Ergonomics

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/terg20

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ERGONOMICS
https://doi.org/10.1080/00140139.2025.2460695

RESEARCH ARTICLE

A fatigue failure framework for the assessment of highly variable low back loading using inertial motion capture – a case study

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ABSTRACT
Workers in manufacturing settings experience highly variable musculoskeletal loading, which current risk assessment methods often fail to fully capture. This study evaluated a Fatigue Failure-Based framework for estimating continuous lumbar loading from variable occupational loads. Worker movements and postures were recorded using Inertial Motion Capture technologies, and L5/S1 joint loading history was estimated through inverse dynamics. Stress cycles were analysed using Rainflow analysis, adjusted with Goodman's method, and summed using Palmgren-Miner rule to estimate cumulative damage. The framework was tested in live industrial settings with eight automotive workers across 108 trials. Logistic regression models demonstrated significant correlations between cumulative damage estimates and self-reported low-back pain (OR = 2.16, 95% CI: 1.30, 3.57). This framework provides a novel method for analysing highly variable loading to estimate cumulative exposure in ergonomics, offering a starting point for future research and potential applications in assessing low back injury risks in similar occupational settings.

PRACTITIONER SUMMARY: This study evaluated a fatigue failure-based framework for assessing low back injury risk due to cumulative lumbar loading in industrial settings using Inertial Measurement Units (IMUs). The investigation involved analysing workers' continuous biomechanical loading to estimate injury risk due to cumulative damage accumulation. The results of this case study revealed a significant correlation between cumulative damage estimates and low back pain.

ARTICLE HISTORY
Received 23 August 2024
Accepted 25 January 2025

KEYWORDS
Musculoskeletal disorders; fatigue failure; biomechanics; cumulative exposure

1. Introduction

Work-related Musculoskeletal disorders (MSDs) are an economic and societal burden across a broad array of industries and demographics (Bureau of Labor Statistics 2020). Many studies have suggested that the cumulative exposure of musculoskeletal tissues to repeated stress appears to be a critical contributor to the development of these disorders (Kumar 1990; Norman et al. 1998; Jäger et al. 2000; Callaghan, Salewytsch, and Andrews 2001; Balogh et al. 2019). Therefore, it would seem prudent to measure cumulative exposure to physical risk factors (such as forceful exertions and repetition) to better understand the relationship between these factors and the risk of adverse health outcomes. The concept of cumulative exposure emphasises that load intensity, duration, and task repetition are key elements in assessing risk (Waters et al. 2006; Koyuncu et al. 2021). Approaching the assessment of risk from the perspective of cumulative risk exposure permits a comprehensive evaluation of multi-task exposure, which is essential for characterising the connections between work-related exposures and the development of MSDs (Veerasammy, Davidson, and Fischer 2022).

Several methods of cumulative loading assessment have been identified by previous authors (Johnen et al. 2022). These techniques, and their constituent issues, have been assessed previously (Waters et al. 2006; Johnen et al. 2022) and have emphasised the challenge of comparing work scenarios using various cumulative loading estimates. For example, comparing different work scenarios using cumulative loading estimates is only feasible if the same method is applied across all scenarios. Additionally, comparisons between different methods show that even the relative differences in cumulative loading values resulting from ergonomic improvements are often not comparable

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between methods (Johnen et al. 2021, 2022). Moreover, further research is needed to establish standardised limits of cumulative loading against which these calculated values can be assessed (Waters et al. 2006; Johnen et al. 2022).

A path to addressing these challenges is provided by fatigue failure theory, which states that materials can mechanically fail through: (1) the application of a single, high-magnitude stress, reaching the material's ultimate stress (US), or (2) the application of lower magnitude stress cycles over time (Peterson 1950; Gallagher and Schall 2017). The rate at which damage propagates in a material depends on loading characteristics and the number (and type) of cycles experienced at various loads. The relationship between applied stress and the number of cycles to failure is typically exponential and can be depicted in an S–N diagram, which illustrates how the number of cycles to failure (N) varies with constant cyclic stress (S) (Figure 1). Higher levels of loading leads to failure after fewer cycles, while lower levels of loading can last an exponentially greater number of cycles. In low-load situations, millions of cycles may be required to cause failure, and many materials exhibit a fatigue (or endurance) limit—usually around 30% of the material's ultimate stress—where failure does not occur regardless of the number of cycles experienced under fully reversed loading conditions (Ashby, Shercliff, and Cebon 2013). However, musculoskeletal issues do not appear to have an endurance limit.

Gallagher and Schall (2017) and Gallagher and Barbe (2022a) summarise evidence suggesting that the material fatigue failure process plays a significant role in MSD development. The theory is supported by ex vivo studies on spinal segments, cartilage, tendons, and ligaments, where a consistent pattern of fatigue failure behaviour under repetitive loading has been observed (Brinckmann et al. 1987; Jager and Luttmann 1991; Schechtman and Bader 1997; Gallagher et al. 2005, 2007; Thornton and Bailey 2013; Huber et al. 2016). Further evidence comes from in vivo animal studies, which have shown that fatigue failure processes occur in musculoskeletal tissues within a living organism (Fung et al. 2009, 2010; Sun et al. 2010; Andarawis-Puri and Flatow 2011; Barbe et al. 2013, 2020). Additionally, epidemiological evidence shows a consistent interaction between force and repetition, which is indicative of the presence of a fatigue failure process (Gallagher and Heberger 2013).

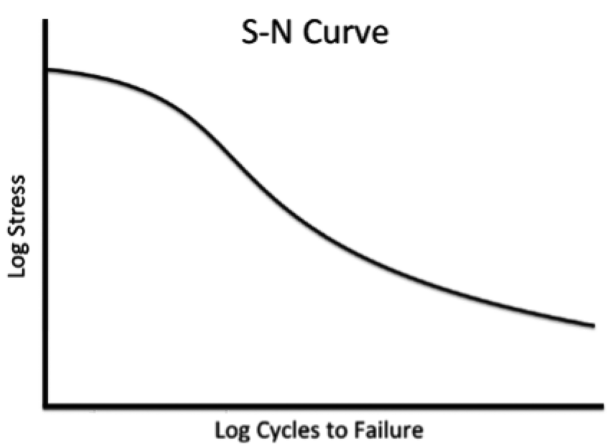

Figure 1. Example of an S–N diagram relating the level of stress (S) to the number of cycles to failure (N) (Gallagher and Schall 2017).

One significant benefit of fatigue failure theory lies in its ability to deconstruct complex loading waveforms into stress reversals and cycles, enabling the estimation of cumulative damage in complex tasks. Therefore, fatigue failure theory is well-suited to utilise new continuous exposure recording technologies and methods validated in material engineering science. However, while the theory provides a robust method for estimating the impact of continuous lumbar loading under theoretical and controlled conditions, it is crucial to assess its effectiveness in real-world settings. Therefore, these methods need to be applied (and evaluated data captured) in live industrial environments to understand their practical implications and limitations.

Ergonomic risk assessment tools based on fatigue failure theory have been developed for the low back (Gallagher et al. 2017; Zelik et al. 2022), distal upper extremities (Gallagher et al. 2018), and the shoulders (Bani Hani et al. 2021). These tools estimate a "daily dose" of cumulative loading exposure with a minimal number of inputs (e.g. weight of the load, distance from the load to the low back, and number of repetitions). However, the estimates are based on the "worst posture," where the maximum moment is expected. Consequently, these tools operate discretely, not considering the complex loading associated with the working cycle.

It has been recognised in the literature that the level of detail and the capture of time-dependent variation can significantly impact the results of ergonomic risk analyses (Johnen et al. 2022). This aspect deserves consideration during the planning of data collection, as it has been identified as a significant research gap in previous studies (Krajcarski and Wells 2008; Johnen et al. 2022). Typically, practitioners gather exposure data regarding worker kinematics and kinetics through direct observation and/or review of video recordings (Lötters and Burdof 2002; Spielholz et al., 2001). Risk assessment tools are then employed in an attempt to determine the risk level based on the exposure data collected (Lowe, Dempsey, and Jones 2019), such as the NIOSH Lifting Equation (Potvin 2014), Occupational Repetitive Action (OCRA) (Rhén and Forsman 2020), Rapid Upper Limb Assessment (RULA) (Kee 2022) or the Lifting Fatigue Failure Tool (LIFFT) (Gallagher et al. 2017). Each of these methods provides valuable information on risk, but none adequately captures the continuous, highly variable loading actually experienced in work activities.

Advancements in technology have made it possible to collect continuous loading exposure data. For example, optical motion capture technology provides an effective means of obtaining kinematic data, such as segment orientation and position, linear and rotational acceleration and velocity, and joint angles by placing reflective markers on anatomical landmarks per the recommendations of the International Society of Biomechanics (Wu et al. 2002, 2005). Kinetic analysis is made possible using force plates, which measure ground reaction forces and moments. However, implementing such technologies in workplace environments is usually impractical, necessitating the examination of alternative technologies that can better adapt to dynamic work environments (Lee and Lee 2022). A promising alternative is the use of IMC systems, which employ small wearable inertial measurement units (IMUs), which have shown the ability to capture continuous loading data for dynamic ergonomics assessment (Lind, Abtahi, and Forsman 2023), including L5/S1 moments and forces (Faber et al. 2016, 2020; Koopman et al. 2018; Larsen et al. 2020; Nail-Ulloa et al. 2021; Skals et al. 2021; Marklin et al. 2024; Nail-Ulloa, Huangfu, et al. 2024; Nail-Ulloa, Zabala, et al. 2024).

The main objective of this study was to apply a Fatigue Failure-Based framework for processing continuous data to estimate cumulative damage development during complex lumbar loading. Using validated methods from fatigue failure theory, we estimated cumulative damage from continuous low-back loading time-series data collected with an IMC system. This approach bridges the gap between theoretical frameworks and field data, representing a novel contribution to ergonomic risk assessment. By leveraging continuous measures, this framework better captures the real-world dynamics of occupational tasks, addressing critical limitations of existing methods. These advancements could facilitate the development of more effective interventions to reduce the risk of low back injuries in occupational settings. A secondary objective was to test the framework in a live industrial setting. Therefore, the proposed framework was tested in an active industrial manufacturing environment in a case study to determine the feasibility and applicability of capturing the requisite data regarding highly variable loads and examining the results of the model against available injury outcome data.

2. Fatigue failure-based framework

Elements and key steps of the data processing workflow are illustrated in Figure 2. Using a motion capture system (IMC) over a full working cycle, exposure data was collected and fed into a dynamic biomechanical model. Through the application of inverse dynamics, estimates of the internal loading history (e.g. moment, compressive or shear force, stress) were obtained. This loading history represents loading over time, but to utilise it in a fatigue failure model requires the loading curve to be decomposed into individual loading cycles.

Rainflow analysis (Matsuishi and Endo 1968) was employed in the workflow due to its widespread use and effectiveness in assessing the cumulative effect of variable amplitude loading (Stephens et al. 2001). This method decomposes the loading curve into *stress reversals*, which refer to the changes in the direction of stress applied to a material during a loading cycle. In the context of this study, stress reversals occur when the loading fluctuates between high and low magnitudes in a working cycle. These reversals are critical for identifying individual stress cycles, as they provide the fundamental data points required to estimate cumulative damage development using standard fatigue failure theory methods (Stephens et al. 2001). The resulting cycles are then adjusted for mean and range stress using Goodman's method (Goodman 1919), as described by Gallagher and Schall (2016). Information regarding Goodman's method can be found in Appendix A.

Next, the adjusted stress cycles are used to calculate the damage per loading cycle based on the ultimate strength of the material—in this case, lumbar spinal segments as characterised by Jager and Luttmann (1991). The individual damage values per loading cycle were then summed using the Palmgren-Miner rule (Palmgren 1924; Miner 1945) to estimate cumulative damage (CD). The CD estimates were then compared against a standard failure threshold. If the CD exceeds this threshold, the material is expected to fail as the fatigue limit has been reached or surpassed (crack initiation) (Miner 1945). In the context of this study, this corresponds to low back injury resulting from the cumulative damage experienced by spinal segments.

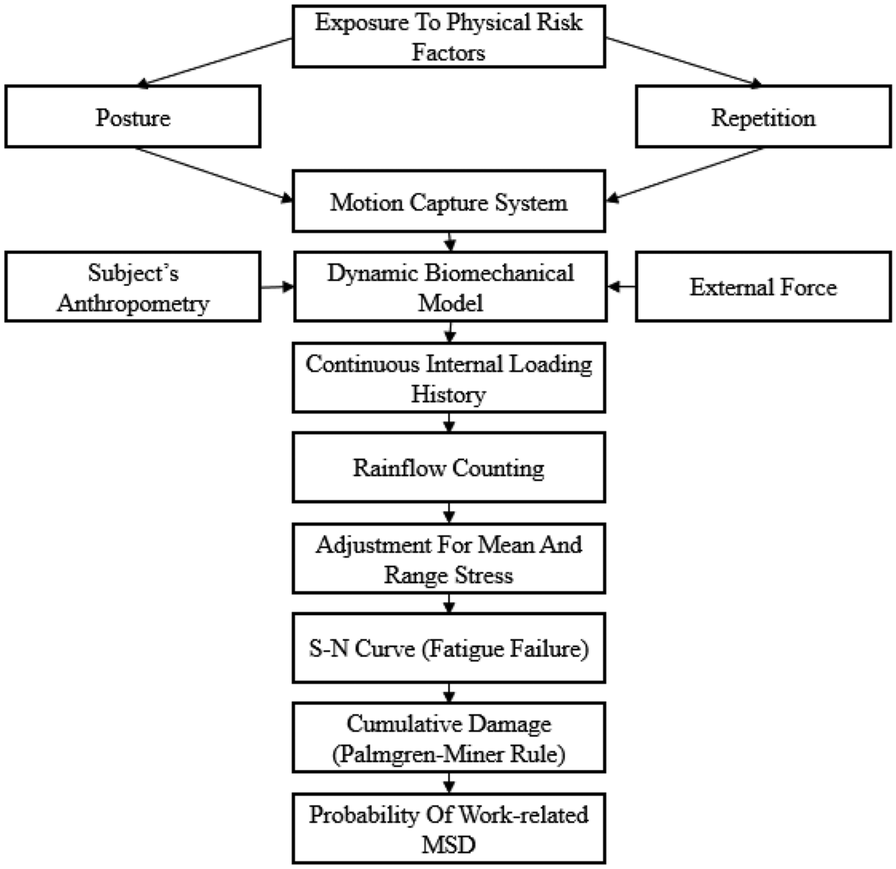

Figure 2. Fatigue failure-based framework for data processing.

2.1. Fatigue failure methods

The following sections describe the processes used to perform the workflow described in Figure 2.

2.1.1. Rainflow cycle counting

Rainflow analysis, introduced by Matsuishi and Endo (1968), has found widespread application in the study of material fatigue and is widely considered the best method of decomposing the highly variable stress cycles seen in complex (spectrum) loading (Stephens et al. 2001). This technique can be used to analyse continuous low back loading data and generate a "real-time" profile of the exposure associated with a specific number of stress cycles range estimates and mean stress estimates. Using this technique, damage associated with each loading cycle can be estimated and summed as cumulative damage.

The operation of the rainflow method consists of the following rules (Stephens et al. 2001):

i. Rearrange the loading history to start with either the highest peak or the lowest valley (Figure 3a).
ii. Starting from the highest peak (or lowest valley), go down to the next reversal (a change in stress from either *increasing to decreasing* or *decreasing to increasing*). The rainflow runs down and continues unless either the magnitude of the following peak (or valley, if we started from one) is *equal to or larger than* the peak from the initial load, or a previous rainflow is encountered (Figure 3b).
iii. Repeat the same procedure for the next reversal and continue these steps to the end.
iv. Repeat the procedure for all the ranges and parts of a range that were identified in previous steps.

Comprehensive instructions on rainflow cycle counting have been issued by the American Society for Testing and Materials (ASTM E1049-8585, 2017).

2.1.2. Cycle loading damage estimation

To characterise the relationship between cycles to failure and different stress levels on lumbar motion segments, Gallagher et al. (2017) utilised fatigue failure studies on cadaveric lumbar spines (Brinckmann et al.

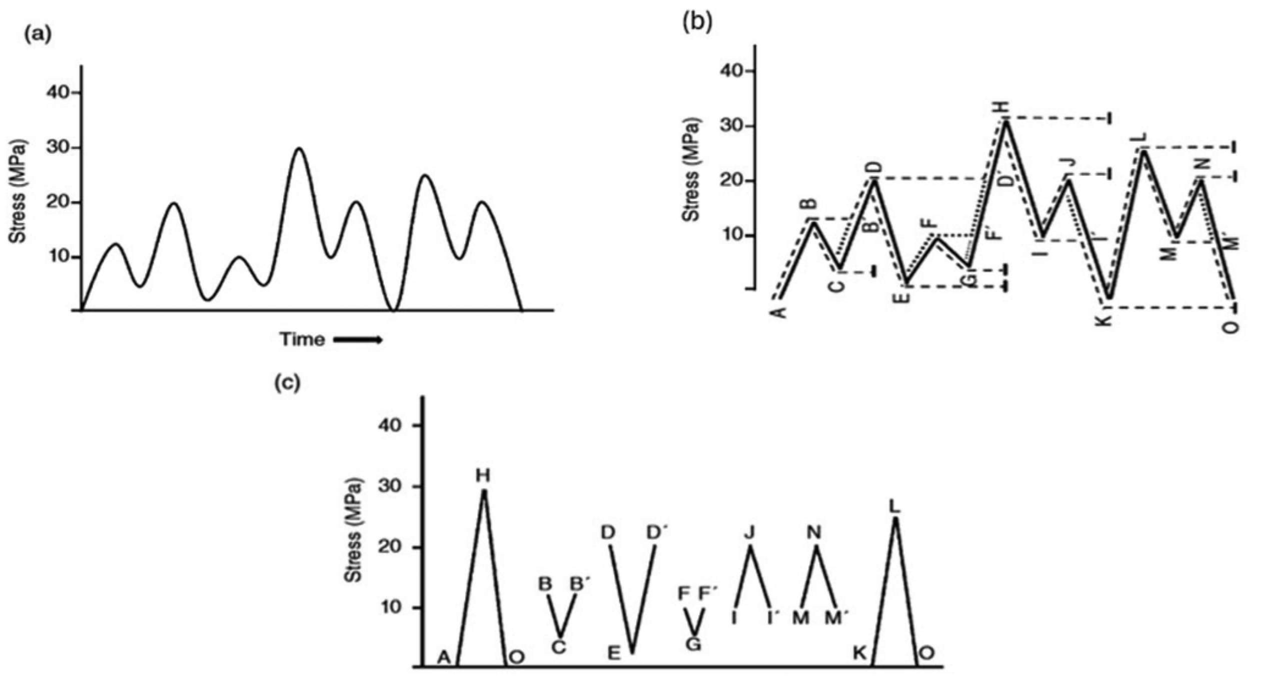

Figure 3. Illustration on the application of the rainflow analysis from Gallagher and Barbe (2022b) where (a) is a stress history for a 30 s work task; (b) is the Rainflow algorithm to identify stress reversals; (c) Complete cycles resulting from rainflow analysis which are used to calculate CD.

1987; Gallagher et al. 2005, 2007; Huber et al. 2016). The relationship between stress level and cycles to failure follows an exponential pattern (Equation 1), similar to non-biological materials like metals or plastics.

$$N = 1{,}099{,}097.56 \times e^{-0.122 \times \%US} \tag{1}$$

Where:

- N = the number of cycles to failure.
- %US = percentage of the motion segment's ultimate strength.

Combining Equation 1 with the adjusted cycles using Goodman's method (Appendix A), it is possible to approximate the number of cycles required to cause failure at each stress amplitude and calculate the damage inflicted by each loading cycle. In this case study, the value used was the average ultimate strength for a 35-year-old male (closest estimate to the average worker who participated in the study) of 7.3 kN (4.51 MPa for a 16.2 cm^2 of the L5-S1 disc) (Jager and Luttmann 1991).

2.1.3. Cumulative damage estimation

To estimate the CD sustained across a sequence of loading cycles, the Palmgren-Miner rule (Equation 2) was used. This technique is commonly used to predict damage due to spectrum loading (Palmgren 1924; Miner 1945).

$$c = \sum_{i}^{k} \frac{n_1}{N_1} + \frac{n_2}{N_2} + \cdots \frac{n_k}{N_k} \tag{2}$$

Where:

- c = a constant (usually set at 1, but subject to variation). In this study, the threshold value for c is 1.
- n_i = the count of loading cycles experienced at force levels at which N_i … cycles would result in material fatigue failure.

After obtaining estimates of cumulative damage, the result corresponding to an average workday was obtained by multiplying the cumulative damage by 480 (8 hours of work converted to minutes, the working period at the manufacturing facility). If the result on the right-hand side of Equation 2 is greater than or equal to 1 (or 100%). In that case the material is estimated to have reached its fatigue limit, in which case the worker would be considered at increased risk of a low-back injury because the cumulative damage would be higher than the threshold value.

It is important to mention that the Palmgren-Miner rule assumes a linear accumulation of damage, which may seem oversimplified. However, it is commonly used because, among other methods for damage estimation, it is the technique that achieves consistently better agreement with data from a wide variety of fatigue tests (Stephens et al. 2001).

3. Application in a live industrial environment

3.1. Case study design

The study was conducted in an automotive manufacturing facility, where workers performed routine tasks during their regular workday. The setting accurately represents workers' real-world conditions and challenges while performing their jobs. Manufacturing vehicles is a complex multistep process involving both automated and manual steps. The manual steps involve multiple repetitive movements, including bending at the waist to pick up/install parts, working above shoulder level, repetitive hand and wrist motion, and handling loads that vary in weight and shape. Workers performed their respective jobs for one and a half to two hours (depending on staffing availability) and then changed to a different station after a break. Each participant typically worked on a particular production line, rotating through an average of five stations on that line during an eight-hour shift.

3.2. Participants

A sample of six males and two females (mean age = 33.11, SD = 10.59 years old) was recruited (Table 1). All participants were workers at an automotive manufacturing facility. Inclusion criteria included 1) being an employee in the manufacturing facility, 2) having no history of physician-diagnosed MSD, injury, or surgery in the lower back, 3) having no history of a physician-diagnosed neurodegenerative disorder that may affect movement (e.g. Parkinson's disease, multiple sclerosis, among others), and 4) not presenting any health conditions that would put the person at heightened risk of severe illness from COVID-19. Health conditions included cancer, chronic kidney disease, chronic obstructive pulmonary disease, a weakened immune system due to an organ transplant, obesity (Body mass index, BMI, of 30 or higher), serious heart conditions, such as heart failure or coronary artery disease, sickle cell disease, and type 2 diabetes mellitus. Inclusion criteria were primarily confirmed through self-report. All participants were volunteers who were aware they could stop their participation in the study at any given time. Details about participants' anthropometry are shown in Table 1. Also, all participants performed the same or similar tasks in the 12 months prior to the study, as task requirements at the identified stations remained stable despite the introduction of new car models.

This study was reviewed and approved (Protocol # 19-165 EP 1904) by the Institutional Review Board at Auburn University. During the consenting process, participants were informed that the research team had established protocols for securing the data and that no individual results would be identifiable to anyone outside the research team.

3.3. Injury data

Injury data were collected from participants through a survey assessing low back disorders. The survey was administered before data collection using IMUs to establish baseline information about participants' low back injury history and potential contributing factors. The primary guideline for developing the surveys in this study was the Oswestry Disability Questionnaire (Fairbank and Pynsent 2000), which was modified to minimise the risk of leading questions, reduce the complexity of the survey, and improve clarity. These modifications included the addition of visual aids (see Appendix B, Figure B1) and were pilot-tested with a subset of the target population to ensure thorough comprehension.

Participants completed the surveys individually, having been pulled from their working lines for 25 to 45 minutes after the consenting process. Surveys were conducted during the first four hours of their shift to ensure sufficient staffing availability. Participants were instructed to answer all questions carefully and to follow the survey instructions. Researchers were present solely to provide clarification on instructions if needed.

Participants who did not report experiencing low back pain (LBP), aches, or burning sensations in the past year were instructed to skip the Oswestry

Table 1. Summary of participants' anthropometry (n = 8). M represents Males (n = 6), F represents Females (n = 2).

	Weight (kg)	Height (cm)	Shoe Length (cm)	Shoulder Height (cm)	Shoulder Width (cm)	Arm Span (cm)	Hip Height (cm)	Hip Width (cm)	Knee Height (cm)	Ankle Height (cm)
Mean M	82.03	178.36	31.54	148.80	37.94	159.39	93.21	25.07	53.73	10.66
SD M	9.70	7.33	2.07	5.64	3.38	63.59	6.25	1.43	3.62	0.93
Mean F	69.85	159.50	27.70	132.65	30.90	156.10	83.60	26.45	46.90	9.25
SD F	14.75	9.19	1.98	8.27	1.41	15.56	9.19	6.86	4.24	0.07

Disability Questionnaire section of the survey, as it would not be applicable to them. It was emphasised to all participants that their responses would remain confidential and would not be shared with anyone outside the research team.

3.4. Biomechanical assessment

3.4.1. Participant preparation and data collection

After completing the informed consent process, participants were fitted with a full-body IMC system of 17 sensors (MVN Awinda, Xsens Technologies B.V., Enschede, Netherlands). Each sensor consisted of a small, wireless, battery-powered unit that measured and stored acceleration, angular velocity, and magnetic field information. The sensors were secured using a combination of elastic neoprene straps and hypoallergenic athletic tape (Figure 4). Anthropometric measurements were used to build a rigid link biomechanical model using the information collected from the IMC system using the Xsens MVN software (Version 2019.2). During the data collection phase of the study, workers wore the IMC system for no longer than one hour while performing various tasks at different workstations. Each collected trial lasted approximately one minute on average but varied to a degree depending on the specific tasks required at each workstation and the particular car model being assessed.

Participants were instructed to perform their manual material handling tasks as they normally would. They were also asked to inform the research team if they noticed any differences in their task performance due to the presence of the IMC system. Data collection took place while three different car models were being manufactured at the plant. The loads handled by workers during their respective tasks were mostly between one and three kilograms, with some heavier parts, such as mufflers, weighing around 25 kg. A video example of a typical trial can be found in Appendix C.

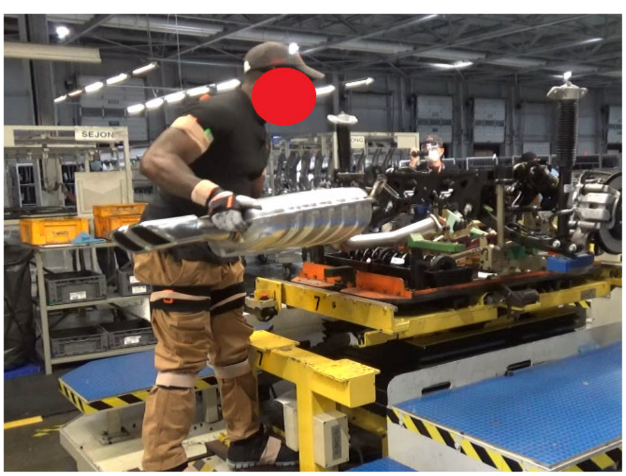

Figure 4. A participant working at a station while wearing the IMC system.

3.4.2. System calibration

Participants were required to follow calibration protocols for the IMC system. Segment calibration on the IMC system was performed to align the motion trackers to specific subject segments (Xsens®, 2021). This procedure consisted of each participant holding a neutral posture for a few seconds (an "N-pose"), then walking forward, turning around, and returning to where they started. The calibration quality was evaluated after each session and required to meet the manufacturer-recommended standard of "Good" to ensure accurate alignment and minimise drift during data collection. Additionally, participants performed a recalibration of the system after completing data collection at each workstation to maintain data quality throughout the experiment. To ensure the quality and reliability of the data, measurements were captured at least twice for each of the three car models for each worker at every station they operated.

3.4.3. Task identification

To identify work postures and activities, videos of each participant's tasks were recorded using two camcorders positioned to capture different angles. The videos were synchronised with the IMC data using a standardised gesture. Specifically, workers were instructed to perform a "thumbs-up" gesture by extending their right arm at the beginning and end of each cycle. This motion was captured both in the videos and by the motion capture system, enabling precise alignment of the two data sources.

The videos were used to cross-reference biomechanical data and determine when external hand loads were applied. Two researchers independently analysed the videos to observe postures and movements, defining various work postures for the shoulder, wrist, back, neck, and legs. Awkward postures included reaching, twisting, bending, neck twisting, hyper-extended or flexed back positions, overhead work, and kneeling. Manual material handling tasks were categorised as lifting/lowering, horizontal pulling/pushing, and forward pulling/pushing. Hand-arm vibration exposure was observed but not included in the current analysis. The weights of handled parts and tools were recorded, and the repetition and duration of tasks were analysed to support the biomechanical analysis.

3.4.4. Data processing

IMC data was collected at a sampling rate of 60 Hz. Both force and kinematic data were filtered using the IMC system's second-order Butterworth filter with a cut-off frequency of 5 Hz, applied bi-directionally (Faber et al. 2020; Marklin et al. 2024; Nail-Ulloa, Huangfu, et al. 2024). Additionally, a moving average of over ten frames was employed to smooth the data and minimise noise.

3.4.5. Biomechanical modeling

A top-down inverse dynamics approach was employed to analyse the biomechanical data. The analysis utilised a 15-segment biomechanical model created in Visual3D (C-Motion®, 2020) based on MVNX motion files exported using Xsens MVN Studio (Version 2019.2). Total moments at the L5/S1 joint were calculated as the vector magnitude of the individual moments in each anatomical plane of motion (X, Y, and Z). Specifically, the squared moments in the sagittal (X), frontal (Y), and transverse (Z) planes were summed, and the square root of this total was taken. This resultant moment provided a single scalar value representing the combined mechanical demands across all three planes of motion, offering a comprehensive assessment of the biomechanical loading experienced at the L5/S1 joint during task performance. This approach was validated in previous studies (Nail-Ulloa, Huangfu, et al. 2024), which compared moment differences between inertial and optical motion capture systems and demonstrated robust agreement across both methods.

External loads were assigned to the hand segments when the participants were lifting, lowering, or carrying (using recorded videos and the IMC avatar). If loads were handled with two hands, the load was assumed to be divided evenly between the hands. This approach simplifies the computational model while still delivering important insights into forces and moments acting on the body during bilateral hand use.

3.5. Case study details

The sampled participants worked on eight production lines and 40 stations with two or three car models in production during the site visits, depending on the day's schedule. The research team collected data for a total of 108 trials (one trial corresponds to an individual worker completing the required tasks for a single car model at a specific station on a given line).

3.5.1. Example trial

In this example, a worker performed their job at one of the trimming stations; the external loads associated with this trial are a 1.5 kg pneumatic rachet (Tool 1) and a 1 kg drill (Tool 2), both handled with the right hand. Figure 5 shows different work postures over the working cycle (1 minute).

The estimated total moment for the example trial is shown in Figure 6. The duration of the task was one minute. Forces at the L5-S1 level were estimated using a lever arm for the erector spinae muscle of 5 cm (Chaffin, Gunnar, and Martin 2006). The line of action of the erector spinae muscles was assumed to act parallel to the normal compression force on the L5-S1 disc.

Next, the obtained forces were applied to an average cross-sectional area of 16.2 cm^2 of the L5-S1 disc (Jager M & Luttmann A, 1991) to estimate the corresponding stress loading history. The stress loading history was processed using the rainflow analysis to obtain the number of cycles, along with the mean and range for the stress history (Figure 7). The stress magnitudes were adjusted using Goodman's method based on the stress range and

Figure 5. Worker performing tasks in the example trial.

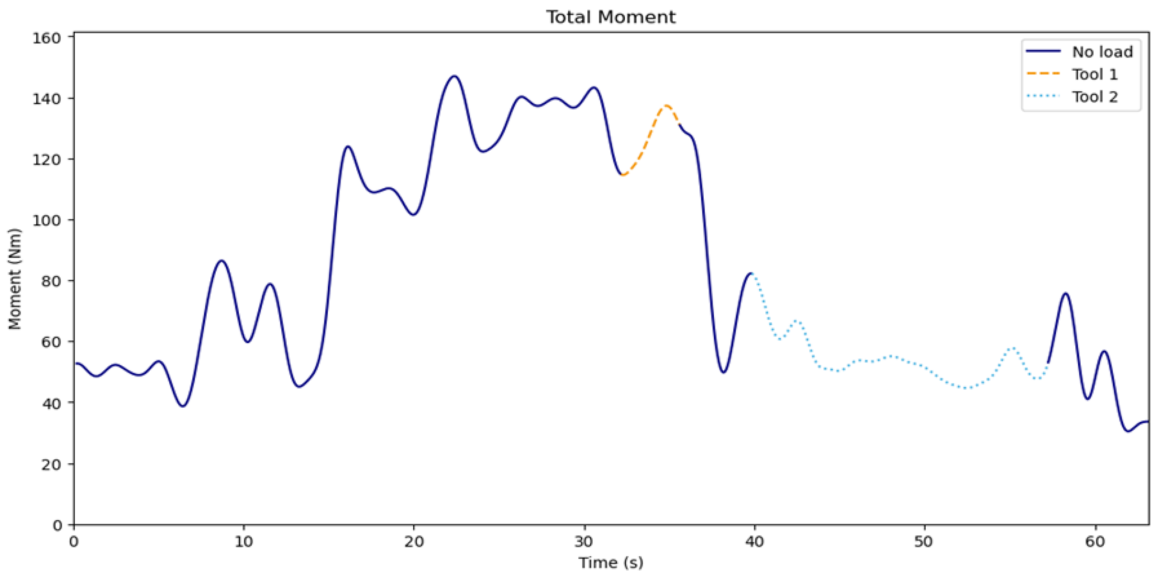

Figure 6. Example of the estimated total moment for the trial.

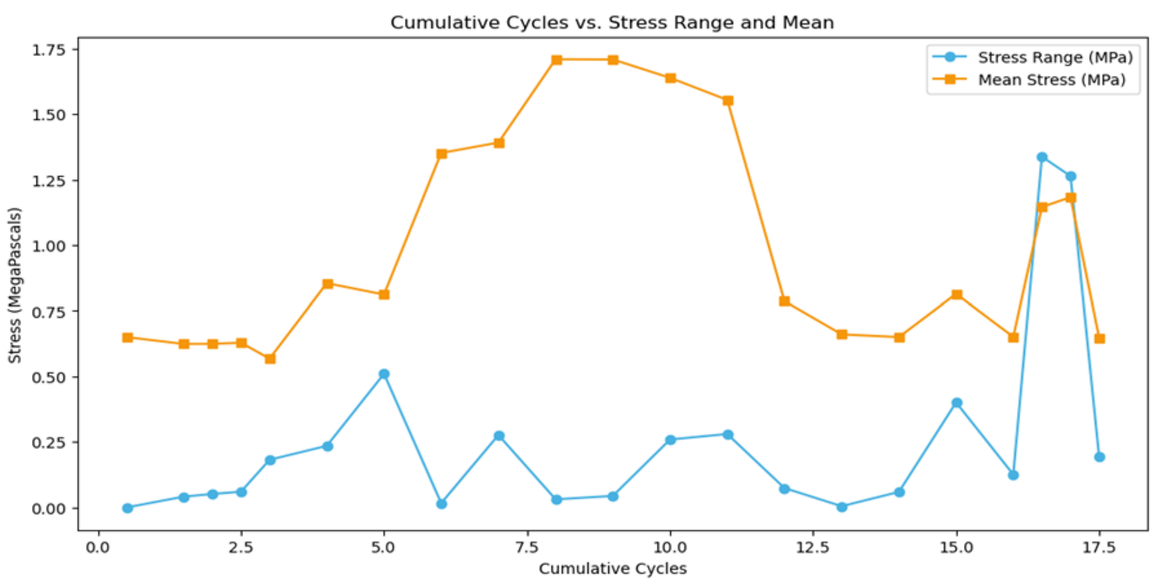

Figure 7. Cumulative cycles and adjusted stress range and mean obtained from rainflow analysis.

mean stresses (Equation A1). Then, the revised stress ranges were used to calculate damage per loading cycle (Equation 1), using the average ultimate spinal strength for a 35-year-old male (closest estimate to the average worker who participated in the study) of 7.3 kN (4.51 MPa) (Jager and Luttmann 1991).

Cumulative damage was calculated using the Palmgren-Miner rule (Equation 2), summing the damage for each individual cycle. After obtaining estimates of cumulative damage, the final result corresponding to an average workday is obtained by multiplying the cumulative damage by 480 (8 active hours of work converted to minutes, the working period at the manufacturing facility). In the example, the result showed a total damage calculation of 0.451, indicating that the average worker would not be exposed to a high risk of low-back pain while working at that particular station for that specific car model because this value is not greater than the threshold for reaching the fatigue life limit ($c = 1$). Results for every participant can be found in Appendix D, Table D1.

3.6. Statistical analysis

Stepwise logistic regression was used to examine the relationship between reported low-back pain and the continuous fatigue failure assessment method estimates. The controlled variables for the stepwise logistic regression were the CD, line, station, car model, and subject (participant). The stepwise logistic

Table 2. Resulting stepwise logistic regression results for self-reported low back injuries.

Resulting Stepwise Model				
Variable	Coefficient	Std Error	Coef/SE	*p value*
Constant	−4.95	1.22	−4.07	<0.01
CD	0.77	0.26	3.00	<0.01
Subject	0.06	0.03	2.27	0.023

regression technique utilised in this analysis was backward elimination (Appendix E, Table E1). An alpha level of 0.05 was used for all tests. Statistical tests were conducted in Statistix® (Version 9, Analytical Software, Tallahassee, FL, USA).

4. Statistical analysis results

After including participants, lines, and stations as covariates, a stepwise logistic regression was performed to determine the relationship between the calculated cumulative damage (CD) and the injury data. The relationship found between the CD estimates and the self-reported low-back pain presented the following results: p-value = 0.002, OR = 2.16, (95% Confidence Interval: 1.30, 3.57). The Subject factor was also statistically significant ($p = 0.023$). Table 2 shows the analysis results after performing the stepwise logistic regression.

5. Discussion

To the knowledge of these authors, this study represents the first attempt to demonstrate the application potential of a fatigue failure-based continuous loading risk assessment method that can accommodate highly variable low back moment history generated using a biomechanical model fed by an IMC system. The model provides flexibility in measuring cumulative damage when dealing with different loads, postures, and occupational tasks observed in the field that could affect the development of occupational low-back disorders. The initial results are promising, as the estimates of risk from the cumulative damage total showed a significant association with self-reported low back pain in the logistic regression analysis.

Traditional risk assessment tools often rely on discretizing the work cycle, which may overlook critical risk-driving components such as non-neutral postures without external load or low-frequency tasks. Evidence indicates that musculoskeletal loading patterns in occupational settings exhibit substantial variability (Mathiassen, Möller, and Forsman 2003; Mathiassen 2006), which discrete methods may not adequately capture. In contrast, a continuous assessment approach allows for the comprehensive analysis of the entire working cycle (in our case, at 60 frames per second). This provides a more comprehensive view of exposure, yielding insights that can inform job design, administrative controls, and engineering interventions. A key strength of the method is the integration of rainflow analysis, which identifies stress ranges as critical for estimating the most damaging cycles during dynamic exertions. By focusing on stress reversals, rainflow analysis highlights the highest-contributing cycles to CD, addressing a gap in existing risk assessment tools.

Our study revealed that, for the workers observed, peak moments during most working cycles were more closely associated with high torso flexion and non-neutral postures rather than the handling of external loads. For example, as shown in Figure 6, the highest total moment peak occurred during an unloaded event when the worker was in a flexed torso posture. This finding aligns with extensive reports in the literature (Marras et al. 1993, 1995; Hoogendoorn et al. 2000; Gallagher et al. 2005; Coenen et al. 2014; Gupta et al. 2022; Capanoglu et al. 2023). By continuously integrating torso and postural dynamics, our method provides a more comprehensive assessment of lumbar loading, offering a detailed perspective that complements the discrete evaluation provided by a tool like LIFFT. The proposed method in this study offers a way to incorporate torso and postural dynamics within a fatigue failure-based framework, providing a more comprehensive approach to assessing cumulative loading and its impact on musculoskeletal health.

It should be noted that the use of this framework for risk assessment could offer numerous benefits. For example, it accounts for changes in key risk factors significantly influencing the risk of low back disorders, including lateral trunk velocity, load moment, lifting frequency, trunk twisting velocity, and sagittal trunk angle, as noted by Marras et al. (1995). Another key advantage is that the framework enables the analysis of various working conditions, such as lifting with one hand or handling two different loads simultaneously, thereby providing a more comprehensive risk assessment. Also, typical ergonomics risk factor analysis (used by many MSD risk assessment tools) often requires subjective estimation of the level of forces being exerted (by either researcher or study participant), which may lead to significant errors in risk estimation. Using more quantitative methods to evaluate such loads may help eliminate this error. A recent alternative to the full-body 17 IMU sensors setup was studied by Matijevich, Volgyesi, and Zelik (2021), where the authors suggest that a single trunk IMU sensor and a pair of pressure insoles to estimate forces could reach high accuracy when assessing lumbar moments compared to the whole-body setup, using gold-standard optical motion capture systems as a reference. Such an alternative could offer a faster donning and doffing of the system (in our study, 15-20 minutes were required to measure and record anthropometry and secure the sensors) and less potential obstruction to the jobs from the hardware on parts of the body that are sensitive to highly dynamic motion like the hands or the forearms. Another option to capture continuous exposure could be using markerless motion capture methods, which have already been reported to accurately estimate 3D L5-S1 moments for symmetrical lifting (Mehrizi et al. 2017).

The ability to derive CD estimates from continuous loading data using fatigue failure methods advances ergonomic risk assessment, providing a more detailed and dynamic evaluation of exposure. There are still some hurdles to implementing quantitative methods such as those discussed here. However, our results suggest such techniques may improve quantitative risk assessment methods in the not-too-distant future.

5.1. Future research

Non-weighted or linear (Norman et al. 1998) and weighted integration (Jäger et al. 2000) methods for estimating CD have been proposed in the literature and are currently used by practitioners and scientists.

However, Huangfu et al. (2018) suggested that the non-weighted or linear integration method may be unsuitable for evaluating high physical exposure. Additionally, there is a precedent of comparison between the CD estimation approaches mentioned above and fatigue failure. Huangfu (2018) compared CD estimates generated by using compressive force estimates from a simple biomechanical model as an input for a fatigue failure-based model, linear, and weighted (squared) integration methods against health outcomes from two different epidemiological databases (Zurada, Karwowski, and Marras 1997; Sesek 1999). The fatigue failure-based model exhibited superior performance compared to the linear integration method, with an odds ratio of 7.54 versus 5.38, demonstrating its ability to differentiate high-risk versus low-risk jobs more accurately. While the fatigue failure model also showed marginally better performance than the squared integration approach, it was particularly effective in identifying jobs with medium and low risk. These findings highlight the advantages of the fatigue failure-based approach in capturing cumulative loading dynamics compared to simpler linear methods. Future research should expand on these findings by directly comparing the fatigue failure-based method presented here with linear and weighted methods using continuous loading data. Such comparative studies could further elucidate the advantages and limitations of each approach, contributing to the development of more robust and precise risk assessment tools.

On the other hand, Johnen et al. (2022) highlighted that weighted approaches are difficult to compare and must establish clear threshold values to estimate cumulative damage accurately. The fatigue failure-based framework presented here offers several advantages, including a clear threshold to determine lifetime exposure limits for cumulative spinal loading, which has been defined as a research need in previous studies (Waters et al. 2006; Gallagher and Schall 2017). However, it is important to note that relying solely on biomechanical material failure principles may overlook critical factors such as reversible physiological responses, including fatigue and recovery (Nussbaum 2001). For instance, Waters, Putz-Anderson, and Baron (1998) emphasise that repetitive exposures are influenced not only by biomechanical factors but also by physiological changes, which play a significant role in risk estimation. While these limitations exist, Gallagher and Barbe (2022b) developed an initial model that incorporates physiological and recovery factors from a fatigue failure perspective. Building upon their efforts, future research should explore how these physiological responses can be further integrated into cumulative damage models, offering a more holistic approach to musculoskeletal risk assessment.

Moreover, the cumulative damage (CD) threshold of 1 used in this study is based on ex vivo data and may not fully capture the complexity of in vivo conditions. Although this threshold has shown predictive validity in epidemiological studies using the LIFFT tool (Gallagher et al. 2017), further research is needed to refine this parameter for more accurate assessments across diverse work settings and populations.

The method presented here can account for personal characteristics such as biological sex and age, which significantly impact critical factors like ultimate strength (Jager and Luttmann 1991). For instance, using values for a 25-year-old male (8.2 kN), a 35-year-old male (7.3 kN), and a 55-year-old female (4.4 kN), the calculated ultimate stresses, assuming the same cross-sectional area of 16.2 cm^2, are approximately 5.05 MPa, 4.51 MPa, and 2.72 MPa, respectively. Under a stress cycle of 1 MPa, the predicted cycles to failure are approximately 98,141 for the 25-year-old male, 73,490 for the 35-year-old male, and 12,391 for the 55-year-old female. When the stress cycle increases to 1.5 MPa, these values drop substantially to 29,326, 19,003, and 1,316, respectively. These calculations illustrate how weaker spinal segments, such as those of older individuals or females, could be far more vulnerable to fatigue failure under the same loading conditions compared to stronger spines.

Moreover, the model could be further refined to incorporate additional personal characteristics, such as variations in cross-sectional areas of the L5-S1 disc and muscle lever arms (Jager and Luttmann 1991; Chaffin, Gunnar, and Martin 2006). These factors also influence the ultimate strength and biomechanical loading of the spine. Integrating these variables would allow for even more personalised and accurate assessments of cumulative damage. Future adjustments using existing data sources could make the fatigue failure-based framework more robust, offering deeper insights into how cumulative damage develops across diverse populations.

The approach used in this study could also be applied to other body parts. For example, some data could be utilised as a reference for the ultimate strength of tendons on fatigue failure-based discrete risk assessment tools already published in the literature for the shoulders, the upper extremities, and even exoskeletons (Gallagher et al. 2018; Bani Hani et al. 2021; Zelik et al. 2022). Injury data and biomechanical estimates of shoulder forces or moments could be obtained from a musculoskeletal biomechanical modelling software such as Opensim™ or the Anybody™ modelling system (Damsgaard et al. 2006; Delp et al. 2007; Aurbach et al. 2020). Such approaches may be advantageous in justifying the effort of working with a full-body model instead of trying less accurate or simplified methods for assessing low back loading (Coenen et al. 2015).

5.2. Limitations

While the results presented in this study are promising, the authors must acknowledge its exploratory nature. To improve the validity, applicability, and generalisability of these methods, further research with larger sample sizes and a broader range of tasks is needed. Another limitation of this study is the assumption of even weight distribution on the hands. It is not likely that a load's weight will be evenly distributed between both sides of the body, especially when loads present irregular geometries. Additionally, this approach does not consider the potential impact on pushing or pulling loads. This limitation could be faced by utilising a system that provides ground reaction force estimates from pressure insoles (Matijevich, Volgyesi, and Zelik 2021). Another limitation is associated with the individual characteristics of the participants. The IMC system performance might be affected by participants' characteristics, such as being obese, as soft-tissue artefacts may be common (Bolink et al. 2016). Additionally, we might not have captured enough postural exposure data to avoid biases in the evaluated tasks (Porta et al. 2020). A longer sampling duration of 50-60 minutes should be examined in future research.

It is worth noting that positioning the sacrum sensor for the IMU system presented certain challenges. The trunk has few anatomical features that can be a stable attachment point for an IMU. Considering the dynamic and varying nature of the evaluated tasks requiring forward bending, we suspect that the sacrum sensor may have shifted (primarily upwards) from its original placement, impacting the results of the moment calculations. Previous studies have raised similar concerns (Larsen et al. 2020; Schall et al. 2021; Nail-Ulloa, Zabala, et al. 2024).

The COVID-19 pandemic significantly affected the performance of this research project, from the industry partner having a constant workforce shortage, which prevented the team from capturing data on some of the lines and stations that were initially planned, to the anticipated final closeout of the data collection because of outbreaks at the manufacturing facility. Although ending the data collection affected the study's sample size and analysis, the significant results from our analysis make further research promising.

Lastly, the current fatigue failure model does not account for the remodelling and healing of musculoskeletal tissues and the impact on these by psychosocial stress, ageing, smoking, and biological sex, which are factors to consider when developing programs to prevent chronic low back pain (Waters et al. 2006; Buruck et al. 2019). However, fatigue failure theory is well-positioned to incorporate the effects of both damage development and tissue healing as sufficient evidence becomes available (Gallagher and Barbe 2022b). Despite the limitations, the methodology and framework presented in this work provide a strong foundation and serve as a starting point for more extensive testing and refinement in future investigations.

Acknowledgments

The authors also want to acknowledge the automotive manufacturing facility that allowed us to work there even during the pandemic. We feel very grateful for their commitment to science in the ergonomics and safety disciplines.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by research funding from the Centers for Disease Control and Prevention (CDC)/National Institute for Occupational Safety and Health (NIOSH, Grant N°: R21OH011208-01-00) and through the Deep South Center for Occupational Health and Safety at the University of Alabama-Birmingham (UAB) and Auburn University (Grant # T42OH008436). The findings and conclusions are those of the authors and do not necessarily represent the views of the CDC/NIOSH.

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Appendix

1. Appendix A

Because the human spine is constantly subjected to a compressive load due to the body's weight in standing and sitting postures, the loading pattern experienced is classified as "fluctuating stress" Gallagher and Schall (2016). As a result, modifications to the stress amplitude and mean stress are required to calculate fully reversed sinusoidal loading. To achieve this, Goodman's method (Equation A1) was used to adjust the revised stress amplitude for each mean stress and stress range pair.

$$\frac{S_a}{S_{Nf}} + \frac{S_m}{S_u} = 1 \tag{A1}$$

Where:

- S_a = alternating stress.
- S_m = the mean stress.
- S_{Nf} = the estimated value of the stress at failure for exactly *Nf* cycles as determined by an S-N diagram.
- S_u = the ultimate stress.

The adjusted stress amplitude was employed to indicate the stress level for each repetition classified by the rainflow analysis technique.

2. Appendix B

Low back region identifier for participants on the low back survey:

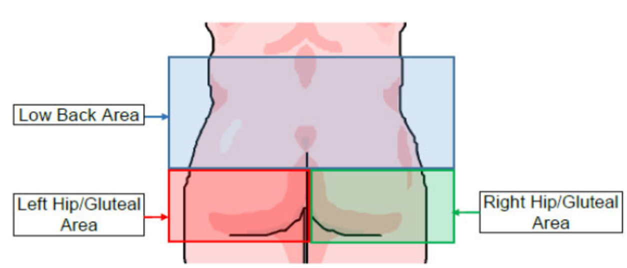

Figure B1. Illustration of the low back region and adjacent areas (left hip/gluteal and right hip/gluteal) used in the participant survey to identify specific regions of discomfort or pain.

3. Appendix C

Please follow this link to find a video of an example trial in the presented study:

- https://youtu.be/ZHOHDtYGSa0

4. Appendix D

Table D1. A. Summary of Trials. Overview of total lines and stations covered, along with average cumulative damage metrics per cycle and using a mixed-model approach for each subject.

Subject	Total Lines Covered	Total Stations	Avg. CD Total Per Cycle	Avg. CD Total Mix Model Making
S001	3	5	0.0056	0.0058
S002	1	5	0.0345	0.0360
S003	1	4	0.0071	0.0076
S004	1	6	0.0884	0.0884
S005	1	6	0.0034	0.0034
S006	1	4	0.0006	0.0006
S007	1	5	0.0280	0.0282
S008	1	6	0.0011	0.0011

5. Appendix E

Table E1. A. Stepwise logistic regression results for self-reported low back injuries.

Step	Variable	Coefficient	Std Error	Coef/SE	Deviance	Difference	*p*
1	Constant	−4.81	2.05	−2.35	54.02		
	CD	0.96	0.29	3.34			
	Line	−0.42	0.29	−1.47			
	Model	−0.12	0.46	−0.25			
	Station	0.14	0.08	1.8			
	Subject	0.08	0.03	2.91			
2	Constant	−5.02	1.88	−2.66	54.09	0.06	0.8
	CD	0.95	0.29	3.33			
	Line	−0.41	0.28	−1.45			
	Station	0.14	0.08	1.79			
	Subject	0.08	0.03	2.9			
3	Constant	−6.56	1.83	−3.58	56.28	2.2	0.14
	CD	0.87	0.28	3.11			
	Station	0.09	0.06	1.43			
	Subject	0.08	0.03	2.44			
4	Constant	−4.95	1.22	−4.07	58.28	0	0.16
	CD	0.77	0.26	3			
	Subject	0.06	0.03	2.27			

Resulting Stepwise Model

Variable	Coefficient	Std Error	Coef/SE	*p*
Constant	−4.95	1.22	−4.07	<0.001
CD	0.77	0.26	3	<0.001
Subject	0.06	0.03	2.27	0.023
Deviance	58.28			
p-Value	0.9999			
Degrees of Freedom	105			