.09	-1.51	5.29
90th Percentile (°)	5.61	4.73	6.07	5.86	5.52	5.14	6.68	6.14	4.28	5.37	5.68	5.52	4.28	5.61	3.83	5.66
90th-10th Percentile (°)	14.39	3.66	12.65	2.87	13.34	3.59	14.94	4.31	11.57	3.42	13.17	4.26	10.69	4.17	10.72	3.81
Neutral (>-20° to <20°) (%time)	97.51	3.71	97.74	5.51	97.64	3.39	97.01	4.10	98.65	2.10	97.68	3.61	98.29	4.78	98.67	2.49
Extreme (≥60°) (%time)	0.00	0.01	0.00	0.01	0.00	0.01	0.03	0.29	0.00	0.01	0.00	0.02	0.00	0.02	0.00	0.00
Movement Speed																
Mean (°/s)	6.02	1.26	7.24	1.56	5.41	1.69	6.45	1.90	5.79	1.67	5.03	1.81	3.86	1.77	3.90	1.91
10th Percentile (°/s)	0.38	0.12	0.46	0.21	0.24	0.15	0.26	0.12	0.36	0.17	0.21	0.13	0.13	0.09	0.14	0.13
50th Percentile (°/s)	3.54	0.90	4.40	1.36	2.57	1.36	3.09	1.28	3.31	1.26	2.38	1.35	1.38	1.10	1.38	1.37
90th Percentile (°/s)	14.93	3.10	18.14	3.52	14.69	3.98	17.55	5.31	14.71	4.10	13.56	4.55	11.14	4.89	11.19	5.10
90th-10th Percentile (°/s)	14.55	3.02	17.68	3.36	14.45	3.87	17.29	5.26	14.36	4.00	13.35	4.45	11.01	4.82	11.06	5.02
Low Speed (<5°/s) (%time)	60.65	6.78	54.15	8.26	66.33	10.14	62.05	8.88	62.29	9.99	68.73	11.24	76.81	10.35	77.55	10.64
High Speed (≥90°/s) (%time)	0.02	0.11	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.04	0.00	0.01	0.01	0.06	0.00	0.01
Rest/Recovery																
Neutral for ≥ 3s (%time)	72.28	11.98	67.74	16.36	77.23	13.08	73.02	12.89	72.70	14.26	78.22	12.37	83.84	10.99	83.93	10.73
Low Speed for ≥ 3s (%time)	19.75	8.52	19.35	10.25	38.94	15.15	32.60	12.30	26.38	15.39	42.33	17.05	55.57	17.39	58.55	15.79
Neutral and Low Speed (%time)	59.41	7.26	53.14	9.25	64.95	10.56	60.39	9.78	61.58	10.33	67.18	11.69	75.67	11.74	76.68	10.95

a Positive values denote right lateral bending; Negative values denote left lateral bending.

Table 11. Mean and standard deviation (SD) of SD_{mean} and SD_{range} across all data collection days for the cyclic and non-cyclic work groups.

Exposure Metric	**Cyclic**		**Non-cyclic**	
SD_{mean} for posture (°)	**Mean**	**SD**	**Mean**	**SD**
Left Arm	8.72	2.75	12.20	3.20
Right Arm	8.37	2.41	11.58	3.14
Trunk Flexion/Extension	10.96	3.44	13.06	4.99
Trunk Lateral Bending	3.13	1.20	3.93	1.16
SD_{range} for posture (°)				
Left Arm	14.50	4.16	17.05	3.64
Right Arm	14.60	4.44	16.96	3.24
Trunk Flexion/Extension	12.63	3.93	13.67	3.60
Trunk Lateral Bending	5.55	1.71	6.66	1.86
SD_{mean} for speed (°/s)				
Left Arm	6.32	1.22	6.87	1.21
Right Arm	6.71	1.34	7.28	1.42
Trunk Flexion/Extension	3.41	0.91	3.74	0.80
Trunk Lateral Bending	2.48	0.55	3.46	0.99
SD_{range} for speed (°/s)				
Left Arm	14.95	3.19	15.78	2.77
Right Arm	15.64	2.95	16.47	2.98
Trunk Flexion/Extension	7.42	1.96	8.16	1.79
Trunk Lateral Bending	5.26	1.13	7.38	2.00

Table 12. Summarized information for the 5th and 95th percentiles of exposure from the Bootstrapping analysis.

Exposure Metric Days of Resampling (Number of Observations)	*Left Arm*						*Right Arm*					
	Cyclic			**Non-cyclic**			**Cyclic**			**Non-cyclic**		
	Mean	**5th %tile**	**95th %tile**	**Mean**	**5th %tile**	**95th %tile**	**Mean**	**5th %tile**	**95th %tile**	**Mean**	**5th %tile**	**95th %tile**
10^{th} Percentile (°)												
One day (N=15)	37.58	33.81	41.87	41.34	36.95	45.22	39.42	34.29	44.42	37.07	32.77	41.17
Fifteen days (N=225)	38.68	37.50	39.90	40.56	39.57	41.55	38.44	37.25	39.69	39.68	38.58	40.81
90^{th} Percentile (°)												
One day (N=15)	50.70	44.38	54.86	55.92	51.91	59.82	53.81	50.20	58.70	55.57	50.61	61.20
Fifteen days (N=225)	52.52	51.11	53.94	54.52	53.29	55.77	52.45	51.08	53.79	53.47	52.29	54.71
Extreme (≥60°) (%time)												
One day (N=15)	6.12	4.23	8.11	10.14	7.30	14.56	7.36	4.81	11.84	6.81	5.05	9.79
Fifteen days (N=225)	6.96	6.31	7.74	8.23	7.55	9.05	7.17	6.48	7.92	7.02	6.49	7.61
50th Percentile (°/s)												
One day (N=15)	6.67	6.03	7.38	4.42	3.34	5.93	6.33	5.47	7.28	4.68	3.53	5.75
Fifteen days (N=225)	6.59	6.36	6.85	4.02	3.74	4.32	7.31	7.08	7.58	4.34	4.04	4.66
90th-10th Percentile (°/s)												
One day (N=15)	36.97	33.46	41.40	29.26	25.48	35.20	41.55	37.83	48.51	29.30	26.48	32.64
Fifteen days (N=225)	36.87	35.94	37.83	30.11	29.04	31.27	39.24	38.35	40.17	31.55	30.62	32.52

Table 13. Results of the Generalized Linear Models for the (Dis)comfort, Distraction, and Burden analysis.

	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	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	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	0.8
Shift 3	-0.02	0.26	0.94	-0.53	0.49	0.01	0.15	0.94	-0.3	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	0.4	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	0.6	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	0.6
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	-0.5	0.31	0.02	0.11	0.83	-0.21	0.26	0.04	0.12	0.72	-0.21	0.3
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	0.3	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	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	0.02
Female	-0.93	0.26	**<0.01**	-1.47	-0.39	-0.3	0.1	**<0.05**	-0.49	-0.1	-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	0.01	0	0	0.24	0	0.01
RA60+	0.02	0.01	**<0.05**	0	0.04	0	0	0.79	-0.01	0.01	0	0	0.55	-0.01	0
FE90P	-0.01	0	**<0.05**	-0.01	0	0	0	0.16	0	0	0	0	0.45	0	0
RANLS	0	0.01	0.78	-0.02	0.01	0	0	0.53	0	0.01	0	0	0.09	0	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 ≥ 60°.
RA60+ = percentage of time with the right arm elevated ≥ 60°.
FE90P = the 90th percentile of trunk flexion/extension.
RANLS = percentage of time with the right arm elevated < 20° and moving < 5°/s.

Table 14. Full-shift left arm elevation exposure metrics across all data collection days (pre n=35; post n=22).

Exposure Metric	Cyclic						Non-Cyclic					
	Pre		Post				Pre		Post			
	Mean	SD	Mean	SD	*p*	*r*	Mean	SD	Mean	SD	*p*	*r*
Posture												
Mean (°)	30.43	7.14	28.42	5.41	**0.04**	-0.11	31.29	6.32	29.03	5.55	**<0.01**	-0.17
10th Percentile (°)	13.91	5.48	12.11	4.86	**<0.01**	-0.16	13.88	4.59	12.24	4.42	**<0.01**	-0.15
50th Percentile (°)	26.20	7.62	23.89	5.32	**0.03**	-0.12	27.02	6.74	24.46	5.79	**<0.01**	-0.17
90th Percentile (°)	53.18	10.64	51.28	9.16	**0.04**	-0.11	54.20	9.16	52.08	8.24	**0.03**	-0.11
90th-10th Percentile (°)	39.27	8.91	39.17	9.21	0.34	-0.05	40.32	7.21	39.84	6.57	0.47	-0.04
Neutral (<20°) (%time)	32.85	18.75	38.20	17.34	**0.01**	0.14	31.32	15.60	36.23	14.21	**<0.01**	0.15
Extreme (≥60°) (%time)	7.41	5.68	6.17	5.39	0.06	-0.11	7.90	5.53	6.55	3.99	**0.02**	-0.12
Movement speed												
Mean (°/s)	14.92	3.64	13.15	4.44	**<0.01**	-0.23	10.83	3.26	12.99	3.98	**<0.01**	0.27
10th Percentile (°/s)	0.49	0.28	0.39	0.18	**0.01**	-0.15	0.22	0.12	0.33	0.25	**<0.01**	0.25
50th Percentile (°/s)	7.16	2.62	6.43	3.20	**<0.01**	-0.17	3.88	2.18	5.64	2.97	**<0.01**	0.30
90th Percentile (°/s)	39.14	9.14	33.78	10.82	**<0.01**	-0.24	29.80	8.33	34.53	9.55	**<0.01**	0.26
90th-10th Percentile (°/s)	38.64	8.93	33.39	10.67	**<0.01**	-0.24	29.59	8.23	34.20	9.36	**<0.01**	0.26
Low speed (<5°/s) (%time)	42.98	7.43	46.64	9.77	**<0.01**	0.17	56.40	9.99	49.79	12.02	**<0.01**	-0.29
High speed (≥90°/s) (%time)	1.64	0.93	1.24	1.06	**<0.01**	-0.19	0.95	0.63	1.26	0.68	**<0.01**	0.24
Rest/Recovery												
Neutral for ≥ 3s (%time)	20.42	16.57	25.79	15.29	**0.01**	0.16	21.48	13.64	23.29	12.76	0.17	0.07
Low speed for ≥ 3s (%time)	14.95	6.19	18.50	6.98	**<0.01**	0.19	32.42	12.27	25.56	13.35	**<0.01**	-0.27
Neutral and low speed (%time)	15.03	8.95	18.90	9.71	**<0.01**	0.18	16.83	9.04	17.38	7.43	0.55	0.03

Table 15. Full-shift left arm elevation exposure metrics across all data collection days for the repeat participants (n=10).

Exposure Metric	Cyclic								Non-Cyclic							
	Pre		Post						Pre		Post					
	Mean	SD	Mean	SD	SW	*p*	*t*	*S*	Mean	SD	Mean	SD	SW	*p*	*t*	*S*
Posture																
Mean (°)	27.70	5.14	26.90	6.01	0.20	0.36	0.94		34.31	6.49	29.61	6.10	0.30	**<0.01**	6.56	
10th Percentile (°)	14.78	3.66	13.02	5.85	0.63	**0.05**	2.10		15.26	4.90	13.26	5.22	0.08	**<0.01**	3.53	
50th Percentile (°)	24.24	4.23	23.16	6.40	0.91	0.23	1.24		29.87	7.28	24.90	6.23	0.23	**<0.01**	6.23	
90th Percentile (°)	45.72	8.91	46.88	5.83	0.59	0.47	-0.74		59.02	8.63	52.60	8.30	0.49	**<0.01**	5.75	
90th-10th Percentile (°)	30.93	5.85	33.87	3.59	0.06	0.08	-1.82		43.76	7.28	39.34	6.11	0.87	**<0.01**	4.44	
Neutral (<20°) (%time)	33.15	16.21	39.10	21.75	0.61	0.06	-1.97		26.07	15.17	34.33	18.08	0.83	**<0.01**	-4.22	
Extreme (≥60°) (%time)	3.88	3.28	3.90	1.91	0.10	0.97	-0.03		10.91	6.62	6.97	4.76	0.76	**<0.01**	6.21	
Movement speed																
Mean (°/s)	11.65	3.23	10.80	1.49	<0.01	0.53		-25.50	11.63	3.49	11.88	3.06	0.03	0.25		-152.00
10th Percentile (°/s)	0.35	0.15	0.35	0.11	<0.01	0.26		-38.00	0.22	0.12	0.24	0.10	0.23	0.13	-1.53	
50th Percentile (°/s)	5.85	1.98	5.28	1.32	<0.01	0.93		-3.50	4.14	2.30	4.81	2.00	0.04	**<0.01**		-416.50
90th Percentile (°/s)	30.37	8.79	28.04	3.79	<0.01	0.53		-25.50	32.11	9.18	32.13	7.83	0.19	0.98	0.03	
90th-10th Percentile (°/s)	30.03	8.66	27.69	3.74	<0.01	0.53		-25.50	31.89	9.08	31.89	7.75	0.24	1.00	0.00	
Low speed (<5°/s) (%time)	47.43	6.09	49.30	5.91	<0.01	0.93		-3.50	54.97	8.92	52.03	8.61	0.05	**<0.01**	3.59	
High speed (≥90°/s) (%time)	0.61	0.72	0.42	0.10	<0.01	0.56		-22.00	1.16	0.72	1.00	0.54	0.01	**0.05**		260.50
Rest/Recovery																
Neutral for ≥ 3s (%time)	19.24	13.29	27.17	18.66	0.31	**0.01**	-2.91		16.21	11.20	23.21	16.57	0.05	**<0.01**		-451.00
Low speed for ≥ 3s (%time)	18.81	4.61	19.13	5.97	0.09	0.84	-0.20		31.07	9.94	27.81	9.49	0.74	**<0.01**	3.02	
Neutral and low speed (%time)	17.00	9.34	20.13	12.08	0.42	0.08	-1.83		13.21	7.85	17.22	9.65	0.29	**<0.01**	-3.89	

Table 16. Full-shift right arm elevation exposure metrics across all data collection days (pre n=35; post n=22).

Exposure Metric	Cyclic						Non-Cyclic					
	Pre		Post				Pre		Post			
	Mean	SD	Mean	SD	*p*	*r*	Mean	SD	Mean	SD	*p*	*r*
Posture												
Mean (°)	30.40	6.53	30.84	5.40	0.33	0.05	30.96	5.55	28.74	4.44	**<0.01**	-0.20
10th Percentile (°)	13.70	5.18	13.04	3.29	0.56	-0.03	13.62	4.80	11.85	3.90	**<0.01**	-0.18
50th Percentile (°)	26.38	7.01	25.65	4.56	0.79	-0.02	26.78	6.30	24.48	4.78	**<0.01**	-0.16
90th Percentile (°)	52.83	10.09	55.99	11.86	0.10	0.09	53.50	9.03	51.04	6.66	**<0.01**	-0.14
90th-10th Percentile (°)	39.13	9.04	42.95	11.60	0.07	0.10	39.88	8.15	39.19	5.97	0.37	-0.04
Neutral (<20°) (%time)	32.44	16.08	33.67	12.26	0.49	0.04	31.46	15.52	36.73	13.91	**<0.01**	0.15
Extreme (≥60°) (%time)	7.36	5.50	9.20	7.15	0.07	0.10	6.94	4.16	5.91	3.42	**<0.01**	-0.13
Movement speed												
Mean (°/s)	16.04	3.94	14.63	4.11	**<0.01**	-0.18	11.51	2.94	13.40	4.17	**<0.01**	0.24
10th Percentile (°/s)	0.55	0.34	0.45	0.23	**0.02**	-0.13	0.25	0.14	0.38	0.30	**<0.01**	0.23
50th Percentile (°/s)	8.02	3.04	7.28	3.27	**0.03**	-0.12	4.28	2.22	5.97	3.15	**<0.01**	0.27
90th Percentile (°/s)	41.78	9.46	37.44	9.45	**<0.01**	-0.20	31.68	7.15	35.36	10.00	**<0.01**	0.19
90th-10th Percentile (°/s)	41.24	9.21	36.99	9.28	**<0.01**	-0.21	31.43	7.04	34.98	9.78	**<0.01**	0.19
Low speed (<5°/s) (%time)	40.50	7.24	43.38	9.62	**0.04**	0.11	54.35	9.71	48.54	12.20	**<0.01**	-0.26
High speed (≥90°/s) (%time)	1.87	1.17	1.53	1.03	**0.03**	-0.12	1.01	0.50	1.36	0.79	**<0.01**	0.19
Rest/Recovery												
Neutral for ≥ 3s (%time)	18.16	13.43	19.46	11.44	0.19	0.07	20.57	13.36	23.91	12.52	**<0.01**	0.13
Low speed for ≥ 3s (%time)	13.89	5.92	17.34	7.30	**<0.01**	0.18	29.18	11.94	23.64	12.87	**<0.01**	-0.23
Neutral and low speed (%time)	13.72	6.93	15.55	6.95	0.07	0.10	15.74	8.44	17.22	6.93	0.07	0.09

Table 17. Full-shift right arm elevation exposure metrics across all data collection days for the repeat participants (n=10).

Exposure Metric	Cyclic								Non-Cyclic							
	Pre		Post						Pre		Post					
	Mean	SD	Mean	SD	SW	*p*	*t*	*S*	Mean	SD	Mean	SD	SW	*p*	*t*	*S*
Posture																
Mean (°)	27.92	2.34	27.43	3.80	0.66	0.56	0.60		33.79	5.17	30.06	4.93	0.45	**<0.01**	5.12	
10th Percentile (°)	14.86	2.31	12.62	3.18	0.86	**0.01**	2.76		14.79	4.61	12.88	4.74	0.29	**<0.01**	3.20	
50th Percentile (°)	25.27	2.14	23.66	3.51	0.28	**0.03**	2.26		28.93	5.68	25.64	5.35	0.80	**<0.01**	4.80	
90th Percentile (°)	44.79	5.71	47.26	7.40	0.22	0.20	-1.31		59.44	9.26	52.75	6.27	0.61	**<0.01**	5.09	
90th-10th Percentile (°)	29.93	6.16	34.64	6.55	0.59	**0.02**	-2.51		44.64	8.77	39.87	5.32	0.61	**<0.01**	4.60	
Neutral (<20°) (%time)	28.70	7.89	36.83	12.78	0.30	**0.01**	-2.82		26.76	13.45	33.00	15.47	0.87	**<0.01**	-3.47	
Extreme (≥60°) (%time)	3.18	2.38	4.47	3.14	0.43	0.10	-1.72		9.63	5.00	6.69	3.79	0.98	**<0.01**	4.60	
Movement speed																
Mean (°/s)	12.56	2.67	12.39	1.88	<0.01	0.25		-46.00	11.94	2.78	12.73	3.21	0.15	**<0.01**	-2.95	
10th Percentile (°/s)	0.37	0.16	0.40	0.20	<0.01	0.17		-51.00	0.25	0.13	0.27	0.11	0.08	0.07	-1.87	
50th Percentile (°/s)	6.49	1.91	6.21	1.92	<0.01	0.78		-11.50	4.47	2.10	5.25	2.11	0.25	**<0.01**	-4.31	
90th Percentile (°/s)	32.27	6.80	32.06	4.60	<0.01	0.10		-65.50	32.90	6.90	34.53	8.60	0.03	**<0.01**		-375.00
90th-10th Percentile (°/s)	31.90	6.67	31.66	4.52	<0.01	0.10		-65.00	32.65	6.79	34.25	8.52	0.02	**<0.01**		-359.50
Low speed (<5°/s) (%time)	44.85	5.92	45.65	7.74	<0.01	0.78		11.50	52.97	8.41	50.20	8.45	0.14	**<0.01**	3.53	
High speed (≥90°/s) (%time)	0.72	0.53	0.71	0.32	<0.01	0.66		-18.00	1.07	0.49	1.19	0.69	0.10	0.08	-1.77	
Rest/Recovery																
Neutral for ≥ 3s (%time)	12.96	5.59	21.65	12.55	0.26	**<0.01**	-3.10		15.99	10.35	21.20	13.33	0.96	**<0.01**	-3.49	
Low speed for ≥ 3s (%time)	17.61	4.62	18.03	7.44	0.02	0.80		10.50	28.56	9.83	25.57	9.07	0.96	**<0.01**	3.07	
Neutral and low speed (%time)	12.87	4.40	16.96	7.36	0.30	**0.03**	-2.34		13.06	6.83	15.80	7.52	0.18	**<0.01**	-3.00	

Table 18. Full-shift trunk flexion/extension exposure metrics across all data collection days (pre n=35; post n=22).

Exposure Metric	Cyclic						Non-Cyclic					
	Pre		Post				Pre		Post			
	Mean	SD	Mean	SD	*p*	*r*	Mean	SD	Mean	SD	*p*	*r*
Posture [a]												
Mean (°)	-6.15	12.07	-0.11	10.77	**<0.01**	0.20	-5.01	11.63	3.46	8.41	**<0.01**	0.40
10th Percentile (°)	-19.87	14.38	-12.84	11.05	**<0.01**	0.21	-22.68	13.95	-11.56	7.59	**<0.01**	0.43
50th Percentile (°)	-7.31	11.67	-1.45	10.28	**<0.01**	0.21	-6.00	11.03	0.62	8.63	**<0.01**	0.35
90th Percentile (°)	8.99	12.62	14.03	13.91	**0.03**	0.13	12.88	16.14	22.19	13.46	**<0.01**	0.33
90th-10th Percentile (°)	28.86	9.60	26.87	11.03	0.12	-0.09	35.56	14.11	33.75	12.21	0.36	-0.05
Neutral (> -20° to <20°) (%time)	74.89	22.93	81.40	18.66	**0.03**	0.13	73.71	18.06	80.65	12.64	**<0.01**	0.19
Extreme (≥60°) (%time)	0.60	0.77	0.79	1.27	0.87	-0.01	1.07	2.90	1.69	1.86	**<0.01**	0.39
Movement speed												
Mean (°/s)	8.23	2.26	7.85	2.18	0.20	-0.08	7.05	1.80	8.13	2.02	**<0.01**	0.27
10th Percentile (°/s)	0.55	0.20	0.48	0.20	**0.04**	-0.12	0.42	0.20	0.48	0.19	**<0.01**	0.14
50th Percentile (°/s)	4.70	1.58	4.39	1.62	0.12	-0.09	3.53	1.50	4.19	1.54	**<0.01**	0.23
90th Percentile (°/s)	19.84	5.20	19.39	4.78	0.58	-0.03	17.95	3.94	20.19	4.72	**<0.01**	0.24
90th-10th Percentile (°/s)	19.29	5.06	18.90	4.61	0.64	-0.03	17.52	3.81	19.71	4.60	**<0.01**	0.24
Low speed (<5°/s) (%time)	53.15	8.41	55.03	9.40	0.17	0.08	60.03	9.75	55.80	10.03	**<0.01**	-0.23
High speed (≥90°/s) (%time)	0.19	0.26	0.13	0.11	**0.04**	-0.12	0.11	0.12	0.22	0.15	**<0.01**	0.47
Rest/Recovery												
Neutral for ≥ 3s (%time)	55.25	20.49	60.47	17.11	0.23	0.07	57.26	16.55	60.63	10.77	0.22	0.06
Low speed for ≥ 3s (%time)	13.53	5.68	17.63	7.45	**<0.01**	0.20	24.53	13.43	21.60	13.44	**0.02**	-0.12
Neutral and low speed (%time)	38.70	14.70	43.65	13.11	**0.04**	0.12	41.00	12.55	43.70	9.18	0.09	0.09

a Positive values denote trunk flexion; Negative values denote trunk extension.

Table 19. Full-shift trunk flexion/extension exposure metrics across all data collection days for the repeat participants (n=10).

Exposure Metric	**Cyclic**								**Non-Cyclic**							
	Pre		**Post**						**Pre**		**Post**					
	Mean	SD	Mean	SD	SW	*p*	*t*	*S*	Mean	SD	Mean	SD	SW	*p*	*t*	*S*
Posture [a]																
Mean (°)	-12.72	11.89	-2.87	9.09	0.78	**<0.01**	-4.25		-2.29	7.07	1.46	7.64	0.95	**0.01**	-2.89	
10th Percentile (°)	-24.43	14.01	-12.68	9.60	0.53	**<0.01**	-4.47		-18.94	10.05	-11.51	6.99	**0.03**	**<0.01**		-507.00
50th Percentile (°)	-12.39	11.91	-3.55	8.73	0.90	**<0.01**	-3.84		-3.65	6.82	-1.07	7.39	0.81	**0.04**	-2.16	
90th Percentile (°)	0.03	11.83	7.05	10.47	0.96	**<0.01**	-2.83		15.52	12.80	17.23	12.33	**0.03**	0.47		-97.50
90th-10th Percentile (°)	24.46	5.71	19.73	6.67	0.23	**<0.01**	3.13		34.47	14.62	28.73	11.95	**<0.01**	**<0.01**		383.50
Neutral (> -20° to <20°) (%time)	67.57	31.26	86.21	18.93	0.03	**<0.01**		-113.50	80.82	11.29	85.15	10.80	**0.02**	**0.01**		-348.00
Extreme (≥60°) (%time)	0.06	0.07	0.24	0.50	<0.01	**<0.01**		-95.50	1.14	1.95	1.29	1.74	**<0.01**	0.45		-101.00
Movement speed																
Mean (°/s)	7.31	1.47	6.47	0.94	<0.01	**0.01**		93.50	7.35	1.98	7.85	1.83	0.21	**<0.01**	-2.98	
10th Percentile (°/s)	0.43	0.18	0.41	0.12	<0.01	0.89		-5.50	0.43	0.21	0.46	0.16	0.28	0.08	-1.80	
50th Percentile (°/s)	4.22	1.13	3.63	0.81	<0.01	0.08		68.50	3.58	1.55	4.03	1.17	0.81	**<0.01**	-3.42	
90th Percentile (°/s)	18.29	3.32	16.12	1.88	<0.01	**<0.01**		117.50	18.72	4.31	19.80	4.77	0.02	**0.02**		-311.00
90th-10th Percentile (°/s)	17.86	3.16	15.71	1.77	<0.01	**<0.01**		128.50	18.29	4.21	19.34	4.72	0.01	**0.02**		-301.50
Low speed (<5°/s) (%time)	55.29	6.40	59.41	6.00	0.01	**0.03**		-83.50	59.30	9.21	56.32	7.48	0.42	**<0.01**	3.65	
High speed (≥90°/s) (%time)	0.05	0.03	0.04	0.03	<0.01	**0.05**		60.00	0.16	0.18	0.16	0.16	<0.01	0.50		-74.50
Rest/Recovery																
Neutral for ≥ 3s (%time)	49.91	26.57	65.54	18.06	0.15	**0.02**	-2.41		61.62	12.77	63.54	10.84	0.85	0.37	-0.91	
Low speed for ≥ 3s (%time)	16.71	4.71	18.78	6.67	0.17	0.17	-1.40		24.74	13.47	21.13	9.03	0.05	**<0.01**	2.93	
Neutral and low speed (%time)	34.64	18.23	49.80	12.57	0.28	**<0.01**	-3.26		45.32	10.70	46.69	7.62	<0.01	0.52		-85.50

a Positive values denote trunk flexion; Negative values denote trunk extension.

Table 20. Full-shift trunk lateral bending exposure metrics across all data collection days (pre n=35; post n=22).

Exposure Metric	Cyclic						Non-Cyclic					
	Pre		Post				Pre		Post			
	Mean	SD	Mean	SD	*p*	*r*	Mean	SD	Mean	SD	*p*	*r*
Posture [a]												
Mean (°)	-1.26	4.64	0.13	4.65	0.10	0.10	-1.01	4.79	-0.17	4.06	0.10	0.09
10th Percentile (°)	-8.41	4.93	-8.17	5.88	0.87	0.01	-8.30	4.98	-7.62	4.11	0.29	0.05
50th Percentile (°)	-1.38	4.73	0.22	4.47	**0.05**	0.12	-1.12	4.91	-0.11	4.14	**0.05**	0.10
90th Percentile (°)	5.95	5.14	7.99	5.01	**<0.01**	0.15	6.37	5.37	7.20	4.49	0.14	0.08
90th-10th Percentile (°)	14.37	3.68	16.16	4.81	**<0.01**	0.16	14.67	4.00	14.82	2.88	0.08	0.09
Neutral (> -20° to <20°) (%time)	97.66	4.18	96.71	3.46	**0.02**	-0.14	97.42	3.27	97.84	1.76	0.30	-0.05
Extreme (≥60°) (%time)	0.00	0.01	0.00	0.00	0.15	-0.08	0.00	0.03	0.00	0.02	0.10	-0.08
Movement speed												
Mean (°/s)	6.11	1.38	7.06	2.68	0.28	0.06	5.56	1.81	6.96	2.82	**<0.01**	0.25
10th Percentile (°/s)	0.30	0.12	0.30	0.14	0.67	-0.02	0.18	0.09	0.25	0.16	**<0.01**	0.20
50th Percentile (°/s)	3.43	1.02	4.08	2.15	0.64	0.03	2.34	1.19	3.40	1.81	**<0.01**	0.29
90th Percentile (°/s)	15.58	3.41	18.20	6.50	0.12	0.09	15.65	4.91	18.83	7.77	**<0.01**	0.21
90th-10th Percentile (°/s)	15.27	3.34	17.90	6.38	0.10	0.10	15.47	4.86	18.58	7.69	**<0.01**	0.20
Low speed (<5°/s) (%time)	60.68	7.15	58.30	12.00	0.64	-0.03	66.93	8.98	60.76	11.96	**<0.01**	-0.28
High speed (≥90°/s) (%time)	0.01	0.09	0.01	0.01	0.17	-0.08	0.01	0.02	0.03	0.04	**<0.01**	0.32
Rest/Recovery												
Neutral for ≥ 3s (%time)	72.38	12.41	69.07	16.58	0.27	-0.06	76.67	11.32	69.33	12.99	**<0.01**	-0.27
Low speed for ≥ 3s (%time)	23.29	8.39	24.44	8.53	0.53	0.04	40.37	12.78	33.07	15.05	**<0.01**	-0.28
Neutral and low speed (%time)	59.52	7.69	56.74	12.01	0.30	-0.06	65.48	9.75	59.67	12.13	**<0.01**	-0.26

a Positive values denote right lateral bending; Negative values denote left lateral bending.

Table 21. Full-shift trunk lateral bending exposure metrics across all data collection days for the repeat participants (n=10).

Exposure Metric	**Cyclic**								**Non-Cyclic**							
	Pre		**Post**						**Pre**		**Post**					
	Mean	SD	Mean	SD	SW	*p*	*t*	*S*	Mean	SD	Mean	SD	SW	*p*	*t*	*S*
Posture [a]																
Mean (°)	-1.55	4.89	0.70	5.37	0.37	0.14	-1.52		-1.16	5.76	-0.15	4.08	0.68	0.24	-1.18	
10th Percentile (°)	-7.45	5.12	-6.24	5.33	0.43	0.41	-0.84		-9.12	5.69	-7.65	4.18	0.71	0.08	-1.80	
50th Percentile (°)	-1.86	5.10	0.53	5.22	0.27	0.12	-1.61		-1.16	6.04	-0.20	4.17	0.71	0.28	-1.09	
90th Percentile (°)	4.60	4.82	7.83	6.12	0.41	**0.05**	-2.04		6.70	6.45	7.40	4.65	0.83	0.44	-0.77	
90th-10th Percentile (°)	12.06	2.18	14.07	3.89	0.95	**<0.01**	-3.39		15.82	4.47	15.05	3.27	0.23	**0.04**	2.09	
Neutral (> -20° to <20°) (%time)	99.25	0.65	97.55	2.79	<0.01	**<0.01**		158.00	96.46	4.55	97.70	1.73	<0.01	**<0.01**		-331.50
Extreme (≥60°) (%time)	0.00	0.00	0.00	0.00	.	.	.	.	0.01	0.05	0.01	0.04	<0.01	0.16		12.50
Movement speed																
Mean (°/s)	6.18	1.48	6.62	2.77	0.16	0.27	-1.12		6.22	1.93	7.42	3.02	<0.01	**<0.01**		-620.00
10th Percentile (°/s)	0.25	0.09	0.28	0.12	0.01	0.11		-63.00	0.19	0.09	0.21	0.08	0.89	0.07	-1.87	
50th Percentile (°/s)	3.36	0.88	3.55	1.55	0.16	0.54	-0.62		2.51	1.26	3.27	1.38	0.14	**<0.01**	-5.28	
90th Percentile (°/s)	16.31	4.07	17.74	7.68	0.15	0.16	-1.45		17.82	5.22	21.00	9.16	<0.01	**<0.01**		-589.00
90th-10th Percentile (°/s)	16.06	4.01	17.46	7.57	0.14	0.16	-1.46		17.63	5.17	20.79	9.11	<0.01	**<0.01**		-592.50
Low speed (<5°/s) (%time)	60.62	6.74	61.12	10.70	0.06	0.79	-0.27		64.79	8.35	60.36	9.10	0.67	**<0.01**	5.52	
High speed (≥90°/s) (%time)	0.00	0.00	0.00	0.00	<0.01	1.00		-1.50	0.02	0.02	0.03	0.05	<0.01	0.83		-12.00
Rest/Recovery																
Neutral for ≥ 3s (%time)	74.94	15.60	72.25	16.20	0.27	0.54	0.63		75.76	11.50	67.94	11.91	0.33	**<0.01**	4.53	
Low speed for ≥ 3s (%time)	26.24	5.80	25.40	7.84	0.04	0.46		29.50	39.20	11.02	34.40	10.42	0.80	**<0.01**	4.10	
Neutral and low speed (%time)	60.26	6.89	59.97	11.04	0.06	0.88	0.15		63.17	10.12	59.14	9.40	0.13	**<0.01**	4.03	

a Positive values denote trunk flexion; Negative values denote trunk extension.

Table 22. Pre- and post-intervention organization-level safety climate survey responses based on work shift (1^{st} vs. 2^{nd}), work category (i.e., cyclic vs. non-cyclic), and among repeat participants (n=10).

SHIFT	1ST						2ND					
	PRE			POST			PRE			POST		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	65.2	12.7	81.5	60.1	15.5	76.1	68.1	10.5	85.1	60.5	18.5	75.6
CYCLIC	YES						NO					
	PRE			POST			PRE			POST		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	66.6	11.2	83.3	63.0	11.9	78.8	67.4	10.6	84.3	59.3	17.8	74.1
REPEAT PARTICIPANTS	PRE			POST								
	MEAN	SD	%	MEAN	SD	%						
	68.9	8.8	86.1	55.6	15.4	69.5						

Mean = Average aggregate score.
SD = Standard deviation of aggregate score.
% = Average percentage of possible points earned of those available.

Table 23. Pre- and post-intervention group-level safety climate survey responses based on work shift (1st vs. 2nd), work category (i.e., cyclic vs. non-cyclic), and among repeat participants (n=10).

SHIFT	1ST						2ND					
	PRE			POST			PRE			POST		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	59.6	17.1	74.4	60.9	15.0	76.2	65.7	15.8	82.2	62.6	16.7	78.3
CYCLIC	YES						NO					
	PRE			POST			PRE			POST		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	59.0	16.6	73.8	64.5	10.7	80.6	66.0	15.0	82.5	60.4	16.8	75.5
REPEAT PARTICIPANTS	PRE			POST								
	MEAN	SD	%	MEAN	SD	%						
	67.5	10.7	84.4	60.6	10.8	75.8						

Mean = Average aggregate score.
SD = Standard deviation of aggregate score.
% = Average percentage of possible points earned of those available.

Table 24. Pre- and post-intervention workplace safety behavior scale responses based on work shift (1st vs. 2nd), work category (i.e., cyclic vs. non-cyclic), and among repeat participants (n=10).

	PRE									POST								
1ST SHIFT	TOTAL			TASK			CONTEXUAL			TOTAL			TASK			CONTEXUAL		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	47.4	10.2	78.9	20.4	3.3	85.0	27.0	7.4	74.9	43.1	14.3	71.8	18.3	6.5	76.2	24.8	8.1	68.8
	PRE									POST								
2ND SHIFT	TOTAL			TASK			CONTEXUAL			TOTAL			TASK			CONTEXUAL		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	51.1	9.3	85.2	21.6	3.3	90.2	29.5	6.2	81.8	53.9	7.2	89.8	22.5	2.3	93.8	31.4	5.9	87.2
	PRE									POST								
CYCLIC	TOTAL			TASK			CONTEXUAL			TOTAL			TASK			CONTEXUAL		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	49.7	9.1	82.9	21.1	3.3	88.0	28.6	6.1	79.5	52.2	7.5	86.9	22.0	2.1	91.7	30.2	5.6	83.8
	PRE									POST								
NON-CYCLIC	TOTAL			TASK			CONTEXUAL			TOTAL			TASK			CONTEXUAL		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	47.9	9.7	79.9	20.8	3.2	86.8	27.1	7.2	75.3	45.1	14.4	75.1	19.0	6.4	79.2	26.1	8.5	72.4
	PRE									POST								
REPEAT PARTICIPANTS	TOTAL			TASK			CONTEXUAL			TOTAL			TASK			CONTEXUAL		
	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%	MEAN	SD	%
	44.8	10.4	74.7	19.8	3.6	82.5	25.0	7.6	69.4	42.9	12.2	71.5	18.5	5.6	77.1	24.4	7.3	67.8

Mean = Average aggregate score.
SD = Standard deviation of aggregate score.
% = Average percentage of possible points earned of those available.

Discussion and Conclusions

Aim 1

Group Differences, Variance Components, & Exposure Homogeneity

Observational studies suggest that increased routinization or repetitiveness of work increases MSD risk (Nordander et al., 2009). However, few field-based studies using direct measures document differences in upper arm and trunk kinematic exposure magnitudes or exposure variability between workers engaged in repetitive work and those engaged in more varied work. Gert-Åke Hansson et al. (2010) examined several measures of upper extremity kinematic exposures among groups of workers categorized by the type of work performed. Work categories included "repetitive industrial" and "varied industrial" work (among others), which broadly correspond to the cyclic and non-cyclic categorization used in the current study. Category-level averages for upper arm posture metrics (e.g., 99th percentile elevation) appeared similar between the "varied industrial" and "repetitive industrial" categories, while category-level averages for movement speed metrics (e.g., 50th percentile) appeared lower for the "varied industrial" category than for the "repetitive industrial" category. Although the results of Hansson et al. (2010) seem consistent with the findings of the current study, the small number of groups (n=3) in the "varied industrial" category and the absence of statistical tests of differences in mean exposure levels between categories limit our ability to make direct comparisons.

In general, the patterns of variance components from analyses of full-shift exposure metrics and between-minute (within-shift) variability in average exposure levels and within-minute exposure variation were consistent with our expectations, i.e., results suggest greater exposure variability between and within workers in the non-cyclic group. Whether our results imply reduced MSD risk among those in the non-cyclic group based on exposure variability is unknown. Furthermore, the value of increasing exposure variability for MSD risk remains an unsettled question. Theoretically and perhaps intuitively, designing jobs to allow for more variation in exposures within and across tasks should promote more varied loading patterns to internal biomechanical structures to minimize MSD risk (Svend Erik Mathiassen, 2006; Straker & Mathiassen, 2009). In some circumstances, however, greater exposure variation may increase MSD risk. Using the trunk as an example, we observed for both cyclic and non-cyclic groups relatively neutral working postures and low movement speeds with respect to suggested thresholds (Ferguson & Marras, 2013; Marras, Ferguson, Burr, Schabo, & Maronitis, 2007; Marras, Lavender, Ferguson, Splittstoesser, & Yang, 2010). In addition, we observed greater between-minute (within-shift) variability in average exposures and exposure variation (for both trunk posture and movement speed) among those in the non-cyclic group, which might imply lesser MSD risk compared to those in the cyclic group. On the other hand, variability in lifting kinematics may contribute to scenarios in which spinal loads exceed recommended tolerance limits despite a "typical" lift being safely below those limits (Granata, Marras, & Davis, 1999; Mirka & Baker, 1996). Ultimately, additional research involving manufacturing workers stratified according to the variability of their work is needed to understand how exposure variability in this context might affect their health.

The results of this study may also have implications for those interested in job rotation as an intervention to prevent MSDs. Job rotation schemes are typically based on more equitably distributing exposure and/or increasing exposure variation (Jorgensen, Davis, Kotowski, Aedla, & Dunning, 2005; Mehdizadeh et al., 2020; Triggs & King, 2000). In particular, "posture, movement frequency, the level of exposure, and the level of task complexity" are aspects of biomechanical loading often used to design job rotation schemes (Padula et al., 2017, pg. 395). One potential reason for using such parameters is that they may be more easily assessed with simple tools that require little training (Dempsey et al., 2005; Lowe, Dempsey, Jones, Safety, & Health, 2018; Wells, 2009) relative to more comprehensive analyses (Leider, Boschman, Frings-Dresen, & van der Molen, 2015). Results of this study suggest that rotating manufacturing workers between cyclic and non-cyclic work tasks based solely on postural exposures would likely not have the desired effect, as posture-based exposure metrics were generally similar both between the work groups and across the work task categories. Instead, our results indicate that movement speed-based exposure metrics may be more promising to consider when developing and implementing job rotation schemes. This finding is consistent with a recent synthesis of epidemiological analyses, in which exposure metrics based on movement speed were more consistently associated with musculoskeletal symptoms than exposure metrics based on posture (Balogh et al., 2019).

Bootstrap Resampling

In epidemiological studies, measurement precision is important for evaluating a study's power and interpreting findings. Lack of precision in exposure metrics may lead to biased results and interpretations (Bonett, 2002; Wolak, Fairbairn, & Paulsen, 2012). Several previous studies have estimated the width of confidence intervals using bootstrap analysis in order to evaluate the precision of kinematic exposure metrics (Andrade et al., 2017; Ferreira, Rabelo, Vieira, Pereira, & Andrade, 2018; Grafton, Ralston, & Ralston, 2019; Hoozemans et al., 2001; Hullfish et al., 2019; Krasoulis, Vijayakumar, & Nazarpour, 2019; S. E. Mathiassen et al., 2012). For instance, Hoozemans et al. (2001) evaluated group-based measurement strategies by estimating the precision of mean exposure in two occupational groups considering the effects of the number of participants and number of replications per participant. Mathiassen et al. (2012) examined the precision of estimates of upper arm postures based on sampling durations from 5 to 240 min. Our study compares group-based measurement strategies between workers performing cyclic and non-cyclic tasks. Our results are generally consistent with previous work suggesting that the range between the 5th and 95th percentiles of the BCa Confidence Intervals decreased for all exposure metrics as the number of days of observation increased. Nine work shifts of data collection or less (depending on the exposure metric of interest) were determined to be adequate to obtain stable kinematic measurements of the upper arms and trunk.

As described previously, the exposure metric results of our bootstrap simulations were generally comparable to other studies. For example, the mean of the 90th percentile posture measurement across workers in our study was similar to previous studies with participants from diverse occupational groups (Balogh et al., 2019). The percentage of time spent in extreme posture was similar to domestic cleaners and manufacturing workers completing form-building tasks (Palm et al., 2018). Therefore, we believe that the characterizations developed through resampling appear reasonable and support the generalizability of our findings.

Ratings of (Dis)comfort, Distraction, and Burden

The results indicated that the manufacturing workers 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 0.02cm on a standard 10cm 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 & Dexter, 1934; Rossetti, Meckler, & Prablanc, 1994). Alternatively, this result may have been a function of the decision to use the easy-to-secure fastener straps selected because of their adjustability and ease of application. Some participants reported loosened sensor straps and the elastic armband irritating after work shifts. Safety and health practitioners should consider the potential negative consequences of using fastener straps 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, Laird, & Haines, 2015). Regardless, the slight increase in discomfort may be considered practically irrelevant, particularly considering the relatively small amount of time 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 (Nathan B Fethke, Schall Jr, Chen, Branch, & Merlino, 2020; Granzow et al., 2018; Lee, Seto, Lin, & Migliaccio, 2017; Schall Jr, Fethke, & Chen, 2016; Schall Jr et al., 2021). Schall et al. (2021) described that 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 underestimating 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. Increased trunk flexion may have led to increased ratings of localized trunk discomfort. Also, the scale only referred to the 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 to collect more detailed feedback.

Another interesting finding 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 actual 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 are of concern as they can lead to safety-related incidents (Canina, Newman, & Trotti, 2006; Leng, Giin, & Chung, 2015; Liu et al., 2015). Workers who primarily performed cyclic tasks reported greater distraction than those who primarily performed non-cyclic tasks. We previously characterized and compared the kinematics of the cyclic and non-cyclic workers (Schall et al., 2021). Significant differences were observed in the movement speeds where the arms of cyclic workers moved faster, on average than the non-cyclic workers. This difference in exposure could partially explain why the cyclic workers considered wearing the sensors more distracting.

Workers who reported higher stress levels also reported higher burden ratings than those who reported lower stress levels. Previous studies have indicated that shift workers that report high psychological demand and low job control are more likely to consider their jobs physically demanding (Buja et al., 2013; Perrucci et al., 2007; Raeisi, Namvar, Golabadi, & Attarchi, 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 of several personal characteristics 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 due to 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, Kanda, Shi, & de Dear, 2015). Wet straps may contribute to feelings of discomfort. Unfortunately, perspiration levels were not measured in this study. Future studies may include the observation of perspiration and its potential adverse 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 challenged to adapt to unaccustomed technologies, such as wearable computer systems (Tedesco, Barton, & O'Flynn, 2017). Therefore, additional research may focus on senior workers' use of wearable computing systems to reduce potential distraction and burden and help improve adoption intention.

The relatively substantial 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, Ehlers, Kurka, Ainsworth, & Buman, 2015). The discomfort associated with using wearable sensors may be related to how it is secured to an individual. Specifically, women may be more tolerant of 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 using wearable inertial sensors in the workplace.

Aim 2

Dashboard Evaluation

The rapid advancement of embedded computing capabilities, wireless communication, and the proliferation of continuous improvement processes in industrial settings since the mid-20th century has led to the increasing use of enterprise application software systems in manufacturing and other industrial sectors. Occupational safety and health applications provide organizations a means to efficiently train employees, evaluate and compare hazards identified following the completion of exposure assessments, and monitor progress in addressing those hazards over time. As new exposure assessment technologies such as wearable inertial sensors are more frequently applied in industrial settings to support OSH processes, applications capable of effectively summarizing that information for use among OSH professionals will be needed.

The comments provided in the heuristic evaluations aid the interpretation of the quantitative SUS ratings. One key area for improvement considers the clarity of the objectives of our system. Several evaluators commented on the challenges in understanding how to interpret the collected data. One evaluator described how "… some sort of red, yellow, green highlight system to show what is considered acceptable and what is not for a quick visual understanding" may be beneficial. A lack of information or understanding of interpreting directly measured kinematic exposures may explain why several users found the system unnecessarily complex (SUS Q2). Although it is not uncommon for many ergonomics exposure assessment tools to provide categorizations of risk in a color-coordinated manner, we chose not to implement this feature as it may oversimplify the concept and interpretation of risk. Additionally, imparting our interpretations of risk may not be relevant for some organizations. For example, we could have developed a feature highlighting the elevation of an arm above 60° as a "red" risk category. However, doing may suggest to some that elevation of an arm in a different color risk category (e.g., assume 59° received an "orange" rating) represents a practically meaningful difference, which may not be the case.

Regardless, the results provided our team with information to further improve the dashboard based on the comments from the evaluators. Example improvements included:

- Appropriate figure header, title, and unit information were added as needed.
- Training videos describing the terms and functionalities of the web app were added. The user may choose to hide the videos after watching them.
- Variable definitions were added with more details on the help web page.
- A box plot view was added under the 'Data' tab. In this view, different variables can be viewed side by side for different jobs, facilitating side by side comparison of the desired variables for each type of job.
- The database schema has undergone several updates to capture the dependencies between the different tables and filter the database more effectively and efficiently.

Since this project began, several research teams have published similar evaluations and proof-of-concept implementations of web-based applications intended to support ergonomics initiatives based on wearable inertial sensors. For example, Vallati, Virdis, Gesi, Carbonaro, and Tognetti (2019) developed "ePhysio," a modular platform designed to support physiotherapy and remote management of MSDs through gamification strategies and social engagement. Vega-Barbas et al. (2019) describe P-Ergonomics as a system based on wearable sensors that calculates exposure statistics to support ergonomic assessments at individual and group levels. Although each system may operate under a shared philosophy and may offer similar features, our experience suggests that flexibility and the ability to personalize the system to an organization will serve as a benefit supporting the adoption and use of wearable AIS technology. This may be particularly true as wearable AISs for ergonomics remains in the early phases of diffusion.

Aim 3

Evaluation of Intervention Effectiveness

Our results suggest that using AISs and OSH dashboard may improve many posture-based exposure metrics, such as the % time with the arm in a neutral posture for ≥ 3s for the upper arms. The trunk flexion/extension movement speeds among the cyclic participants improved post-intervention, whereas the movement speeds among the non-cyclic participants generally worsened. Unfortunately, we cannot directly attribute these differences to the introduction of the AISs and OSH dashboard as we did not include a control site.

The mediation analyses suggested that introducing the AISs and OSH dashboard did not sufficiently override the potential adverse effects of changes to the facility management team on the perceived safety climate. Information collected during the safety committee meetings supports this conclusion. The following excerpt from a safety committee meeting in early 2020 illustrates a perceived reduction in the quality of communication, particularly surrounding safety, which had resulted from changes to the organization's management:

Ergonomist: "So, what's the uhhh… I don't know… like the climate out there right now? People feeling… how do they feel?"
Floor Employee 1: "Not good."
Admin Employee: "Uh uh. No."
Ergonomist: "Not good?"
Admin Employee: "No. Mmm mmm."
Ergonomist: "There's a lot of frustration?"
Floor Employee 2: "And morale is..."
Admin Employee: "Morale is pretty low and consistent… it's pretty consistent across the plant."
Floor Employee 2: "… we hear [organization name] is this, [organization name] is that… the morale is just… and this is coming from people who have been here a year."
Admin Employee: "The feedback I've gotten is from folks who have been here a while. That's the ones who talk with me about it… say [organization name] used to be a really good place to work…"
Floor Employee 1: "Yeah."
Admin Employee: "… Get a job done. They used to kind of take care of us. Now they don't."
…
Floor Employee 1: "I think that morale is going to directly affect the safety out there."
Admin Employee: "It does!"
Floor Employee 1: "Cause, if you don't give a damn…"
Admin Employee: "It does."
Floor Employee 2: "I swear… a lot of 'em, they come in, they don't care. They don't care. They don't care about production. They don't care about quality. And they don't care about… They care about their safety. But, the quality part at their station, don't care about the safety of the next operation."
Admin Employee: "They're looking out for themselves."
Floor Employee 2: "They're looking out for themselves!... "

This conversation excerpt took place during one of the few meetings following the reconvening of the safety committee following a planned annual plant shutdown and several changes to the facility management team. Shortly after this meeting, the COVID pandemic began forcing the facility administration to halt safety committee meetings again for social-distancing purposes. The conversation served as an important indicator of how the participating safety committee team members perceived the organization's safety climate. It is important to note that although the AIS and OSH dashboard intervention did not positively affect the perceived safety climate, changes in perception of organizational safety climate were strongly related to task and contextual safety behaviors, as expected. It is well-recognized that the establishment of a strong safety climate (e.g., demonstrating a prioritization of safety and wellbeing by committing resources and supporting OSH practices) increases safety motivation, safety knowledge, safety compliance, safety participation, and decreases accidents and injuries (Christian, Bradley, Wallace, & Burke, 2009; Clarke, 2013). The statistically significant reductions in perceptions of top management's consideration of a person's safety behavior when moving/promoting people, investment of time and money in safety training for workers, use of available information to improve existing safety rules, and holding regular safety-awareness events suggest that the sub-sample of participants (n=10) that enrolled in the pre and post-intervention phases of the study did not feel as though the facility management was committed to safety and health. The lack of commitment may have contributed to inefficient use of resources to modify workstations following identifying opportunities for kinematic improvements from the AISs and OSH dashboard.

Ultimately, we believe that our results generally support additional research exploring the use of AISs and software that leverage summaries of key performance indicators for guiding the prioritization of work design improvement systems. However, the literature indicates that technologies such as AISs will be more likely to succeed in an organization with a strong safety climate where improvements based on the objective exposure measurement information will be pursued.

Limitations

This repeated-measures, field-based exposure assessment intervention study had several limitations. To begin, we did not assess several job stressors commonly associated with MSDs, including direct measurements of force or physical fatigue. We also did not assess many important cognitive stressors such as mental workload (e.g., information overload) and time pressure. The random selection of participants paired with the existence of gender-dominated roles in the manufacturing plant (e.g., men more commonly held non-cyclic jobs; a high prevalence of older females worked cyclic jobs) may have inadvertently contributed to the uneven distribution of sex, age, height, and body mass index characteristics between the work groups. Although the differences in age, height, and body mass index between the work groups were not found to be statistically significantly different (in analysis not presented), the differences in work group composition may partially explain statistically significant differences in upper arm and trunk kinematic exposure magnitude and exposure variability findings. Our results indicate, however, that differences in movement speed were likely not a function of differences in posture (e.g., shorter workers covering a more extensive range of motion). Instead, the demands of the work activities (i.e., higher speeds needed to operate machinery and assemble parts completed primarily by the cyclic participants vs. slower speeds needed to complete maintenance and set-up activities completed primarily by the non-cyclic participants) appear to explain the differences better.

Given the data collection's broad scope and the research team's need to limit interference with production at the manufacturing facility, the research team elected to use quick to secure and adjust fastener bands rather than potentially more burdensome approaches (e.g., sensors taped directly to the skin). The fastener straps were also considered a practical means of securing the sensors that an occupational health and safety practitioner at a typical manufacturing facility may employ regularly. This decision, however, contributed to shift-to-shift inconsistencies in sensor placement and sensor movements throughout each shift that likely increased between-shift variance estimates (Dahlqvist, Nordander, Forsman, & Enquist, 2018). The trunk sensor, in particular, was susceptible to shifting down the sternum towards the xiphoid process. This shifting likely contributed to an overestimation of the amount of trunk extension and an underestimation of the amount of trunk flexion as the sensor may have become tilted as it rested near the abdomen, which was often distended among our sample of workers with an average body mass index >30 kg/m^2.

The shifting may have also contributed to an increase in transient artifacts that we replaced with the mean posture of the entire recording duration. The decision to replace transient artifacts rather than exclude those periods allowed for more straightforward time synchronization between our kinematic measures and the daily work diaries collected from participants. However, it may have affected our measures of exposure variability. Along these lines, it is important to note that we did not apply a zero-angle reference measurement to compensate for any offset with the gravity vector for the upper arms. The reliability of the zero-angle reference method applied for the trunk is unknown. We also did not mark the skin to identify where research team members secured AIS units, a step that would have allowed measurement of the magnitude of sensor movement throughout a shift. Movement speeds were also calculated as a derivative of inclination, resulting in a noisier signal than direct velocity measurements.

The criteria for categorizing participants into cyclic and non-cyclic work groups were similar to those reported in previous research (Paulsen et al., 2014). They were considered reasonable by the site safety director. Although our frequency analyses suggest that our cyclic and non-cyclic groups of workers completed tasks of different repetitiveness as would be typically anticipated (i.e., workers in the cyclic group performed more repetitive work than the non-cyclic workers), broadly categorizing participants into cyclic or non-cyclic groups as a surrogate for the "routinization" or "repetitiveness" of their work likely oversimplifies the construct of repetition as a physical risk factor for MSDs. Given these data collection limitations, a pragmatic interpretation of the results is recommended.

Several challenges were encountered by the research team that affected the safety committee and the iterative development and implementation processes. One challenge was that management at the partnering manufacturing facility experienced significant personnel changes, including hiring a new plant manager, a new safety director, and many area managers during this project. These personnel changes led to the administration's pausing of safety committee meetings for approximately nine months. Despite these challenges, the research team maintained open communication with the facility and continued to advance the project and dashboard to the greatest extent possible while the safety committee meetings were delayed. When the safety committee was reconvened, participation in safety committee meetings was poor. The poor participation may have resulted from challenges the new safety director experienced gaining support from management. Shortly after efforts to convene meetings, the Coronavirus disease of 2019 (COVID-19) pandemic began. The pandemic forced the facility administration to halt safety committee meetings again for social-distancing purposes. As a result of the combined delays, the development of the OSH dashboard may have suffered and may not be indicative of a proper participatory ergonomics approach as intended.

Despite all the challenges we faced due to COVID 19, the designed platform supports simultaneous risk assessment and work technique training. Using a modular platform, a range of sensor types can be connected depending on the specific need of each situation. As demand rises for assessing an increasing number of risk factors, this platform can be quickly developed to include additional risk factors, allowing for integrating more or alternative sensors and expanded analyses. Moreover, machine learning algorithms can further improve the monitoring and detection process.

The simplicity of the scales included in this study is an important limitation. Discomfort, distraction, burden, and stress may be considered complex, multifaceted terms. For example, Knight and Baber (2005) suggested six dimensions (emotion, attachment, harm, perceived change, movement, and anxiety) that may affect a user's perception of comfort when using wearables. Given this study's broad scope of data collection, it was impossible to have participants complete several multidimensional scales. Thus, our findings must be interpreted cautiously (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. The manufacturing facility employees 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 than those who did not volunteer.

Along these lines, one participant (of the total 36 enrolled) withdrew from the study during the first data collection shift. Although the participant did not provide an assessment of the discomfort, distraction, and burden associated with using the sensors during that time, he was 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 not to wear the sensors during some work shifts is important to note. Similarly, undesirable ratings, particularly data points exceeding the upper quartile of the collected data, indicate that discomfort, distraction, and burden can present 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., the 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 minor 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.

For the bootstrap analyses, the physical exposure measurements used in the analysis were summarized across the entire work day. Time-series data were not used to examine how each variable changed over the work day. Moreover, workers assigned to each work group performed different tasks based on their job positions (e.g., tasks associated with machine-paced production, tasks associated with running a machine). Instead of cyclic and non-cyclic categories, future bootstrap analyses could investigate the sampling durations required for each task assignment. The task-based analysis may provide more specific information on the sampling duration needed to estimate the task content performed by participants at work. Additionally, a fixed block length and non-overlapping blocks accounted for within-subject correlations. Future work may seek other ways to optimize block length or create a moving block bootstrapping solution.

We also used a conservative criterion to determine a sufficient sample size based on a <10% increase in the confidence interval widths. However, this criterion may not be practical for all measures. For example, after eight days of observations, increases in the confidence interval widths for RA50V were less than 0.1 °/s. The marginal contribution of increasing study power while increasing the number of replication observations may not be resource-efficient. In some situations, the conservative criterion may overestimate the number of observations required to reach a sufficient sample. However, it provided a more reliable and precise sampling strategy for researchers to consider. Finally, the influence of the number of participants on the precision of exposure measurements was not evaluated. In future research, the nested effect of combining different numbers of workers and numbers of observation days should be examined. Thus, exposure sampling approaches could be obtained based on the number of workers and repeated observation days when using IMUs in assembly-based manufacturing.

Regarding the evaluation of the intervention, our study was limited by not including a control site. Another limitation of our design was that we did not break our intervention into program components. If we had, we might have been able to assess better where our intervention program failed and how it may be improved in future studies. Additionally, the limited effect of our intervention may also suggest that our measures of the mediator were unreliable or valid enough to detect changes. However, we used psychometrically sound scales (Zohar & Luria, 2005, 2010)that industrial and organizational psychologists widely apply, so we are less confident that this was an issue in our study. It is also possible that the intervention effects may have emerged had we used AISs more regularly among our participants. However, the logistical complexity and pilot nature of this study prevented a more robust data collection plan, which was already among the most extensive conducted in a manufacturing environment.

Conclusions

Despite its limitations, this study represents one of the most robust field-based exposure assessment studies involving AISs in a manufacturing setting. The results suggest that AISs may be comfortably used to quantify and compare occupational exposures to kinematic risk factors (e.g., non-neutral postures and high movement speeds) among manufacturing workers over extended durations. Furthermore, the results generally support additional research exploring the use of AISs and software systems that leverage "dashboard" summaries of key performance indicators for guiding the prioritization of work design improvements. This study's findings can directly benefit the manufacturing industry and improve the science and practice of kinematic assessment in future research across a broad range of occupational settings.

PUBLICATIONS

Peer-reviewed journal articles

Schall Jr, M.C., Chen, H., & Cavuoto, L. (2022). Wearable inertial sensors for objective kinematic assessments: a brief overview. *Journal of Occupational and Environmental Hygiene*. (PMID: 35853137)

Zhang, X., Schall Jr, M. C., Chen, H., Gallagher, S., Davis, G. A., & Sesek, R. (2022). Manufacturing worker perceptions of using wearable inertial sensors for multiple work shifts. Applied Ergonomics, 98, 103579. (PMID: 34507084)

Schall Jr, M. C., & Chen, P. (2021). Evidence-based strategies for improving occupational safety and health among teleworkers during and after the coronavirus pandemic. Human factors, 0018720820984583. (PMID: 33415997)

Schall Jr, M. C., Zhang, X., Chen, H., Gallagher, S., & Fethke, N. B. (2021). Comparing upper arm and trunk kinematics between manufacturing workers performing predominantly cyclic and non-cyclic work tasks. Applied Ergonomics, 93, 103356. (PMID: 33454432)

Chen, H., Schall Jr, M. C., & Fethke, N. B. (2020). Measuring upper arm elevation using an inertial measurement unit: An exploration of sensor fusion algorithms and gyroscope models. Applied Ergonomics, 89, 103187. (PMID: 32854821)

Theses

Zhang X: [2020] Challenges and Opportunities Associated with the Adoption of Wearable Technologies in the Workplace. PhD dissertation, Auburn University.

Conference Presentations/Abstracts

Schall Jr MC, Michel, J. (2020). Leadership Styles in Participatory Ergonomics Programs: A Bibliometric Analysis. Proceedings of the 64th Annual Meeting of the Human Factors and Ergonomics Society; 2020 October 5-9, Chicago, IL. (Virtual Meeting). Awarded Best Paper in the Occupational Ergonomics Technical Independent Research Category.

Schall Jr MC, Zhang X. “Wearable Sensors for Ergonomics: Worker Ratings of Discomfort, Distraction, and Burden.” 23rd Annual Applied Ergonomics Conference. 2020 August 4-6. (Virtual Meeting).

Haight J, Sesek RF, Castillo D, Schall Jr MC, Gesinger S. “Automation and its Impact on Safety and Health of the Workforce.” Safety 2020: the American Society of Safety Professionals’ Professional Development Conference. Lecture Panelist; 2020 June 23–25. (Virtual Meeting).

Schall Jr MC. Wearable Sensors for Ergonomics in the Industry 4.0 Era. 32nd Annual Alabama Governor’s Safety and Health Conference; 2019 August 26-28; Orange Beach, AL.

Zhang X, Bani Hani D, Gallagher S, Schall Jr MC. (2019). Manufacturing Worker Perceptions of Wearing Ambulatory Inertial Sensors in the Workplace: An Exploratory Cluster Analysis. 2019 Annual Conference of the International Society for Occupational Ergonomics and Safety; 2019 June 12-13; New Orleans, LA.

Schall Jr MC (2019). Advancing Workplace Safety Surveillance with Ambulatory Inertial Sensors: A Research to Practice to Research Study. 2019 Annual Conference of the International Society for Occupational Ergonomics and Safety, Research to Practice to Research (RtPtR) Invited Panelist; 2019 June 12-13; New Orleans, LA.

Zhang X, Schall Jr MC, Sesek RF. Perceived Barriers of Using Wearable Sensors among Industrial Workers in the Internet of Things Architecture. Southeast Regional Research Symposium; 2019 April 4-5; Tampa, FL.

Bani Hani D, Zhang X, Gallagher S, Schall Jr MC. Are wearable sensors unobtrusive for long-term assessment in the workplace? An exploratory cluster analysis. Southeast Regional Research Symposium; 2019 April 4-5; Tampa, FL.

Schall Jr MC, Bevly D, Davis GA, Gallagher S, Sesek RF, Zabala ME. "Operator 4.0: Collaborative Research to Improve Worker Performance and Safety during the 4th Industrial Revolution" This is Research: Faculty Symposium, 2018 October 23; Auburn, AL.

Cumulative Inclusion Enrollment Report

This report format should NOT be used for collecting data from study participants.

Study Title: Advancing Workplace Safety Surveillance with Ambulatory Inertial Sensors

Comments: This report does not include the ten participants that participated in the Aim 2 evaluation using the Qualtrics survey engine.

Racial Categories	Ethnic Categories									Total
	Not Hispanic or Latino			Hispanic or Latino			Unknown/Not Reported Ethnicity			
	Female	Male	Unknown/ Not Reported	Female	Male	Unknown/ Not Reported	Female	Male	Unknown / Not Reported	
American Indian/ Alaska Native										0
Asian										0
Native Hawaiian or Other Pacific Islander										0
Black or African American							17	12		29
White							3	17		20
More Than One Race										0
Unknown or Not Reported										0
Total	0	0	0	0	0	0	20	29	0	49

INCLUSION OF GENDER AND MINORITY SUBJECTS

Women and those of minority racial/ethnicity were not excluded from participating in the research project.

INCLUSION OF CHILDREN

N/A – No children were included in this study.

MATERIALS AVAILABLE FOR OTHER INVESTIGATORS

MATLAB programs are available to facilitate analyses time-series data at: https://github.com/how-chen/imu-inclination

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