

# Verification and Application of Workwear-Integrated Sensors for Ergonomic Injury Risk Assessment

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## SUMMARY

Risk assessments are a central part in Work-related Musculoskeletal Disorder (MSD) risk management. Wearable sensors integrated into workwear present a promising approach for industrial ergonomic risk assessment. This paper has three objectives: first, we assess the accuracy and efficacy of a workwear-integrated sensor system in estimating the MSD risks comparing it to an optical measurement technique, secondly, we outline approaches for using the system for continuous MSD risk assessment using industry standard methods and a Cumulative Damage (CD) exposure metric based on Fatigue Failure Theory (FFT) and third, we demonstrate feasibility by applying the system and approach for assessing 3 manual-handling tasks within the rail industry. Results confirm that the system, and approach can enable a proactive and data-driven approach to MSD management. Key considerations necessary for the wider adoption are also presented.

## KEYWORDS

Musculoskeletal Disorders, risk assessment, sensors, rail industry

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## Introduction

Musculoskeletal Disorders (MSDs) are a significant contributor to workplace sickness absence. Assessing risks and reducing them to be As Low As Reasonably Practicable (ALARP) is central to any MSD risk management. Most of the current risk assessment tools rely on snapshot assessments of single postures, often those believed to be hazardous or problematic (A. D. J. 2002). These risk assessments primarily rely on visual inspections, which are subjective and suffer from accuracy issues. Additionally, the lack of continuous assessment may prevent these methods from capturing risks across the entire work shift and accurately reflecting staff behaviours. MSDs are one of the leading causes of absence for the rail workforce (RSSB, 2024) and failure to conduct and apply the findings of a suitable and sufficient risk assessment has been reported as underlying cause (ORR, 2019). Recent advances in movement sensor technology and algorithms allow workwear-integrated sensors to track ergonomic risks. This study reports accuracy verifications conducted on the workwear-integrated sensor system, approaches for using workwear-integrated sensor systems to assess MSD risks in a continual and cumulative basis and evaluates the feasibility on 3 rail -sector manual tasks.

### Accuracy verification of the work wear integrated sensor system

The system features 9-11 sensors measuring movement (SpatialCortex MOVA) embedded into standard workwear at key locations (limbs, torso and lower back) and a wearable data logger.

Accuracy of the sensor system was verified against a novel optical measurement system. The reliability of the optical system was measured initially. Accuracy verification of the sensor system relied on markers placed at various locations of participants adopting a range of poses, sensor data and camera images captured concurrently, and each data frame analysed to extract, joint angles, horizontal distance from lower back and vertical distance from the ground. The study also considered the effect of clothing, participant variability and sensor attachment methods on system accuracy.

**Camera-based optical measurement technique**

A novel optical measurement technique was developed using readily available materials, including reflective markers, a standard camera, and a free image analysis software package. The method aims to provide an accessible and practical approach for benchmarking sensor system accuracy in various work environments. The measurement process involved placing at least two markers (separated by a set distance) per sensor unit’s front face, attaching the sensors to the participant, and capturing 2D images alongside sensor data while the participant adopted a series of predefined poses. Data acquisition was synchronised via a Python-driven script using the MOVA software suite. Three additional reflective markers defined the origin, horizontal, and vertical datums of the measurement environment. A 2D digital image processor (PlotDigitizer package) extracted marker coordinates based on these datum references. The orientation of each sensor was determined from the coordinates of its marker pair, enabling joint angle calculations when sensors were placed on multiple body segments (e.g., upper arm and hand). Segment lengths measured and the orientation from marker data facilitated the measurement of horizontal and vertical distances. While previous research (Aydin, 2021) reported high reliability for the software tool and approach in extracting scientific data from 2D images, the manual nature of the process warranted additional Repeatability and Reproducibility Assessments (RRA) to evaluate the method's reliability comprehensively.

RRA were conducted using three selected frames (Figure 1, a-c) and three operators, each manually extracting sensor segment orientations with reflective markers using the PlotDigitizer package, performing three repetitions per operator. For repeatability, the Standard Deviation (SD\_r), Coefficient of Variation (CV%), and Intra-Class Correlation (ICC) ranged from 1.07° to 5.38°, 1.2% to 5.6%, and 0.85 to 0.98, respectively.

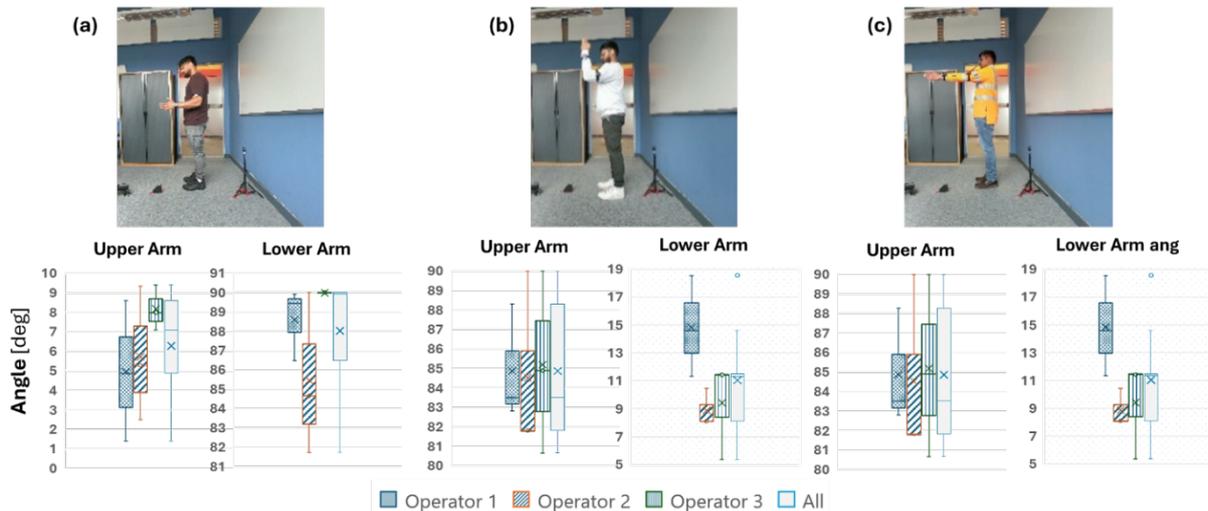


Figure 1: Repeatability and Reproducibility assessment of the camera-based optical technique

For reproducibility, the Standard Deviation (SD\_o), Inter-Operator Variability (IOV%), and Intra-Class Correlation (ICC) ranged from 0.44° to 2.20°, 0.5% to 2.5%, and 0.89 to 0.98, respectively.

The optical measurement system demonstrates good reliability, with results consistent within the reported bands.

**Angular and spatial accuracy verification**

The study focused on measuring the elbow flexion joint angle, where the orientation of the upper and lower arm was measured using both the sensor and optical techniques. While the approach is transferable to other joint groups, this report presents findings exclusively from the elbow joint measurements.

Measurements were obtained from six predefined postures, repeated across three participants to capture person-to-person variability. To evaluate the influence of clothing and sensor attachment methods, the following conditions were tested: (a) short-sleeve shirt with sensors attached directly to the skin using Velcro straps, (b) long-sleeve shirt with sensors attached over a fabric layer using Velcro straps, (c) orange high-visibility long-sleeve top with sensors attached similarly to condition b, and (d) green high-visibility jacket with sensors inserted into specialized pockets containing elasticated segments for sensor stability.

The results (Figure 2) indicated that the mean absolute error (MAE) for upper arm orientation ranged from 4.6° to 6.1° across individuals, with an overall MAE of 5.1°, standard deviation of 4.7°, and a maximum error of 15.8°. For lower arm orientation, the MAE ranged from 7.3° to 10.1°, with an overall MAE of 8.7°, standard deviation of 3.8°, and a maximum error of 14.8°. These angular errors translated to spatial errors of 3.5 cm MAE, 3.0 cm standard deviation, and 9.0 cm maximum error for horizontal distance from the lower back, and 4.2 cm MAE, 4.3 cm standard deviation, and 13.0 cm maximum error for vertical distance from the ground.

Analysis of the effect of clothing and attachment methods (Figure 3) revealed minimal impact compared to person-to-person variability. Measurements were consistent regardless of whether sensors were directly attached to the skin or placed within pockets over elastic segments.

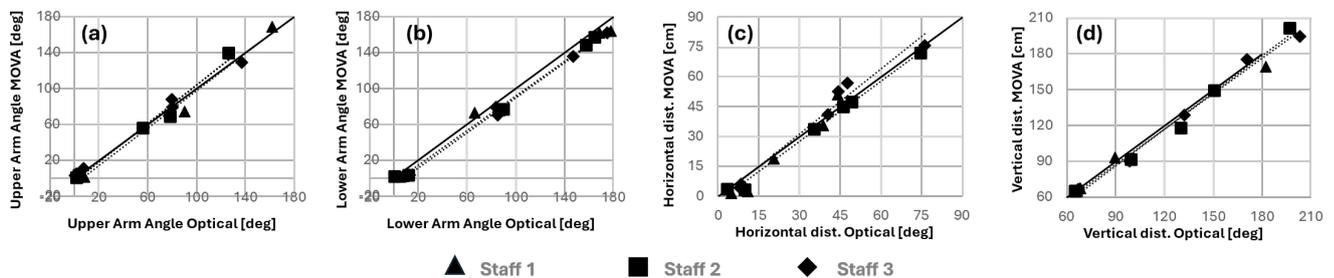


Figure 2: Accuracy of workwear integrated sensor system: Staff-to-Staff variability

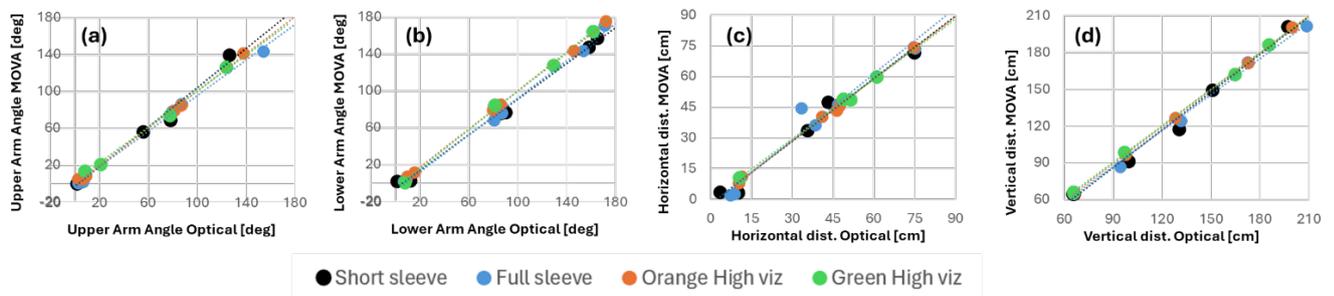


Figure 3: Accuracy of workwear integrated sensor system: Effect of clothing

### Sensitivity Analysis of lower back biomechanical parameter estimation

To quantify the impact angular and spatial measurement errors on estimates of key biomechanical parameters; L5/S1 Moment ( $M_{L5/S1}$ ) and L5/S1 Spinal compression ( $F_c$ ), a Sensitivity Analysis (SA) was conducted. These parameters were calculated following the approach presented by Chaffin, D.B. (2006),

$$M_{L5/S1} = E \cdot F_M = (b \cdot mg_{BW} + h \cdot mg_{Load}) \quad (\text{Equation 1})$$

$$F_c = -\text{Cos}(\alpha)[mg_{BW} + mg_{Load}] - F_M \quad (\text{Equation 2})$$

where E is the erector spinae moment arm,  $F_M$  is the effective reactor spinae muscle force, b is the upper body centre of gravity - lower back horizontal distance, h is the load - lower back horizontal distance,  $mg_{BW}$  is the upper body weight,  $mg_{Load}$  is the load weight and  $\alpha$  is the sacral cutting plane angle with the horizontal.

A Monte Carlo based SA was conducted, assuming a baseline posture depicted in Figure 4(a), a load weight of 15 kg, and SD for the upper and lower arm orientations derived from the accuracy measurements. A  $\pm 15\%$  bound was able to explain the observed variability in  $M_{L5/S1}$  and  $F_c$  (Figure 4, b-c). Conservatively, a 15% margin can be applied to any estimates of L5/S1 compression force derived from the sensor system's data. It is important to note that this analysis does not account for potential errors in torso angle measurement. Therefore, the bounds should be increased further for a more conservative and safer estimation.

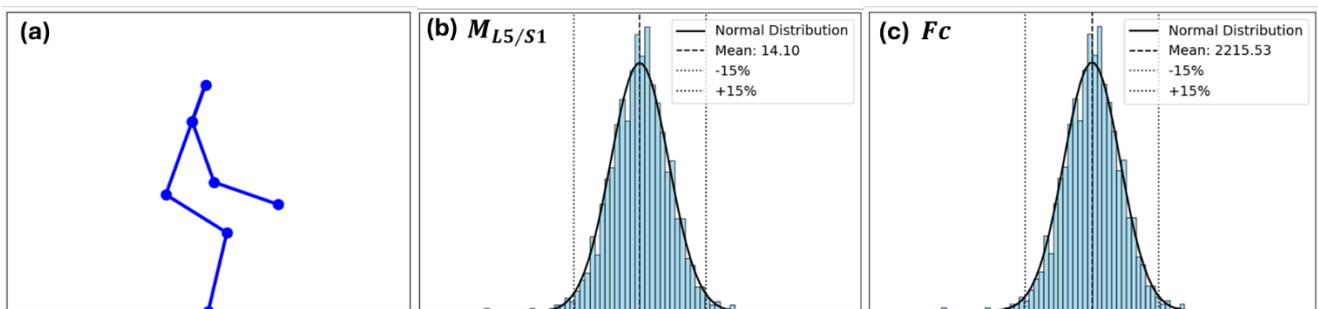


Figure 4: SA of biomechanical parameters;  $M_{L5/S1}$  and  $F_c$ , using inputs from workwear-integrated sensor system

All results presented here were based on data collected within two hours of participants wearing the sensor system after calibration. A critical consideration for future work is to investigate the impact of prolonged sensor use, such as an 8-hour work shift, where sensor movement due to physical activity could introduce additional variability into the measurements.

### Approaches for MSD risk assessment with data from workwear-integrated sensors

Two methods were chosen for MSD risk assessment; Health and Safety Executive's (HSE) Manual Handling Assessment Charts (MAC) and a method based on Fatigue Failure Theory (FFT) for continual and cumulative risk exposure assessment respectively.

#### Continual MSD risk assessment using HSE MAC risk factors

The MAC tool evaluates risks in lifting, lowering, carrying, and team manual handling tasks using a numerical and color-coded scoring system to identify high-risk activities based on established risk factors. The V-MAC tool extends this capability by assessing tasks with variable load weights. The MAC tool was selected due to its ease of use and suitability for manual handling risk assessment

(Pinder, 2002). Validation studies identified 'Horizontal distance' as a significant predictor of work-related Lower Back Pain (Pinder, 2014).

### **Cumulative MSD risk assessment using an improved Fatigue Failure Theory (FFT) based model**

Recent evidence suggests that MSDs such as Lower Back Pain may be due to a fatigue failure process (Gallagher and Schall, 2016) accumulating during repeated loading cycles, which allows predicting a Cumulative Damage (CD) metric. Gallagher, S et al., 2017, presents the Lifting Fatigue Failure Tool (LiFFT), with three inputs (load weight, peak horizontal distance from spine to load, and repetition) and provides validation against two existing epidemiological databases; mono-task jobs (Marras et al., 1993; Zurada et al., 1997), variable loading jobs (Sesek, 1999), the model explained deviance within 92% and 72-95% in the database respectively.

The LiFFT model calculates CD by computing the Peak Load Moment (PLM), the product of the object's weight and its horizontal distance from the spine. It then estimates spinal compression and calculates damage per cycle (DPC), comparing this compression to the average spine's compressive strength (6 kN; Jager & Luttmann, 1991). DPC is multiplied by the task repetitions, and a CD threshold is applied to determine risk. The model's simplicity, minimal input requirements, and ability to estimate daily CD dose across multiple subtasks are key advantages.

However, the accuracy of the compression force ( $F_c$ ) calculation is critical. The simplified  $F_c$  calculation (Equation 3) omits factors like torso posture and upper body weight, which are significant and considered in Equations 1 and 2. This simplification can cause errors, especially when loads are held away from the body. To address this, a scaling factor is applied to the CD estimate, though this remains a coarse adjustment.

$$F_{c_{LiFFT}} = \frac{1}{E} h \cdot m g_{Load} \quad (\text{Equation 3})$$

The workwear-integrated sensor system provides a key advantage by enabling complete, time-dependent  $F_c$  calculations based on sensor estimates when the task's peak load weight is known. This allows for real-time tracking of cumulative damage (CD) throughout the work shift.

### **Feasibility assessment: application to rail industry manual-handling tasks**

The workwear-integrated sensor system was evaluated in three rail industry manual-handling tasks:

1. **Manual-material transfer:** Staff moved construction materials, such as concrete bags, from access points to platforms for loading onto rail trolleys. Certain access points presented logistical challenges, making mechanized transfer impractical in all cases.
2. **Rail ramp deployment:** Onboard hosts, station staff, and passenger assistance staff regularly deploy ramps of varying designs. Heavier ramps are equipped with wheels to reduce manual lifting, while lighter (~10 kg) ramps are often carried. Ramp storage locations, onboard or on platforms, further influence carrying demands.
3. **Manual vegetation clearance:** Maintenance staff manually cleared vegetation along the rail infrastructure using chainsaws. The task involved repetitive cutting at ground level and manual debris removal to maintain safe clearance from the running line.

These tasks were selected to demonstrate the system's applicability for ergonomic risk assessments across diverse job roles in the rail sector. Future task selection may use alternative metrics, such as historical injury data or lost-time incident records.

System setup: Participants wore standard rail-specific workwear with sensors attached using Velcro straps, requiring no garment modifications. Data was logged on a datalogging device kept in the worker's pocket. The system was calibrated with static and dynamic poses in under five minutes on average. Basic anthropometric data was collected beforehand to personalize posture risk thresholds for each participant.

### ***Continual MSD risk assessment using HSE MAC risk factors***

The HSE MAC assessment of manual lifting and handling tasks considers various risk factors, including A. Load weight/frequency, B. Horizontal distance from the lower back, C. Vertical lift distance, D. Torso posture, E. Postural constraints and additional factors include carry distance, grip, floor surface, obstacles, and environmental conditions.

The workwear-integrated sensor system can directly measure risk factors D, B, and C, as shown in Figure 5 (b)., for manual material transfer tasks. The load handled was concrete bags each weighing 20Kg. These risk factors are plotted continuously over time. The torso posture (risk factor D) chart tracks torso flexion and sideways angles, showing spikes during lifting or lowering events. The flexion angles range from 30° to 70°, with the worst-case posture during lowering showing the largest flexion and horizontal load distance (B) extending into the red zone. This data indicates opportunities to train staff on improving posture.

The vertical lift distance (C) indicates that lifting starts above elbow height, while lowering often extends below knee level, compromising posture. The torso posture chart (D) can also help infer repetition and frequency, data shows repetitive lifting and carrying in bursts, with high-intensity transfer phases followed by lower-intensity periods. The maximum lift frequency during a burst can elevate the risk associated with this factor. A conservative approach using the worst-case posture and lift frequency rates the task as moderate-to-high risk. Additionally, gait patterns estimating the number of steps taken. The median carry distance was found to be 6.6 meters, aligning closely with the actual work environment value of 6 meters.

This data provides valuable insights for Health and Safety (H&S) duty holders to evaluate control measures, such as eliminating manual transfer where feasible, substituting lighter loads, implementing mechanized transfer where practical, training staff on proper lifting techniques, improving job planning to reduce postural constraints, using job rotations to minimize exposure to high-risk tasks.

Data gathered from the rail ramp deployment task involved staff walking to the train, accessing the ramp stored onboard, carrying it to the entrance, and deploying it. The data also covered the reverse operation of stowing the ramp away. The analysis revealed during ramp deployment staff spent extended time in high flexion, with hands extended away from the lower back and below knee level. The data also suggested that finer adjustments may be necessary to ensure proper ramp deployment. Such patterns can help identify opportunities for improving staff training, ramp design, and addressing ergonomic challenges related to ramp maintenance and deployment.

Similar data gathered from manual vegetation clearance tasks showed that staff engaged in ground-level cutting adopted various postures, often holding those positions for extended periods. While the load weight (chain saw) may not be significant, the prolonged postures contribute to ergonomic risks. This data can guide H&S stakeholders in evaluating appropriate controls, following the hierarchy of controls, such as mechanization where feasible, providing alternative tools to maintain good posture, offering task-specific training, promoting postural best practices, and implementing job rotations to minimize prolonged exposure to risky postures.

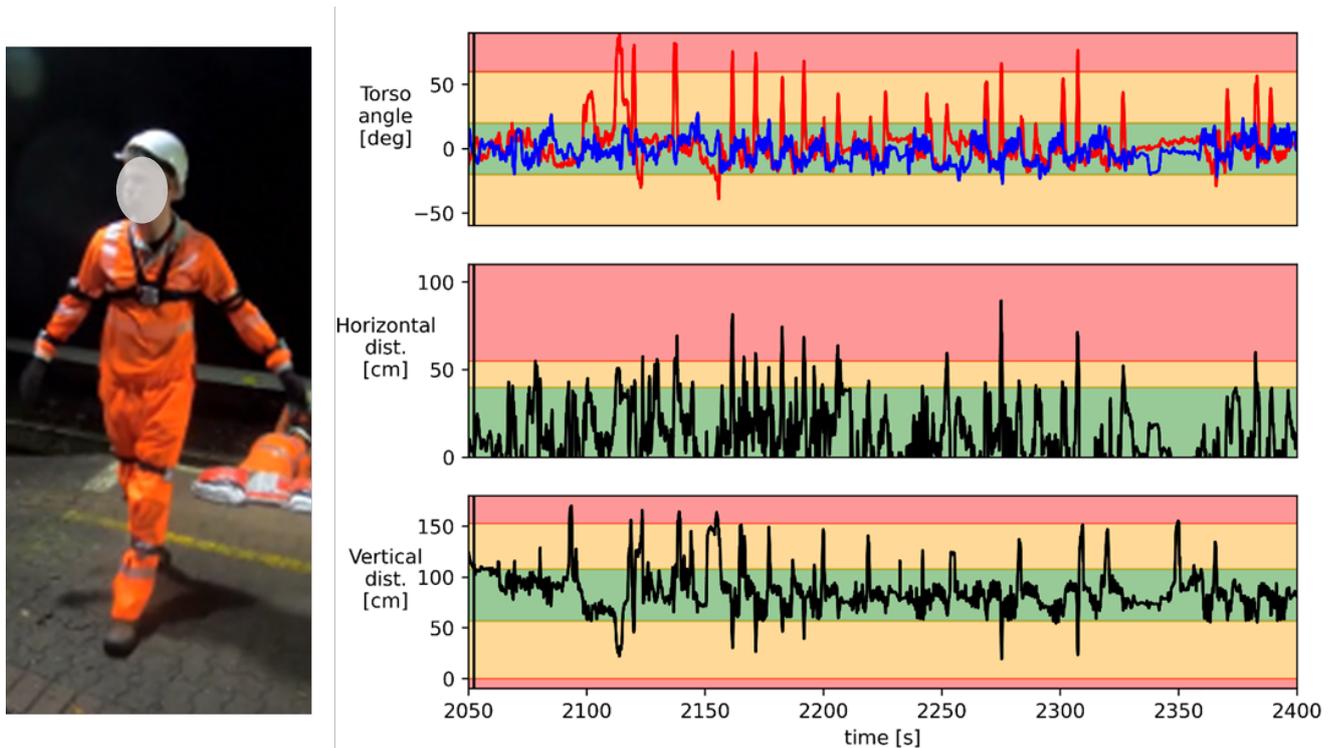


Figure 5: (a) staff with workwear-integrated sensor conducting manual-material transfer task in rail infrastructure (b) HSE MAC risk factors (D, B, C) from workwear integrated sensor system

The HSE MAC tool is effective for manual handling risk assessment due to its simplicity and intuitive RAG (Red-Amber-Green) colour coding. However, it relies on subjective, snapshot assessments during visual inspections, which capture risks only at a single point in time and require significant H&S officer involvement, limiting scalability. The workwear-integrated sensor system overcomes these limitations by continuously capturing posture risk data throughout the work shift. This data, when analysed alongside load weights, reveals high-risk manual handling activities and highlights discrepancies between 'task as planned' and 'task as conducted.' Continuous, objective risk monitoring enables more accurate, data-driven interventions. Insights support targeted mitigations following the hierarchy of controls, such as elimination and substitution where feasible, task redesign, equipment modifications, and training, for maintaining manual handling risks at ALARP levels.

#### ***Cumulative MSD risk assessment using an improved FFT model***

CD scores derived using L5/S1 compression metrics, highlighted material transfer and vegetation clearance had high risk due to repetitive bending and sustained postures. These metrics can enable designing work shifts and task planning in a data-driven manner to reduce risk exposure and considering individual staff circumstances during job planning like managing return-to-work.

The Borg Rating of Perceived Exertion (RPE) is a psychophysiological scale designed to assess an individual's subjective perception of physical exertion during activity. The RPE scale is widely used in ergonomic assessments to evaluate physical workload, muscle fatigue, and task demands, particularly in manual handling tasks where it can complement objective measures (Borg, 1998).

Staff feedback showed a strong correlation between CD scores and perceived exertion (RPE) which reinforces the reliability of the risk ranking. The sensors, when integrated into well-fitted workwear, were reported as comfortable and non-intrusive, with no impact on task performance.

Table 1: Cumulative Damage (CD) score based on FFT model

Task	$mg_{Load}$ [N]	Cumulative Damage (CD)	Borg RPE rating
Manual material transfer	196.2	0.01904	14
Ramp deployment	98.1	0.00021	10
Vegetation clearance	78.5	0.00919	13

## Conclusion

MSDs are a leading cause of workplace absence, especially within the rail sector. Effective MSD risk management requires robust risk assessments, yet failures to conduct or apply such assessments are commonly reported. Traditional risk assessment methods rely on subjective, single-moment observations, often missing evolving risks. This study introduces workwear-integrated sensors for continuous, objective ergonomic risk monitoring without requiring visual inspections.

- Firstly, the workwear integrated sensor system's accuracy was verified using a camera-based optical measurement technique built with readily available hardware and software. Repeatability and reproducibility analyses confirmed acceptable reliability. Angular errors were measured within  $5.1^\circ$  (upper arm) and  $8.7^\circ$  (lower arm), translating to spatial distance errors of 3.5 cm MAE horizontal distance (max 9 cm) and 4.2 cm MAE vertical distance (max 13 cm). These results demonstrate the system's capability to reliably classify ergonomic risk boundaries.
- Secondly, the system's feasibility for continuous MSD risk assessment using HSE MAC guidance and cumulative risk estimation using a fatigue failure-based model was explored.
- Thirdly, the system was deployed in three distinct manual-handling tasks in the rail sector, confirming its practical applicability in real-world environments. The workwear-integrated sensor system enables proactive, data-driven risk mitigation. Insights can guide targeted interventions, such as task redesign, equipment modifications, and tailored training, work shift redesign supporting the reduction of manual handling risks to ALARP levels.

The findings support the potential of workwear-integrated sensors as a scalable, quantitative tool for MSD risk assessment in complex, dynamic work environments.

## Outlook

Workwear-integrated sensors offer significant potential for MSD risk assessment, but broader adoption requires further development. Technologically, long-term validation over entire work shifts is necessary to assess sensor durability, accuracy over time, and practical considerations such as battery life, data transmission, and ease of deployment. Further refinements in sensor algorithms and integration with existing digital safety infrastructures could enhance usability. From a workforce perspective, ensuring comfort, usability, and minimal disruption to daily tasks is essential for staff acceptance. Transparent data protection policies must address privacy concerns, particularly around individual performance monitoring and data ownership. At the organizational level, seamless integration with existing H&S protocols is crucial. Demonstrating tangible benefits—such as injury reduction, improved work planning, and cost savings—will strengthen the business case for adoption. Additionally, cultural factors play a vital role; fostering a workplace environment that prioritizes ergonomic risk management and proactive safety interventions is necessary for sustained implementation. Collaboration between industry stakeholders, regulatory bodies, and technology providers can drive standardization and ensure that sensor-based risk assessments align with evolving occupational health frameworks. With further validation and integration, workwear-integrated sensors have the potential to revolutionize MSD risk management, offering real-time, data-driven insights that enable targeted interventions and long-term workforce protection.

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