National Safety Council

Solutions Lab
an nsc program

Research to Solutions:

Findings from the MSD Solutions Lab Grant Program 2024-2025

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Introduction

Musculoskeletal disorders (MSDs) affect a quarter of the global population and continually represent the largest category of workplace injury. MSDs impact the muscles, nerves, tendons, joints, cartilage and spinal discs and typically result from common workplace risk factors such as forceful exertions, awkward or static postures, and repetitive movements. When the work environment or job tasks cause, worsen or extend these conditions, they are classified as work-related MSDs. According to the **Liberty Mutual Workplace Safety Index**, for the past 25 years, MSDs have cost employers billions of dollars annually in lost productivity, workers' compensation, absenteeism, presenteeism, turnover and recruitment challenges. These disorders are also the leading causes of disability, involuntary retirement and limitations to gainful employment. Moreover, low-wage workers and communities of color disproportionately occupy jobs with greater MSD risk, often having little control over their work environments (Seabury et al., 2017; Mulcahy et al., 2020). In addition to being a good business investment, MSD risk reduction efforts contribute to a more equitable workplace (National Safety Council, 2024).

To address this critical issue, the MSD Solutions Lab was established in 2021 as a strategic initiative to engage key stakeholders, conduct research, identify new technologies, support innovative solutions and scale the results so that all workplaces can benefit. The lab operates under four pillars:

- **Engage:** Meaningfully engage employers, workers, researchers, and innovators.
- **Research:** Conduct impactful, practical research, analyze data, and disseminate insights across industries.
- **Solve:** Identify, pilot, scale and promote unique solutions.
- **Amplify:** Create a global effort to engage operations and safety leaders across all industries.

The lab developed many activities across all four pillars, including the Research to Solutions and MSD Solutions Pilot grants, which are key aspects of the Solve pillar. These grant programs are designed to increase collaboration among academic institutions, businesses, industries and emerging technology providers to mitigate MSDs. The goal of the Research to Solutions grant program is to develop, evaluate and/or disseminate effective solutions for MSDs, focusing on occupational injury risk reduction.

MSD Solutions Lab Research to Solutions Grant Program Overview

The 2024-2025 Research to Solutions grant program awarded up to $50,000 to projects focusing on specific priority research areas:

- **Emerging technologies for risk assessment and mitigation:** Examples include leveraging computer vision, machine learning, natural language processing, smart sensors, exoskeletons and exosuits, robotics (including collaborative and service), augmented/virtual and mixed reality, digital twins, and automation in addressing issues of musculoskeletal health and disorders.
- **Legacy MSD high-risk jobs or tasks:** Examples include solutions to jobs or tasks known to have high MSD risk but for which there is insufficient evidence regarding methods to sufficiently mitigate the risk. These can come from any industry sector, including health care and social assistance, retail trade, manufacturing, transportation and warehousing, and construction.
- **Future of work:** Examples include the role of non-traditional work (e.g., hybrid, work from anywhere, remote and gig work), demographic shifts (aging, sex/gender, racial inequalities, obesity, and social determinants of musculoskeletal health and disorders) and the role of COVID-19 on musculoskeletal health and disorders.
- **MSD management systems:** Examples include systems that incorporate or could be integrated with MSD solution strategies, emphasize the hierarchy of controls to "design out" hazards and risk using Prevention through Design, and integrate ergonomics with process optimization through Modular Arrangement of Predetermined Time Standards, Methods-Time Measurement and Lean Six Sigma.
- **Worker wellbeing:** Examples include integrating occupational safety and health interventions and worksite health promotion programs addressing musculoskeletal health and disorders.

Faculty members at academic institutions, graduate students, post-doctoral fellows, and organizations pursuing or developing unique solutions in one or more priority areas were invited to submit proposals. A review committee consisting of internal National Safety Council research staff, volunteers from the MSD Solutions Lab advisory council, external research experts and past grant recipients evaluated each proposal and scored each proposal based on the following criteria:

- **Scientific Importance/Relevance to Priority Area:** Does the proposal address an important scientific, technical or practical question? Will the potential findings substantially add to understanding the priority area investigated?
- **Significance of Research/Field Knowledge:** Is the project original and innovative? Will the proposed work develop, test and evaluate a new methodology or solution? Will the proposed work demonstrate a strong understanding of the area of inquiry and the underlying scientific issues? Will the proposed work make a clear case for how the research fits into the larger context of the issue under consideration for the study?
- **Approach:** Are the variables and controls clearly defined for the study design, if relevant? Are correct quantitative/qualitative measures utilized for evaluating potential research outcomes? Are proper data/statistical analyses described, if relevant?
- **Impact of Work:** Does the proposal clearly state the strategies for MSD prevention and solution development so they can be easily implemented? Can claims of the uniqueness of the proposal or additions to the existing solutions be justified? Can this solution be transferable to other similar industries?
- **Dissemination of Findings and Budget Logistics:** Does the proposal document sharing findings through virtual MSD Solutions Lab symposium or presentations at NSC events, research papers, and knowledge transfer documentation? Is the budget justified and itemized appropriately?

Upon completion of the grant, grant recipients were expected to present their findings at NSC Safety Congress & Expo.

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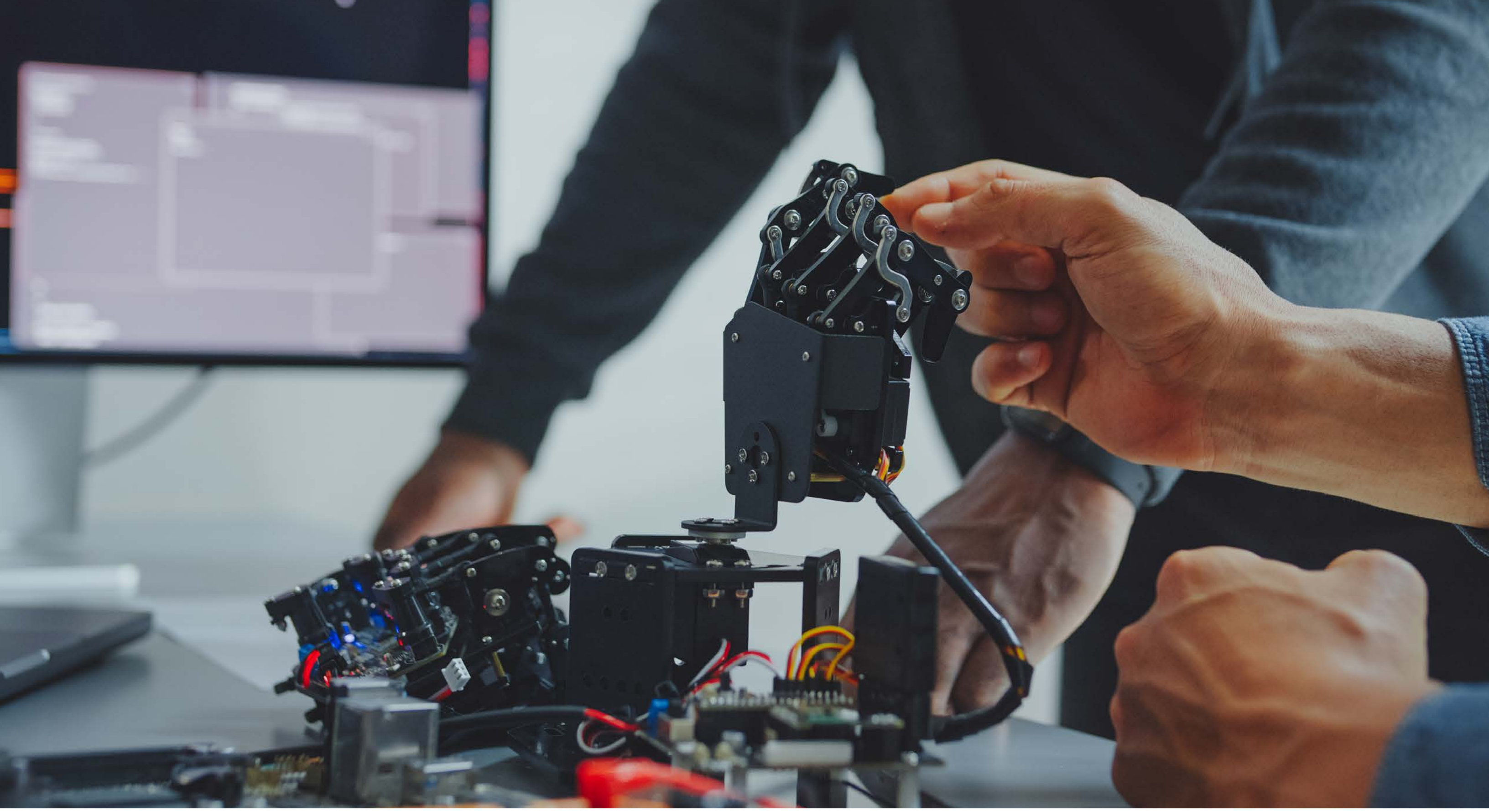


Brief Description of Projects for 2024-2025

North Carolina State University (Raleigh, NC): Awarded $49,999 to explore how mobile-based augmented reality, paired with sensor technology, can support real-time visualization of recommended reach and work zones to help assess and correct object placement in the workplace.

Wichita State University (Wichita, KS): Awarded $48,467 to assess the feasibility of arm support exoskeletons for overhead construction tasks, evaluating their impact on musculoskeletal health, worker perceptions and practical usage intentions.

Oregon State University (Corvallis, OR): Awarded $49,999 to develop a noninvasive biomechanical assessment tool for estimating lower-back injury risk in real-world settings by adapting and evaluating an open-source markerless motion capture system.

Virginia Tech (Blacksburg, VA): Awarded $50,000 to investigate algorithmic biases in machine learning- and artificial intelligence-based biomechanical exposure assessments across diverse worker populations and to develop mitigation strategies that promote fair and equitable use of wearable sensing systems by practitioners.

The following sections present an overview of each Research to Solutions project and provide a more detailed discussion of the problems being solved, project aims, study methods, accomplishments and lessons learned. This report serves as a resource for safety professionals, offering invaluable insights into the challenges and benefits of rigorous research-based solutions for mitigating risk for MSDs. Furthermore, the report can be used to better understand how to leverage these innovative solutions, ultimately improving worker safety, health and wellbeing.

Develop and Evaluate Augmented Reality-Based Workplace Reach Zone Visualization and Optimization Tool – North Carolina State University

What's the Problem?

Manufacturing and warehouse workers frequently perform tasks requiring awkward postures and repetitive motions, particularly of the upper extremities and lower back, leading to work-related MSDs. A primary driver of these injuries is working outside recommended ergonomic guidelines for vertical height and horizontal reach, which forces workers to unnecessarily extend or bend their trunks. Despite this, many employers remain unaware of established workplace design guidance or lack practical tools to help their employees quickly assess and correct ergonomic risks at their workstations.

Traditional training methods and paper-based ergonomic guidelines have shown limited effectiveness in addressing these challenges. With the rise of Industry 4.0, emerging technologies offer an opportunity to deliver low-cost, immersive and personalized approaches to applying work design guidelines in real time. Augmented reality (AR), which overlays computer-generated information onto the physical environment, is particularly well-suited for this purpose. AR has demonstrated success in workplace training and ergonomic guidance, including procedural support and safe posture instruction, by aligning virtual content with physical surroundings to improve learners' motivation, comprehension and retention.

Project Aims

This project aims to develop and evaluate an AR reach zone visualization tool capable of displaying acceptable and unacceptable reach zones in 3D, overlaid on the physical environment in real time. Two specific objectives guide the delivery of this tool:

- Develop a functional AR tool that visualizes ergonomic reach zones, validated through ergonomics practitioner feedback in a lab setting
- Evaluate its real-world usability and acceptance by deploying it across three manufacturing and/or warehousing facilities with end users in actual work environments

Research Methodology

This study accomplished two major activities:

Application development: The research team developed an AR application using Unity (v2022 LTS, Unity Technologies, San Francisco, CA), a widely used game engine that can render visual content across a variety of virtual reality (VR) and AR platforms. The app is compatible with a range of supported devices and, for this project, was run on the Meta Quest 3 (Meta Platforms Inc., Menlo Park, CA), a headset capable of delivering both VR and AR experiences.

The app's content was built around ergonomic guidelines provided by The Ergonomics Center of North Carolina. Its main feature displays semitransparent 3D hemispheres representing primary, secondary and undesirable reach zones, overlaid onto the user's actual physical environment in real time (Figure 1). These zones are based on how far a person can comfortably reach while standing or sitting, allowing the tool to reflect realistic work conditions across common workplace settings. Early feedback from ergonomics practitioners helped shape key improvements to the app, such as adding a view reset function and the ability to switch between standing and seated posture modes. These refinements laid the groundwork for subsequent development.

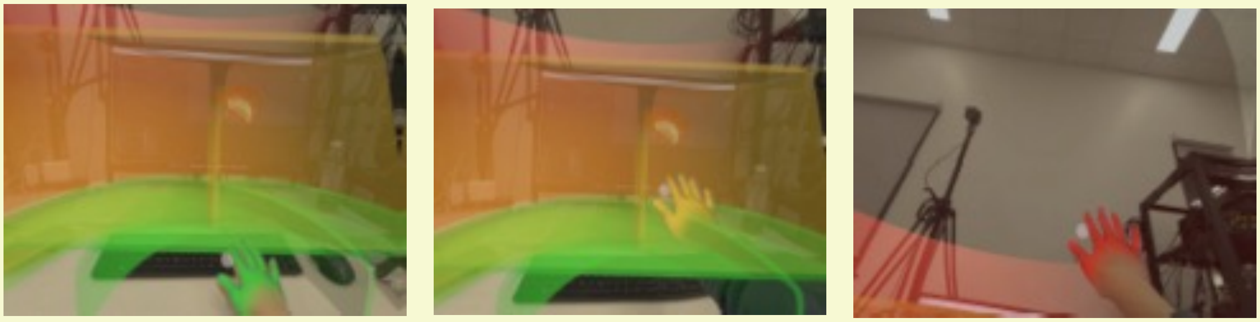


Figure 1. *Primary (left), secondary (middle) and undesirable (right) reach zones visualized in the AR reach zone app. A user's hand changes color from green to yellow to red, indicating the desired and undesired reach zones.*

Usability evaluation: To evaluate the AR tool in real-world settings, the team brought the complete app, installed on a Meta Quest 3, to three different client sites of The Ergonomics Center of North Carolina. This allowed the researchers to gather hands-on performance data and direct feedback from 20 actual target users in their own work environments. The three sites represented a diverse range of industries: a corporate office for an agricultural machinery manufacturer, a manufacturing facility for public transportation infrastructure and a production site for a multinational pharmaceutical company. Data collection took place across these sites over a period of approximately two months.

Following the completion of field data collection, the team analyzed all usability data gathered across the three study sites to draw meaningful conclusions about the AR tool's performance and user experience.

Results and Lessons Learned

All results were drawn from data collected during the in-field usability evaluation sessions. The evaluation aimed to (1) examine user performance in terms of task completion time, which suggested how well users utilized the AR reach zone tool; (2) quantitatively examine the perceived usability of the tool using a validated questionnaire; and (3) understand overall perception of the tool's practicality in real workplace settings. In addition, users were encouraged to "think aloud" while using the AR reach zone tool, verbally describing what they were doing and thinking and any confusion or expectations. This data was used solely to understand why some participants took longer to complete tasks and was not typically reported as an outcome measure.

User performance was measured by how long it took participants to complete specific tool functions, or "tasks." For example, one task asked participants the following: "How would you reposition the tool using the drag and drop feature?" Overall, users completed tasks quickly – the average completion time for any given task was under one minute, with the fastest task averaging 9.04 seconds and the longest averaging 40.8 seconds (Figure 2).

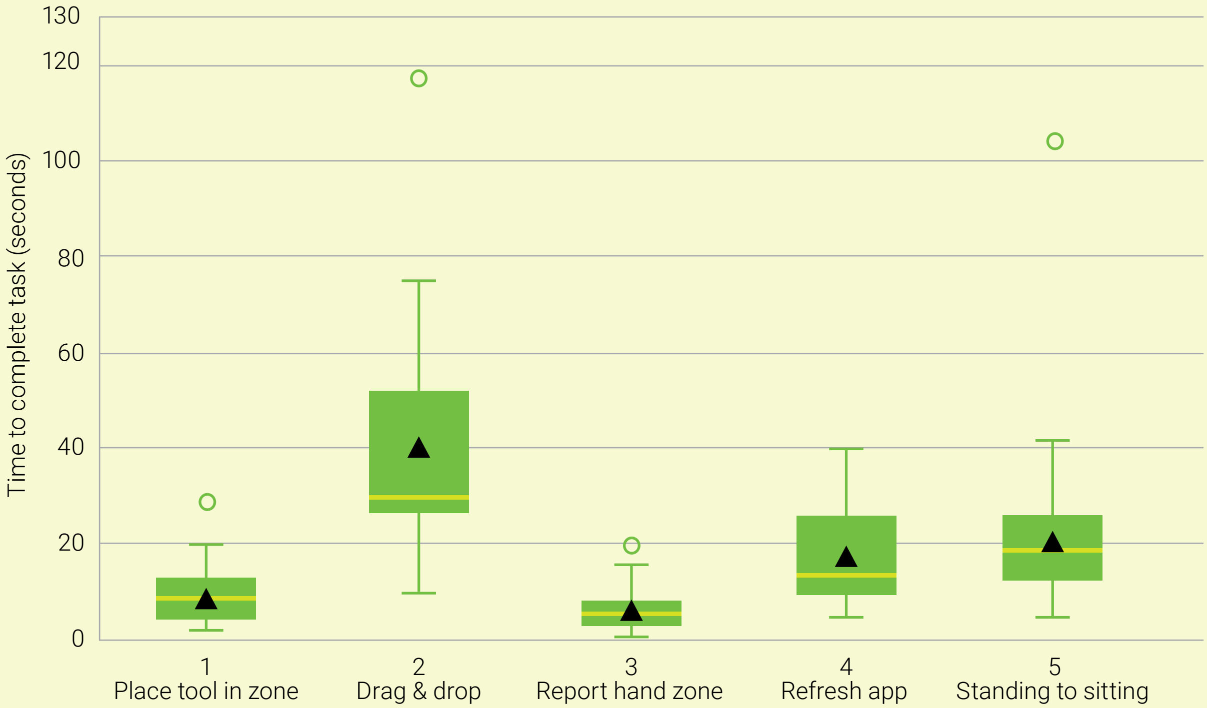
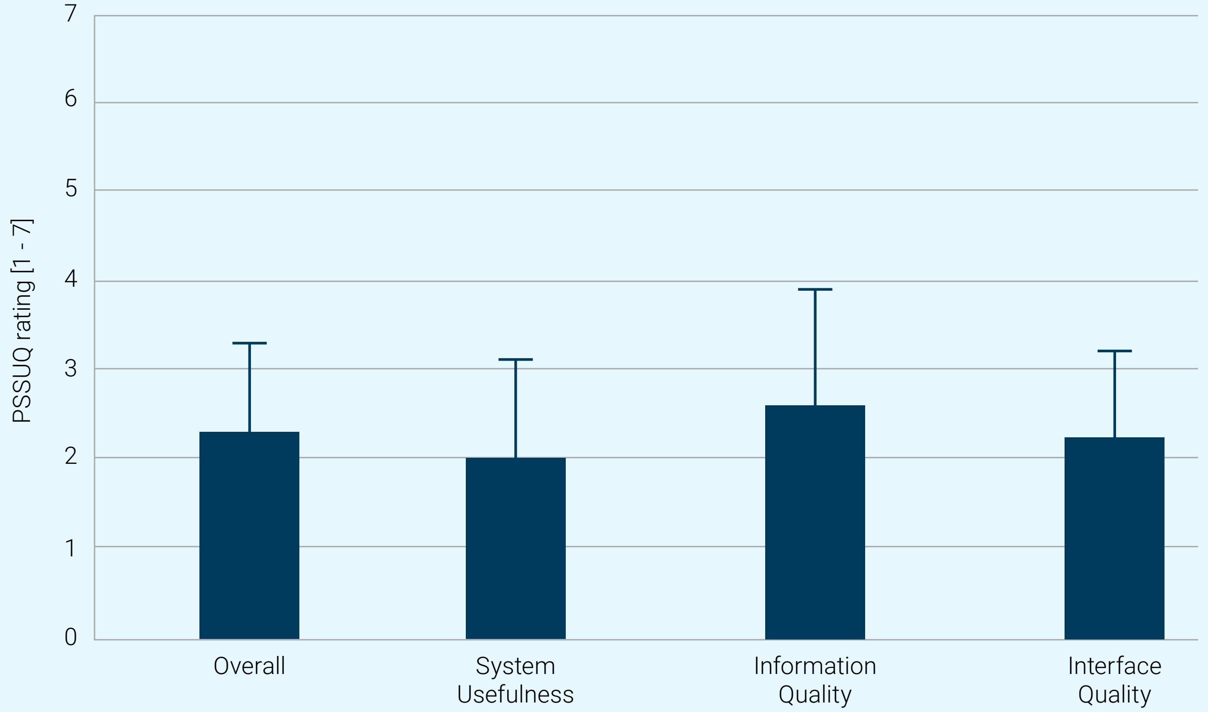


Figure 2. *Task completion time (seconds). Task 1 was to place a tool in the riskiest reach zone. Task 2 was to reposition the tool using the drag-and-drop feature. Task 3 was to determine and report the current hand placement with respect to the reach zone. Task 4 was to show how to refresh the app. Task 5 was to change the view from a standing to a sitting posture. Boxes represent the interquartile range with median lines; whiskers indicate the range, and triangle markers denote the mean. Outliers are shown as individual points.*

Perceived usability was measured using the Post-Study System Usability Questionnaire (PSSUQ), a validated usability assessment tool. Results were encouraging, as participants generally rated the tool favorably, with most responses falling between 1 (strongly agree) and 3 (somewhat agree) on a 7-point Likert scale across usability items, indicating a satisfactory overall user experience (Figure 3).



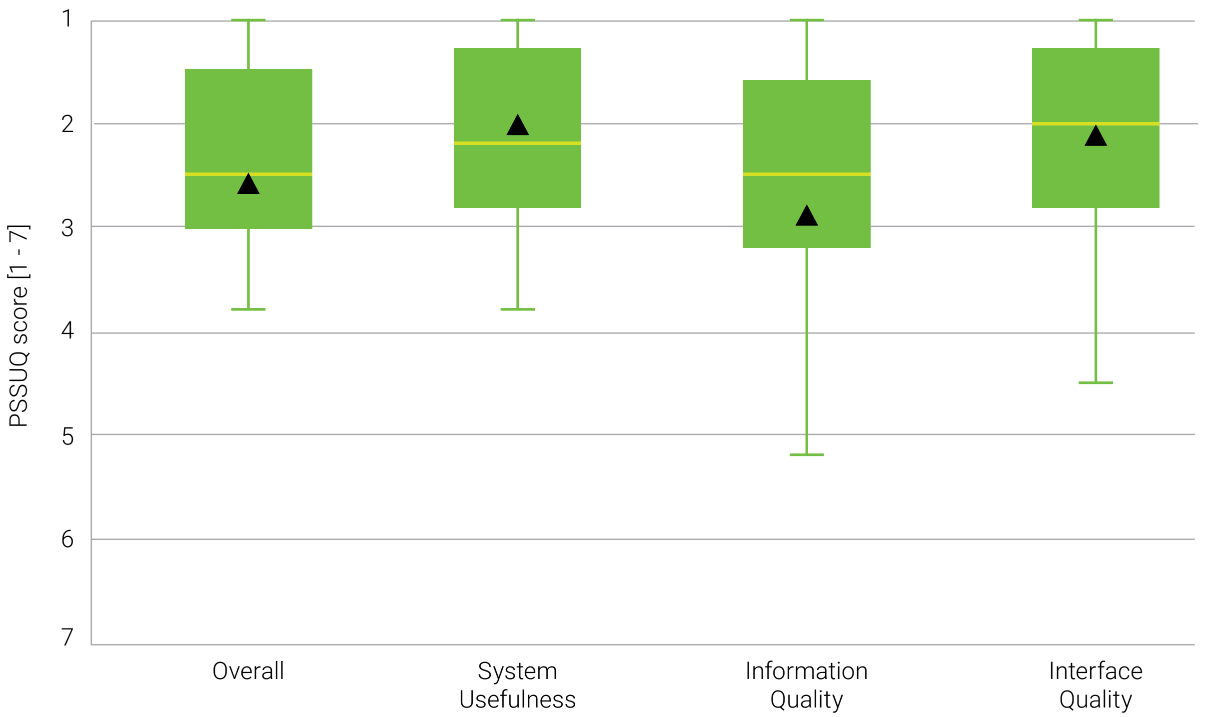


Figure 3. *Distribution of Post-Study System Usability Questionnaire scores across overall usability, system usefulness, information quality and interface quality. Boxes show the interquartile range with median lines; whiskers indicate the range, and triangle markers denote the mean. Scores are reported on a 1-7 Likert scale (1 = strongly agree, 7 = strongly disagree), with lower values indicating more favorable perceived usability.*

Participants' **perceptions and practicality** were gathered through semi-structured interviews conducted at the end of each usability evaluation session. Overall, feedback was positive and constructive. Participants found the color-coded reach zones – green, yellow and red – intuitive and easy to understand, using them naturally to evaluate the risk levels associated with different work postures. In terms of practicality, participants felt the tool was best suited for targeted use cases, such as onboarding new employees or setting up new workstations, rather than everyday use on the shop floor. Despite this, participants expressed a willingness to recommend the tool to others, reflecting a generally favorable impression of its value in the right context.

Overall, a fully developed AR reach zone visualization tool gives workers an intuitive way to assess ergonomic risk in their reach postures. Beyond the tool itself, usability evaluation with target users provided valuable real-world feedback that affirmed both the tool's usability and its potential practical value, including new-hire onboarding and training, as well as occasional workstation ergonomics reassessment.

Research Study 2:

Field Assessment of Passive Arm-Support Exoskeletons on Musculoskeletal Health in Overhead Construction Tasks – Wichita State University

What's the Problem?

Shoulder MSDs, including rotator cuff tendinitis and bicipital tendinitis, are a significant source of lost work time and medical costs in construction. Sustained or repeated arm elevation and working with elbows above shoulder height are well-established risk factors for MSDs. While reducing overhead work and limiting elevated arm exposure are effective interventions, they are often not feasible in construction, where the nature and location of many tasks make overhead work unavoidable.

Passive arm-support exoskeletons, which mechanically support the arms to reduce shoulder muscle loading, have shown promise in laboratory settings. However, the majority of industrial exoskeleton research has been conducted in laboratory settings simulating workplace tasks, with limited investigation of their effectiveness in actual work environments. This gap between controlled lab findings and actual field conditions is a core problem because without field evidence, the feasibility and practical value of arm-support exoskeletons (ASEs) for construction workers remains unknown.

Project Aims

This research aims to evaluate the feasibility of arm-support exoskeletons for overhead construction tasks through three objectives:

- Identify tasks in different construction trades that may be suitable for ASE use
- Determine worker perceptions on ASE usability and future intention of ASE use
- Assess the impact of ASE use on musculoskeletal discomfort, shoulder strength and musculoskeletal joint mobility after using the ASE

Research Methodology

Construction workers from multiple trades were recruited to use an ASE (Hilti EXO-S; Hilti, Plano, TX) for up to three weeks, providing feedback on its practical use across different construction tasks.

Aim 1: Eight workers from four construction trades – drywall (residential and commercial), plumbers-pipefitters, sheet metal and electricians – were observed onsite while utilizing the ASE (Figure 4). Trade-specific tasks were also documented and compiled using O*NET[1]. Participants were then surveyed on the helpfulness of these tasks for ASE use using a 5-point Likert scale (1 = not helpful, 5 = extremely helpful), with tasks rated above 3 being considered more than moderately helpful.

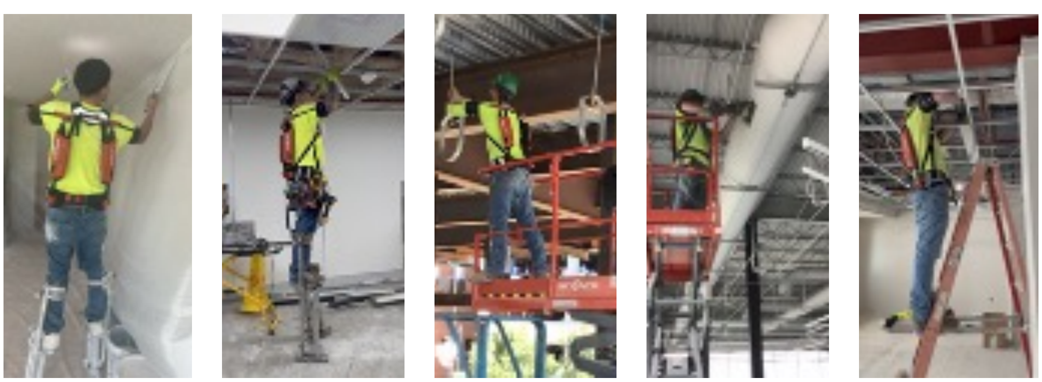


Figure 4. *Trade-specific tasks performed using an arm-support exoskeleton: (a) residential drywall, finishing ceiling (knock down); (b) commercial drywall, installing ceiling grid; (c) plumber-pipefitter, installing hangers in ceiling; (d) sheet metal, sawing/cutting register opening; and (e) electrician, installing light fixtures.*

[1] O*NET (Occupational Information Network) is the U.S. Department of Labor's primary comprehensive database of occupational information describing jobs in terms of required knowledge, skills, abilities, tasks, work activities and work context.

Aim 2: Eight participants were surveyed on ASE usability following the intervention period. The survey assessed three categories – comfort and movement, performance of tasks, and ease of exoskeleton usage – using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). An additional question assessed participants' future intention to use the ASE, rated on a separate 5-point scale (1 = definitely not, 5 = very much/definitely yes).

Aim 3: Musculoskeletal health was assessed from baseline to the end of the ASE intervention by measuring three outcomes: body part discomfort, shoulder strength and joint mobility. Discomfort was evaluated using the Cornell Musculoskeletal Discomfort Questionnaire, which accounts for discomfort magnitude, frequency and interference with work. Shoulder flexion and abduction strength were measured at 90 degrees using a push-pull dynamometer. Shoulder and mid-back joint mobility were assessed using a DARI markerless motion capture system (DARI Motion, Overland Park, KS), during which participants performed a series of shoulder and torso movements.

Results and Lessons Learned

Aim 1 Outcome: Table 1 provides detailed ratings for various trades. Briefly, for drywall workers, overhead and ceiling-level tasks were consistently rated as tasks for which an ASE was "more than moderately helpful", including sanding ceiling details, painting ceilings, installing ceiling drywall, and finishing drywall. Commercial drywall workers also rated ASEs for ceiling grid installation, soffit installation and framing bulkheads as "more than moderately helpful", while rating ASEs for tasks at lower heights, such as sanding walls or masking walls, as "moderately helpful" to "not helpful."

For plumbers-pipefitters, tasks considered "more than moderately helpful" for ASE use included operating heavy tools overhead, racking and joining pipe, installing hangers in ceilings, and unloading and carrying pipe. ASEs for tasks performed at lower heights or ground level, such as installing underground piping systems or piping layout and planning, were rated as "moderately helpful" to "not helpful."

For sheet metal workers, tasks considered "more than moderately helpful" for ASE use included sealing ducts, operating heavy tools overhead, setting anchors overhead with a hammer drill, and cutting and installing register grilles and boxes. ASEs for tasks such as fabricating and altering parts – which typically occur at lower work heights – were rated lower for helpfulness.

For electricians, tasks considered "more than moderately helpful" for ASE use included drilling holes overhead and installing and mounting light fixtures, while pulling wire overhead and installing electrical conduits overhead were rated as only "moderately helpful" to "not helpful."

Table 1. *Trade-specific tasks rated more than moderately helpful (>3 on survey Likert scale) and moderately or not helpful (≤3 on survey Likert scale) for the use of arm-support exoskeletons.*

Trade: Drywall – Residential	
Use of ASE for Tasks Rated More than Moderately Helpful:	**Use of ASE for Tasks Rated Moderately Helpful to Not Helpful:**
• Ceiling detail sanding (block or pole) • High-detail sanding • Painting ceilings • Installing ceiling drywall • Finishing drywall (taping, mudding, sanding)	• Masking walls • Texturing ceilings • Applying plaster/gypsum to ceilings • Sanding walls • Operating heavy tools overhead (sanders, screw guns) • Low-detail sanding • Overhead drywall demolition
Trade: Drywall – Commercial	
Use of ASE for Tasks Rated More than Moderately Helpful:	**Use of ASE for Tasks Rated Moderately Helpful to Not Helpful:**
• Operating heavy tools overhead (sanders, screw guns) • Overhead drywall demolition • Ceiling grid installation • Soffit installation • Framing bulkheads or ceilings • Installing ceiling drywall • Finishing drywall (taping, mudding, sanding)	• Painting ceilings • Applying plaster/gypsum to ceilings
Trade: Plumbers-Pipefitters	
Use of ASE for Tasks Rated More than Moderately Helpful:	**Use of ASE for Tasks Rated Moderately Helpful to Not Helpful:**
• Operating heavy tools overhead • Racking pipe • Joining pipe • Unloading/carrying pipe • Installing hangers in ceilings	• Installing closure clamps • Cutting, threading and hammering pipe to specifications • Unloading/carrying materials (nuts, bolts, fixtures, clamps, etc.) • Installing risers (vertical pipe) • Piping layout/planning • Installing underground piping systems
Trade: Sheet Metal	
Use of ASE for Tasks Rated More than Moderately Helpful:	**Use of ASE for Tasks Rated Moderately Helpful to Not Helpful:**
• Sealing ducts • Operating heavy tools overhead • Fastening seams or joints together (bolts, caulking, etc.) • Setting anchors overhead (hammer drill) • Cutting/installing register grills and boxes • Installing flex ducts	• Drilling to screw sheet metal • Fabricating/altering parts using shears, hammers, punches and drills • Connecting HVAC systems to ceiling units • Installing overhead HVAC ductwork
Trade: Electrician	
Use of ASE for Tasks Rated More than Moderately Helpful:	**Use of ASE for Tasks Rated Moderately Helpful to Not Helpful:**
• Drilling holes overhead • Installing and mounting light fixtures	• Pulling wire overhead • Installing electrical conduits overhead

Collectively, results across all trades showed a clear and consistent preference for ASE use during overhead and ceiling-level tasks, while ASE use for mid-to-lower-height tasks was generally rated as less helpful. These findings offer practical guidance for construction companies seeking to identify where ASEs may provide the greatest benefit in their operations.

Aim 2 Outcome: Figure 5 indicates general agreement that the ASE reduced work-related fatigue, was comfortable during joint movements, and could be used safely without risk of cuts or injuries from contact points. Figure 6 shows general agreement that the ASE helped participants perform their tasks and that work was easy to perform while wearing the ASE.

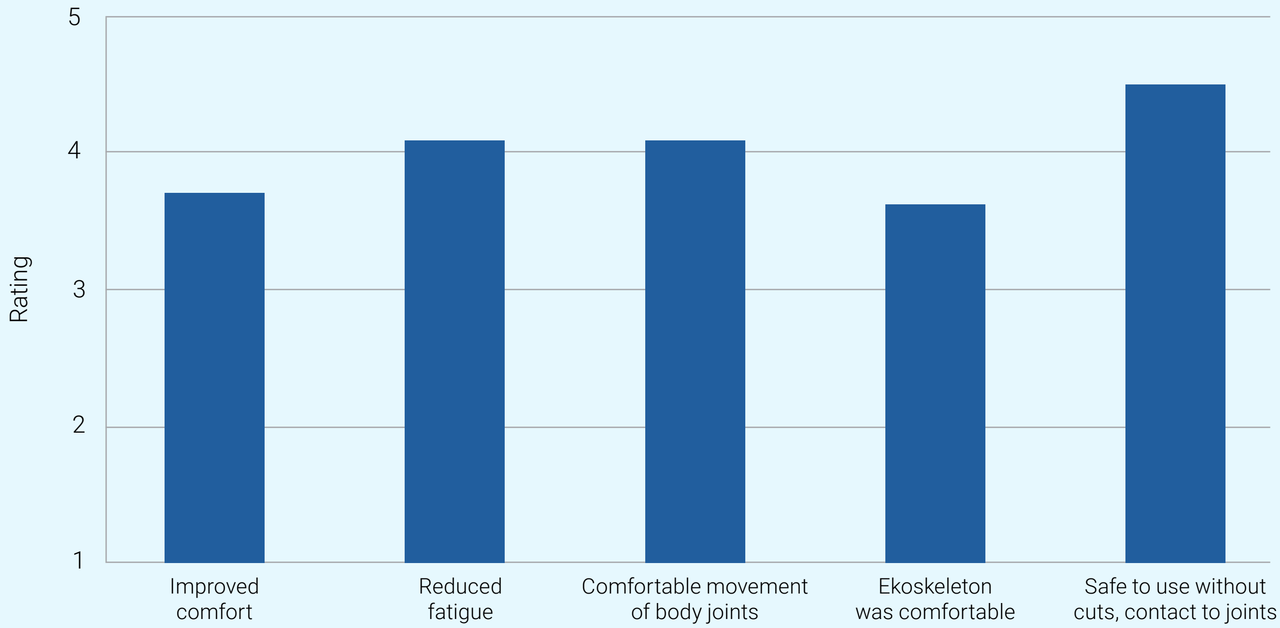


Figure 5. *Mean ratings related to comfort and movement of the arm-support exoskeleton*

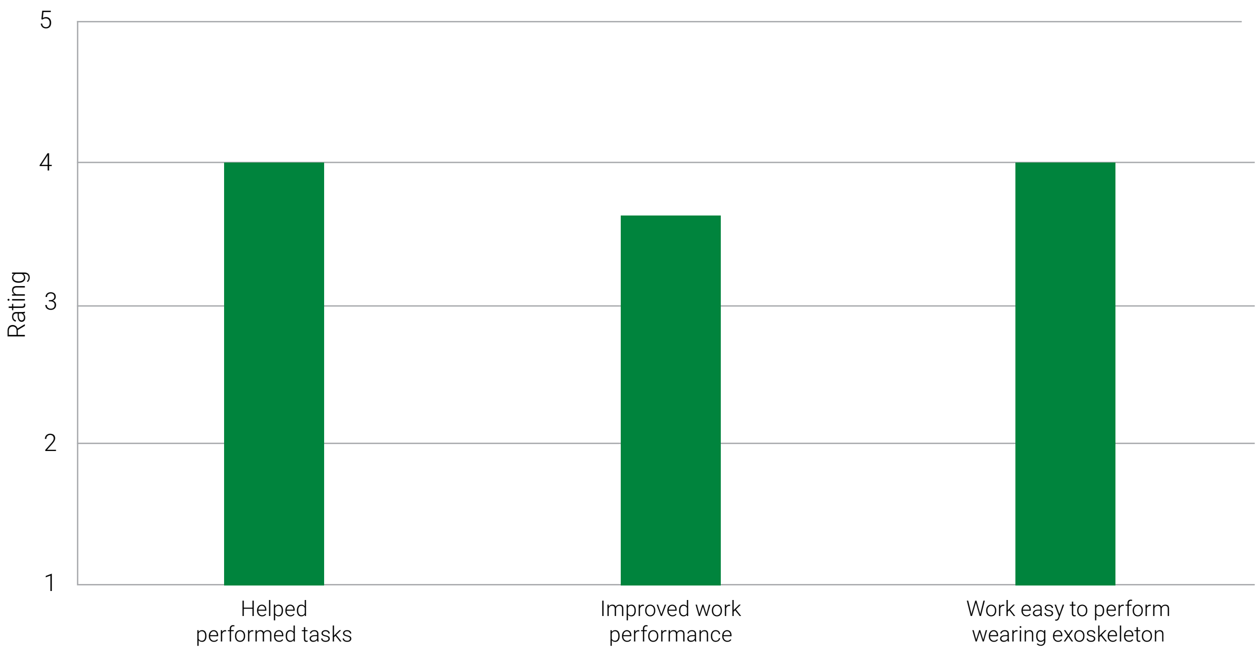


Figure 6. *Mean ratings related to performance of tasks using the arm-support exoskeleton*

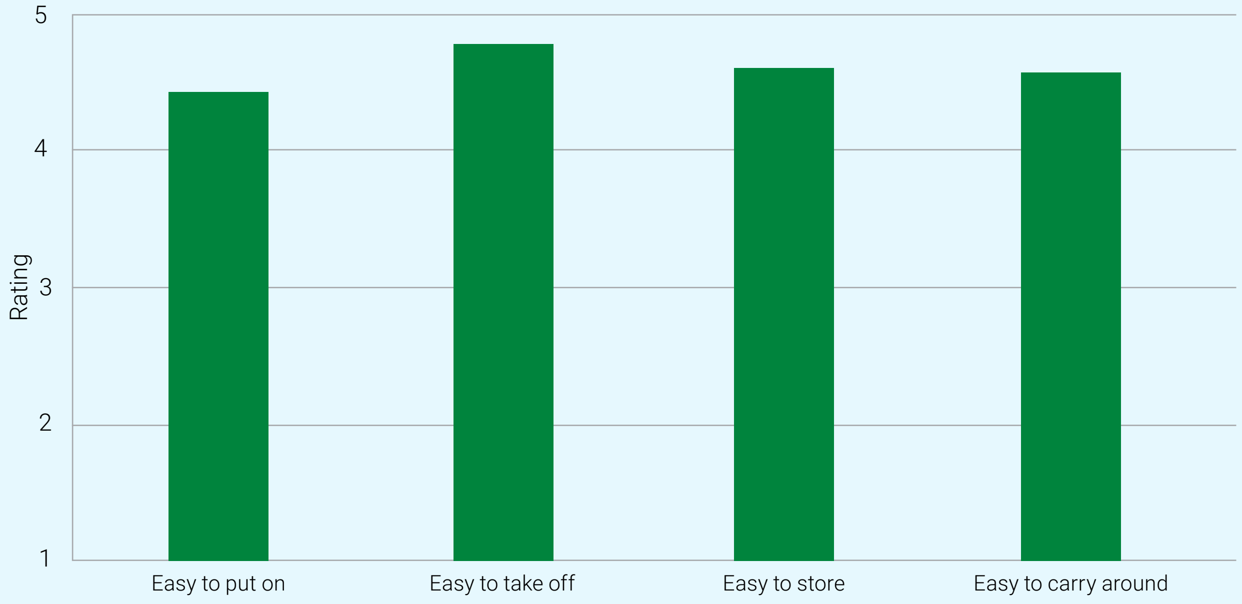


Figure 7. *Mean ratings related to arm-support exoskeleton ease of use*

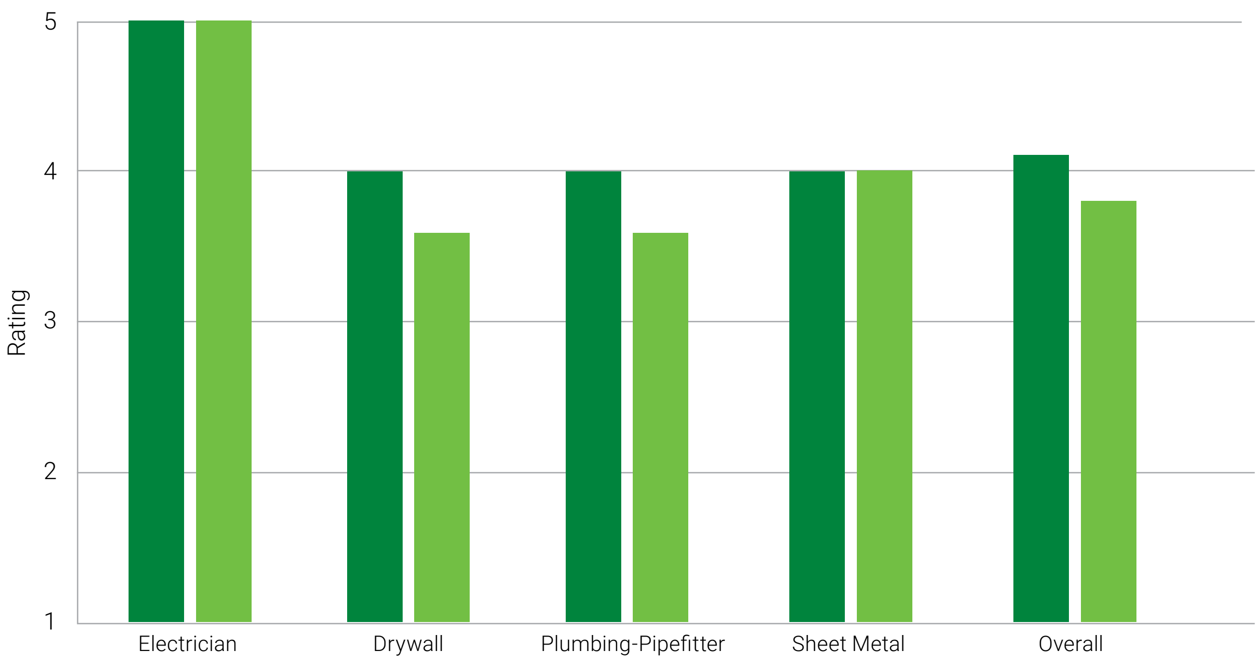


Figure 8. *Mean ratings of future intention to use the arm-support exoskeleton as a function of trade and overall*

Figure 7 shows agreement that the ASE was easy to put on, take off, store and carry around. Figure 8 shows that participants "moderately" to "very much/definitely yes" intended to use the ASE in the future, and there was very little change in the participants' intentions for future ASE use over the course of the study (*$p > 0.05$*).

Collectively, it appears that participants generally agreed that the ASE was comfortable to use, helpful with some tasks and easy to utilize, and their intention for future use did not change over the course of the intervention period.

Aim 3 Outcome: As shown in Figure 9, there was no change in the body part discomfort index (final week score minus baseline score) for any body part ($p > 0.05$ for all body parts). There was also no significant difference in shoulder strength measures from baseline to end of ASE use (Figure 10; $p > 0.05$ for all strengths), nor was there any change in shoulder or mid-back joint mobility performance (Figure 11; $p > 0.05$ for all body joints).

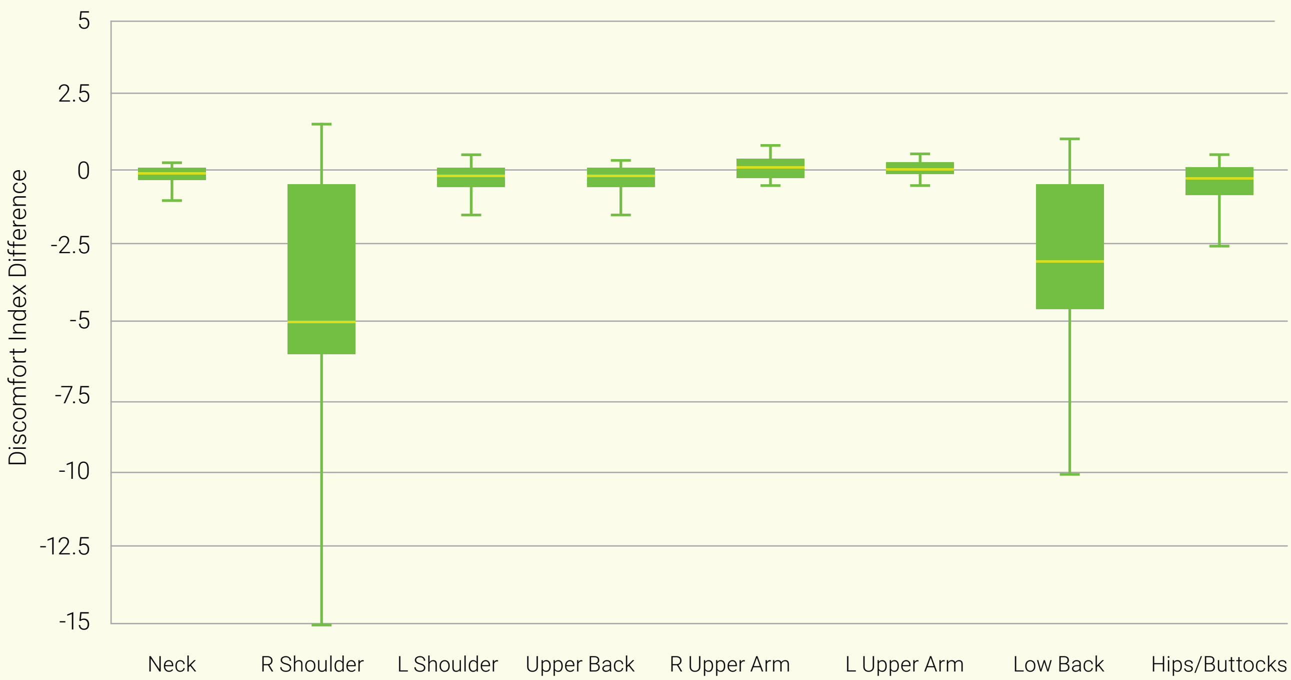


Figure 9. *Mean change in body part discomfort index (baseline index score subtracted from the final index score; n = 8)*

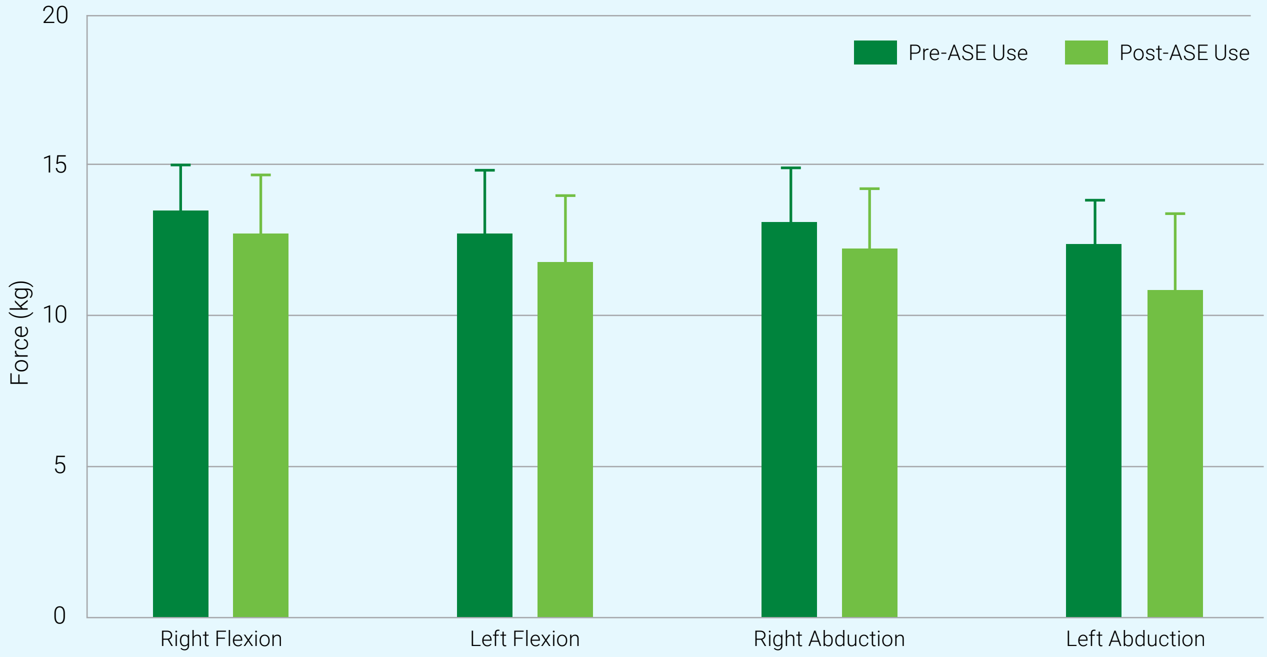


Figure 10. *Mean shoulder flexion/abduction strength, pre- and post-ASE use (n = 5)*

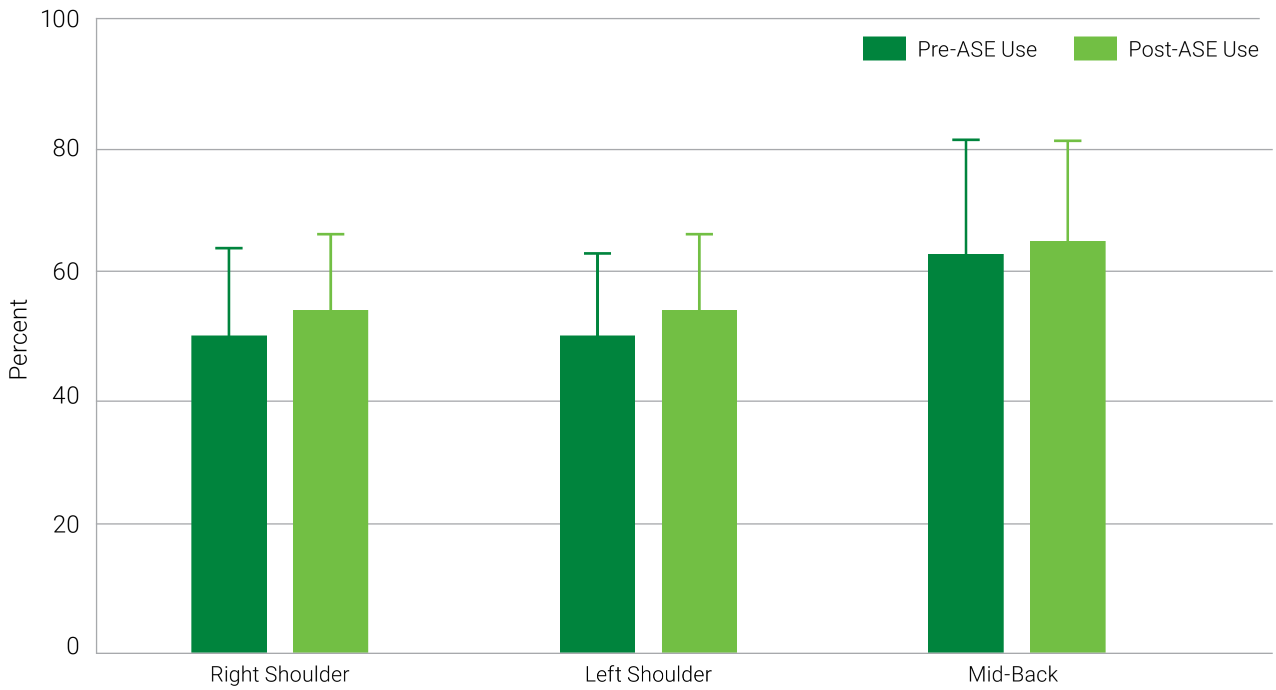


Figure 11. *Mean shoulder and mid-back joint mobility performance, pre- and post-ASE use (n = 5)*

In summary, this study yielded three key findings. First, ASEs were most helpful for construction tasks involving sustained overhead work and heavy tool use, adding to the existing knowledge of trade-specific applications. Second, workers generally perceived ASEs as easy to use, recognized potential performance benefits, and maintained or increased their intention to use ASEs over the intervention period. Third, despite positive perceptions, ASE use showed limited to no measurable improvement in body part discomfort, shoulder strength, or shoulder and upper-back joint mobility over the intervention period.

Research Study 3:

Noninvasive Biomechanical Evaluation of Occupational Lifting Tasks Using Smartphone-Based Markerless Motion Capture and Machine Learning – Oregon State University

What's the Problem?

Overexertion due to manual lifting is a leading cause of work-related lower back injuries, making accurate spinal load measurement essential for injury prevention. The gold-standard approach using 3D motion capture, reflective markers and force plates is effective but costly, intrusive and impractical for real-world workplace settings. As a result, practitioners rely on observational assessment tools, which are limited by assessor bias and poor consistency. Research supports integrating objective biomechanical measures to improve injury risk prediction, highlighting the need for a practical, low-cost and noninvasive alternative.

Markerless computer vision systems have shown promise but remain either too expensive for field use or insufficiently accurate for whole-body movement analysis. OpenCap, an open-source smartphone-based tool combining machine learning pose estimation with musculoskeletal simulation, represents a compelling solution. It has demonstrated acceptable accuracy for lower-body kinematics in simple tasks but has never been validated for complex occupational tasks like lifting. Its musculoskeletal model also lacks trunk and upper-body muscles, limiting full spinal-load estimation. Furthermore, the effects of camera configuration and lifting variables, such as load weight, height and asymmetry, on its accuracy remain unknown. This study addresses these gaps by adapting and evaluating OpenCap for manual lifting assessment, with the goal of establishing a minimally intrusive, affordable and field-ready tool for workplace injury risk assessment.

Project Aims

This project has two specific aims:

- Evaluate the performance of a markerless motion capture system adapted for manual lifting tasks in measuring 3D joint kinematics and assessing the feasibility of predicting spinal loads without reflective markers
- Investigate how lifting conditions, including height, asymmetry angle and load weight, along with camera configuration, affect the accuracy of estimated kinematic and kinetic measures

Research Methodology

A total of 21 healthy adults from the Oregon State University community completed a series of laboratory lifting tasks under varying conditions, including three vertical lifting ranges (low to medium, medium to high and low to high), two asymmetry angles (zero and 30 degrees), two load levels (5 and 10 kg), and two camera configurations (two cameras and three cameras), with two repetitions per condition – yielding 48 trials per participant. Whole-body movement data was simultaneously captured using the markerless OpenCap system (Stanford University, USA), and an eight-camera marker-based motion capture system (Prime 13; Natural Point, Corvallis, OR), while ground reaction forces were recorded via two force plates. The experiment produced a large-scale dataset of 919 lifting sequences across all conditions.

Following data collection, marker-based data was processed in OpenSim to establish ground-truth 3D joint kinematics. The markerless OpenCap platform was then modified for lifting-specific analysis through retraining its deep learning model on the collected dataset, adjusting the marker set, replacing the musculoskeletal model and refining inverse-kinematic settings. Kinematic outputs from both systems were filtered, aligned and time-normalized for joint-by-joint error comparison.

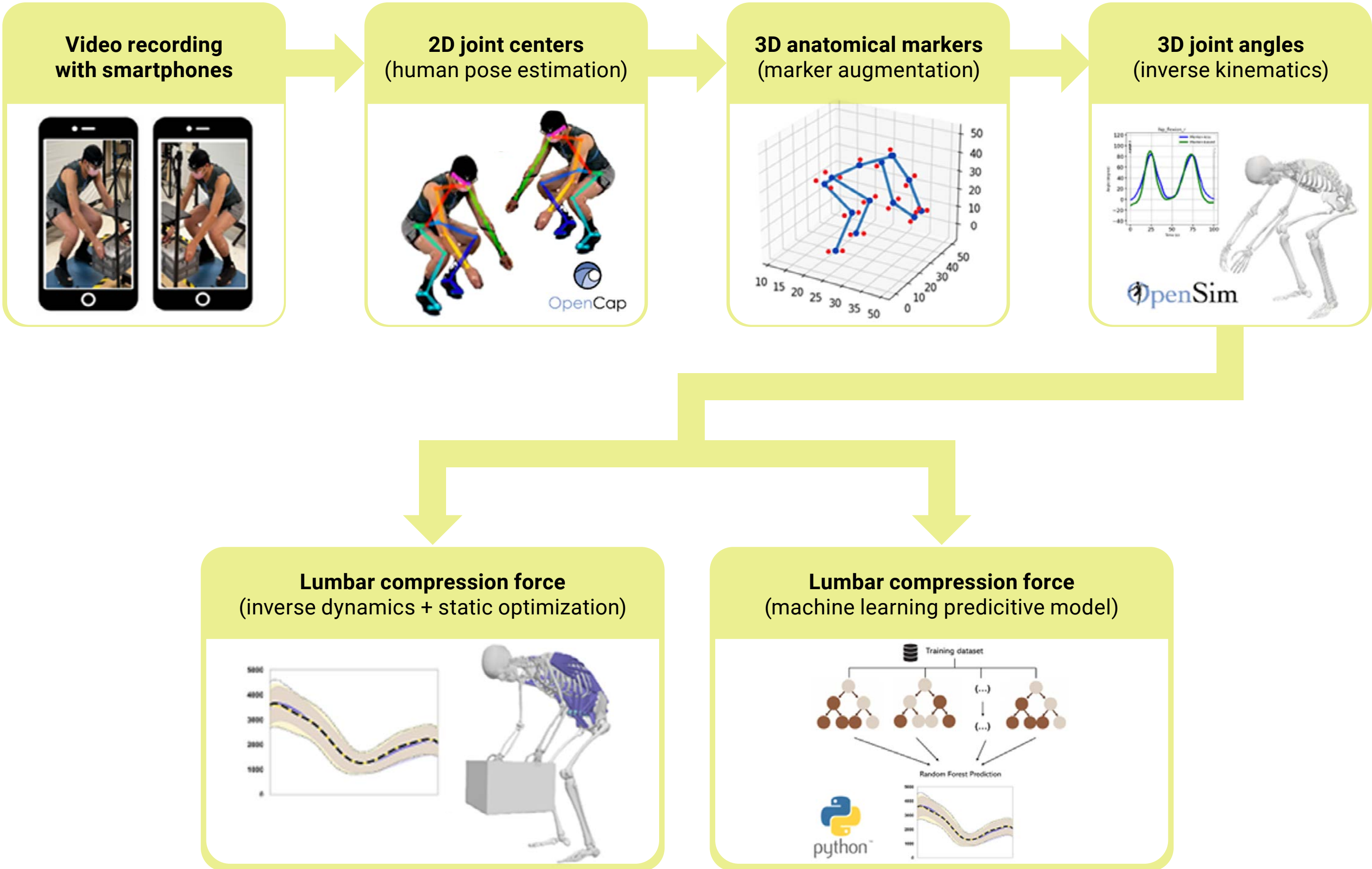


Figure 12. *Overview of the proposed workflow for 3D joint kinematics measurement and lumbar compression force prediction during occupational lifting tasks. Smartphone videos are first processed with a human pose estimation algorithm to extract 2D joint centers, which are then used to estimate the position of 3D anatomical markers using a deep learning–based marker augmentation model. The estimated marker trajectories serve as inputs to inverse kinematics to compute 3D joint kinematics. This kinematic data is subsequently used to predict lumbar compression forces using either conventional musculoskeletal modeling in OpenSim or a machine learning–based predictive model.*

Lumbosacral (L5/S1) compression forces were estimated using both marker-based and markerless kinematic data. Two markerless prediction strategies were tested: a top-down musculoskeletal model relying solely on joint kinematics and external hand forces and a Random Forest machine-learning model trained to predict spinal load directly from anthropometric data, lifted weight, object position, and trunk and knee kinematics – eliminating the need for ground reaction force data or time-consuming simulations (Figure 12).

Kinematic accuracy was assessed using root mean square error (RMSE) across major joints and movement planes, while spinal load prediction accuracy was evaluated using normalized RMSE (nRMSE). Statistical parametric mapping was applied to compare full kinematic and kinetic waveforms across the lifting cycle, and linear mixed-effects models were used to determine how lifting height, asymmetry angle, load weight and camera configuration influenced both kinematic and spinal load prediction errors.

Results and Lessons Learned

Kinematic accuracy of the markerless system varied by anatomical plane and body region, with mean RMSE values of approximately 5 and 8 degrees in the frontal and sagittal planes, respectively, and higher errors in the transverse plane (mean RMSE = 13.9 degrees), particularly in the upper body, likely due to frequent limb occlusion during lifting. Despite these limitations, spinal compression forces were successfully predicted using both musculoskeletal modeling and machine learning, with the machine-learning approach outperforming the musculoskeletal model (nRMSE of 9% vs. 12%), likely reflecting its greater robustness to markerless kinematic inaccuracies. While lifting height and asymmetry angle had statistically significant effects on errors, effect sizes were small, and camera configuration had no significant impact. Overall, the system demonstrated consistent performance across lifting conditions, and adding a third smartphone did not meaningfully improve accuracy over the two-camera setup.

This project demonstrated the potential of OpenCap as an open-source, practical tool for capturing 3D kinematic data during manual lifting tasks, providing a foundation for ergonomics researchers and practitioners to adapt it for task-specific applications. Importantly, it showed that spinal compression force, a key but rarely used injury risk metric due to its laboratory demands, can be estimated with reasonable accuracy by combining markerless kinematics with a machine-learning model, eliminating the need for expensive equipment or specialized modeling expertise. However, future work is needed to validate this approach for more dynamic tasks, realistic workplace conditions and diverse populations, while further refinement of the markerless system is required to address limitations in axial rotation accuracy and occlusion sensitivity.

This work is also explained in more detail in the following publication:

- Salehi, M., Taheri, A., Choi, S., & Kim, J. H. (2026). Evaluation of a markerless motion capture to measure 3D joint kinematics during occupational lifting tasks using mobile devices. Applied Ergonomics, 134, 104743.

Research Study 4:

Contributing to Responsible Artificial Intelligence-Based Biomechanical Exposure Assessment – Virginia Tech

What's the Problem?

Wearable inertial measurement unit–based systems combined with machine learning (ML) and artificial intelligence (AI) algorithms have become increasingly adopted in ergonomics for automated, real-time biomechanical exposure assessment during manual material handling tasks. However, these algorithms assume that worker posture reflects only extrinsic factors such as load and workstation layout, when in reality, posture is also substantially shaped by individual characteristics such as age, sex, strength and anthropometry. This flawed assumption raises serious concerns about algorithmic fairness across diverse worker populations. While bias in ML/AI systems has been studied in other fields, evidence supporting the fairness of these algorithms for biomechanical exposure assessment remains limited. Preliminary findings from research conducted by the investigators of the current study revealed sex-based disparities in hand load estimation that persisted even with balanced training data, suggesting that increasing data diversity alone is insufficient. Proactively identifying the sources of algorithmic bias and developing effective mitigation strategies is therefore critically needed before these tools can be responsibly deployed in workplace risk mitigation applications.

Project Aims

This project has two specific aims:

- Investigate algorithmic biases that may compromise the fairness of ML/AI-based biomechanical exposure assessments across worker populations with diverse demographics and anthropometry
- Develop and evaluate mitigation strategies for building responsible and equitable ML/AI algorithms for biomechanical exposure assessment

Research Methodology

Data was drawn from a previously collected dataset comprising 22 healthy adults (12 males, 10 females; mean age 34.4 ± 10.9 years; BMI 25.1 ± 3.3 kg/m²) with no history of back injury. Participants carried a weighted box along a 24-meter corridor using four occupational carrying methods – right-handed, left-handed, two-handed side and two-handed anterior – at three load levels (4.5, 13.6 and 22.7 kg), with two trials per condition in randomized order. Twelve inertial measurement units (IMUs) (BioStamp nPoint®; MC10 Inc., Lexington, MA, USA) were placed at key anatomical locations across the lower and upper extremities and trunk, recording 3-axis acceleration and angular velocity at 80 Hz.

To prepare the data, gait cycles were identified from continuous IMU signals. Shank sensors placed on the lower legs were used to detect when the heel touched the ground and when the toes lifted off. Each gait cycle was defined as the time from one right-foot heel strike to the next right-foot heel strike (Rahman et al., 2026). Each of the 12 IMU sensors recorded six types of movement – three directions of acceleration and three directions of rotation – resulting in 72 data channels for each walking cycle.

All sensor data was passed through a smoothing filter to remove rapid, noisy fluctuations that could interfere with the analysis, and the recordings were rescaled via linear interpolation to a consistent length of 128 data points each so that all measurements could be directly compared and analyzed together. The resulting dataset comprised 4,046 gait cycles structured into a 4,046 × 128 × 72 matrix – meaning each of the 4,046 gait cycles contained 128 time points, and each time point captured 72 sensor channels. Each walking cycle was labeled with the weight of the box being carried (4.5, 13.6 or 22.7 kg). Data from all four carrying methods was combined so the model focused on estimating the weight being carried, regardless of how the box was held.

Machine learning models: To examine algorithmic bias in hand load estimation (aim 1), three conventional ML algorithms – k-Nearest Neighbors, Support Vector Machine (SVM), and Random Forest – were used as baseline models given their diverse learning strategies and established use in sensor-based prediction tasks. None of these models incorporate fairness enhancements, making them suitable baselines for bias evaluation.
To create a fairer model (aim 2), this study introduces a new approach called a Debiasing Variational Autoencoder (DVAE). This model is based on a deep learning method that learns compact summaries of movement data (Rahman et al., 2026). The DVAE separates the motion data into two parts: one that captures differences related to sex and another that captures movement patterns that are shared across sexes. The sex-related information is used only to identify sex, while the shared movement information is used to predict the weight of the box.
This design helps ensure that weight predictions are based on common movement patterns rather than sex-related differences.

During training, the model was guided by three goals. First, it learned efficient summaries of the data to keep predictions stable. Second, it was trained to clearly separate sex-related features from shared movement features while improving both sex classification and weight prediction. Third, it was penalized if sex-related information influenced weight predictions or if shared movement features revealed sex. When making final predictions, only the part of the model that used shared movement information was active. Weight predictions for each trial were calculated by averaging the results across all walking cycles in that trial.

Model performance evaluation: Models were trained across five male-to-female ratios (0.9:0.1, 0.7:0.3, 0.5:0.5, 0.3:0.7 and 0.1:0.9) and evaluated separately on male-only and female-only test sets using leave-one-subject-out cross-validation to assess how training data composition influences bias and generalizability. Overfitting was addressed through regularization, random search hyperparameter tuning and loss curve monitoring. Performance was assessed using mean absolute error (MAE) and three fairness metrics – Statistical Parity, Positive Residual Differences and Negative Residual Differences – with two-way analysis of variance used to evaluate the effects of training composition and participant sex, at $p < .05$ with post hoc test slice comparisons.

Results and Lessons Learned

Aim 1 Outcome: Conventional ML models showed clear sex-based disparities in prediction accuracy, driven largely by training data composition. Compared to conventional ML models, such as k-Nearest Neighbors (MAE = 6.13 kg) and Random Forest (MAE = 4.89 kg), deep generative models performed substantially better, with Variational Autoencoder (VAE) achieving an MAE of 4.17 kg and the proposed DVAE achieving the highest accuracy at 3.42 kg. This improvement reflects VAE's ability to learn rich representations from complex IMU data and its probabilistic robustness to movement noise. In contrast, SVM demonstrated a persistent bias toward female predictions, even when trained on balanced datasets. Across all models, accuracy improved for the sex most represented in the training data, highlighting a fundamental sensitivity to dataset composition rather than true task-related patterns. Beyond accuracy, DVAE also achieved the best fairness metrics among all models evaluated, establishing it as both the most accurate and most equitable approach for hand load estimation across diverse worker populations.

Aim 2 Outcome: The DVAE model works by separating motion features that are specific to sex from those that are relevant to load estimation. Visualizations confirmed that its sex-agnostic features clustered by box weight regardless of sex, while its sex-specific features separated by sex regardless of load – demonstrating successful disentanglement. In contrast, the standard VAE mixed these boundaries, risking unintended sex-based influence on load predictions. In terms of overall performance, DVAE achieved the lowest prediction error, the smallest sex-based performance gap and the most consistent results across all training conditions. While the standard VAE improved accuracy over conventional models, it still exhibited notable female bias, reinforcing that accuracy alone does not ensure fairness. DVAE showed the least sensitivity to training imbalance and consistently achieved fairness metric values (Statistical Parity, Positive Residual Differences and Negative Residual Differences) closest to ideal. An example of the new model performance for the fairness metric of Statistical Parity is provided in Figure 13. For a more detailed explanation of findings for aims 1 and 2, see Rahman et al. (2026).

Substantial Improvements with DVAE in Model Perfromance & Fairness Metrics

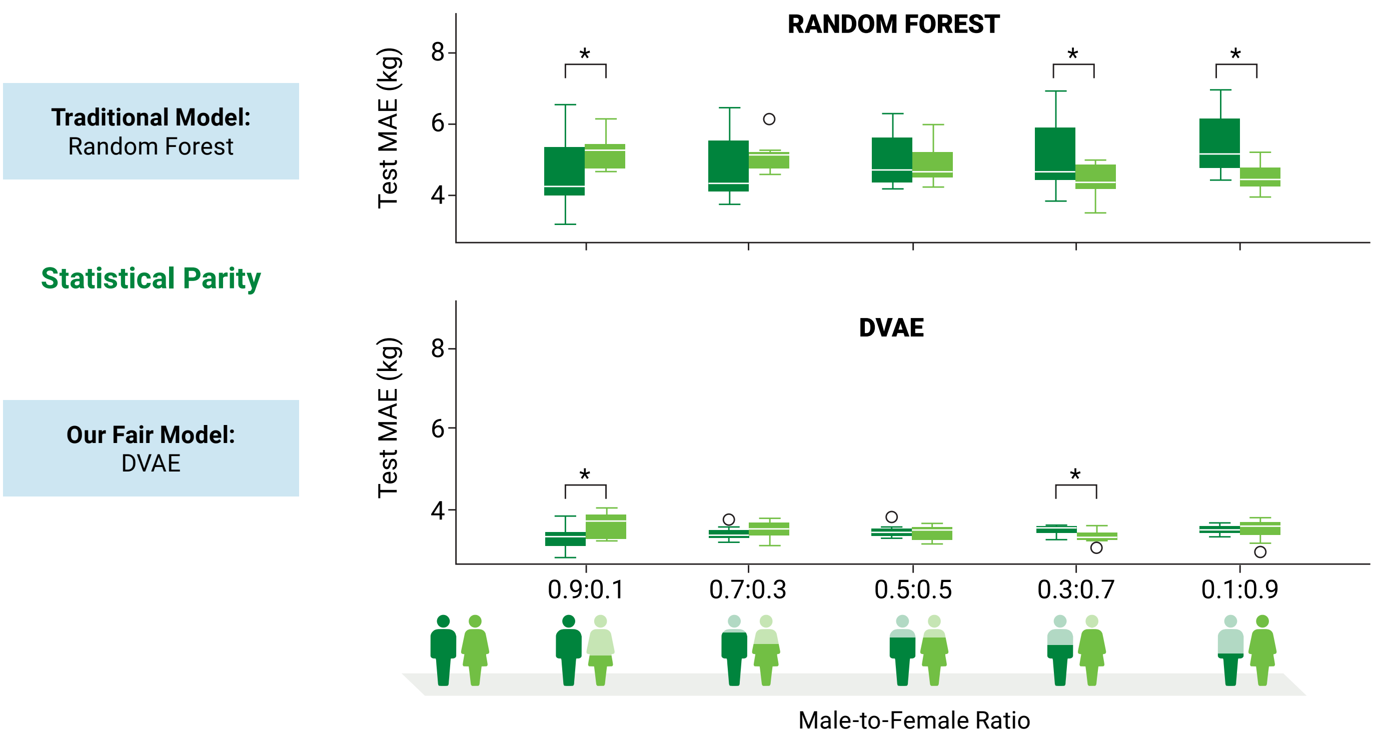


Figure 13. *Statistical parity: Difference in mean predicted outcomes between groups (where RF representing Random Forest and DVAE representing Debiasing Variational Autoencoder)*

Overall, DVAE was the only model to simultaneously achieve high accuracy and equitable performance, making it a strong candidate for responsible ergonomic risk assessment across diverse worker populations. The DVAE's advantage lies in its ability to separate task-relevant information from sex-related features. It learns a sex-agnostic representation driven by load-related movement patterns and a sex-specific representation capturing demographic differences. By explicitly preventing sex-related characteristics from influencing load predictions – a limitation observed in both conventional models and the standard VAE – DVAE produces estimates that are simultaneously more accurate and more equitable across sex groups.

This work is also explained in more detail in the following publication:

- [Rahman, A., Lim, S., & Chung, S. (2026). Fairness in machine learning-based hand load estimation: A case study on load carriage tasks. *Applied Ergonomics, 130*, 104642.]

Key Takeaways

The four research projects highlighted in this report reflect innovation in approach, breadth in scope and a clear commitment to translating research into meaningful workplace impact. The research project from **North Carolina State University** translated evidence-based ergonomics principles, grounded in occupational biomechanics, anthropometry and human factors research, into an AR tool that delivers real-time, visual feedback directly in the workplace. Unlike traditional ergonomic assessment methods, this approach empowered workers to actively visualize their own workspace envelopes, recognize risk factors and make immediate adjustments to their work setups without requiring specialized expertise. Its development through collaboration between ergonomics professionals and AR technology researchers further strengthened its scientific rigor and practical relevance. Additionally, the tool's evaluation for content accuracy, usability and field acceptance ensured it is both technically sound and practically deployable, making it a meaningful step forward in accessible, real-time ergonomic intervention.

The **Wichita State University** project addressed a critical gap by investigating the real-world applicability of ASEs in construction – a high-risk industry with elevated rates of musculoskeletal injury yet limited exoskeleton research. By combining worker perspectives on usability and adoption barriers with objective measures of torso and shoulder musculoskeletal function, the project offered a uniquely comprehensive evaluation that extends well beyond laboratory testing. Its focus on trade-specific task suitability adds further practical value, providing actionable guidance for targeted exoskeleton deployment across construction trades. Collectively, these exoskeleton-related findings are poised to advance both the scientific understanding and real-world adoption of ASEs as an effective ergonomic intervention in physically demanding work environments.

Researchers from **Oregon State University** pioneered the use of smartphone-based video analysis to estimate lumbar spine compression force through detailed musculoskeletal modeling – a significant advancement over prior work that relied on simpler modeling approaches. Their work also employed advanced deep learning algorithms to reconstruct 3D full-body movement from video-detected body landmarks, overcoming long-standing limitations of video-based joint tracking and enabling comprehensive biomechanical analysis. Perhaps most importantly, the approach can be implemented using only two smartphones and a standard computer, reducing the need for specialized cameras and technical expertise typically required by conventional methods and making objective lower-back injury risk assessment more practical and accessible in field settings.

As ML-driven ergonomic assessment tools become increasingly widespread, unaddressed algorithmic bias poses a real risk of producing inequitable risk evaluations and misguided interventions – making the **Virginia Tech** study both particularly compelling and timely. The findings from this study emphasize several important considerations for practice. First, model choice is critical: Approaches such as a fairness AI model that explicitly accounts for and disentangles demographic datasets (i.e., sex-based bias) are better suited for real-world deployment than conventional models. Second, fairness must be evaluated directly and comprehensively; relying on a single metric is insufficient, and the use of multiple complementary fairness measures (e.g., Statistical Parity, Positive Residual Differences and Negative Residual Differences) is necessary to fully capture potential biases. Together, these insights emphasize that achieving equitable and reliable ergonomic risk assessment requires deliberate attention to model design, evaluation strategy and input features.

Conclusion

The 2024-2025 Research to Solutions grant program provided a dedicated opportunity to advance innovative research on workplace MSD prevention and interventions. The four projects highlighted in this report represent a diverse and forward-looking portfolio of research aimed at advancing the science and practice of risk-reduction solutions for MSDs. Collectively, they address key limitations of traditional approaches – from the inaccessibility of laboratory-based biomechanical tools to the subjectivity of observational methods – by leveraging emerging technologies, including AR, wearable exoskeletons, smartphone-based motion capture and AI-driven assessment algorithms. These projects push the boundaries of what is possible in workplace injury prevention, making objective, evidence-based ergonomic assessment more accessible, practical and equitable for diverse worker populations in real-world settings.

The MSD Solutions Lab is excited to continue the Research to Solutions grant program through our 2026-2027 grant projects with a goal to inspire collaboration among academic institutions, businesses and industries to uncover promising, scalable and transferable solutions that mitigate injury risk across sectors. More information about the grant programs can be found **here**.

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Authors

Ram Maikala, Ph.D., ASP, FHFES
Marley Reynoso, MPH
Paige DeBaylo, Ph.D.

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