

Decision-Support and Optimization Framework for
Selection of Low-Cost Wearable Devices to Improve the
Health and Safety of Mechanical-Trade Workers

by

Omar Attalla

A thesis

presented to the University of Waterloo

in fulfillment of the

thesis requirements for the degree of

Doctor of Philosophy

in

Civil Engineering

Waterloo, Ontario, Canada, 2026

©Omar Attalla 2026

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner

NAME: Tarek Zayed

Title: Professor, Building and Real Estate

Hong Kong Polytechnic University

Supervisor

NAME: Tarek Hegazy

Title: Professor, Civil and Environmental Engineering

University of Waterloo

Internal Member

NAME: Carl Haas

Title: Professor, Civil and Environmental Engineering

University of Waterloo

Internal Member

NAME: Nadine Ibrahim

Title: Professor, Civil and Environmental Engineering

University of Waterloo

Internal-External Member

NAME: Ayman El-Hag

Title: Professor, Electrical & Computer Engineering

University of Waterloo

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

The construction industry is a major contributor to the Canadian and U.S. economies. However, it continues to face persistent challenges related to worker attrition, productivity loss, and cost inefficiency, driven in large part by the physically demanding nature of the work. Among the injuries that burden this workforce, work-related musculoskeletal disorders (WMSDs) represent one of the largest single categories of nonfatal lost-time injury, consistently occurring at rates higher than the all-industry average. This burden is especially severe in the mechanical trades, including plumbers, pipefitters, welders, refrigeration technicians, and HVAC mechanics, whose work combines overhead installation, kneeling and crouching in confined spaces, manual material handling, and prolonged awkward postures within a single workday. U.S. data show that mechanical trades such as HVAC mechanics and sheet metal workers experience WMSD incidence rates up to 2.5 times the construction average. Canadian workers' compensation data further identify overexertion and repetitive motion as the leading contributors to lost workdays and claim costs in the mechanical trades, with the WMSD-related burden increasing over the past decade. In British Columbia alone, WMSD-related injuries in the mechanical trades accounted for approximately 69,800 lost workdays (39% of the trades' total) and \$39.5 million in claim costs (28%) from 2020 to 2024. WMSD risks vary by task, affected body region, and worker-specific anthropometric, demographic, and health-related characteristics, indicating a clear need for targeted, cost-effective ergonomic interventions matched to each worker and the body regions requiring support.

While wearable support devices, including exoskeletons and exosuits, can mitigate physical loading, full-body systems may provide broader support than a given worker requires, introducing unnecessary costs and adoption barriers related to bulk, motion constraints, and donning burden. To address this gap, this research investigates the physical demands of mechanical-trade work, which is among the most physically taxing in construction, to understand mechanical-trade workers' exposure to WMSD risk factors and the body regions most affected. Building on this understanding,

it develops a multi-criteria decision-support framework that recommends worker-specific combinations of low-cost, lightweight wearable support devices to reduce exposure to WMSD risk factors and enhance worker health, safety, and productivity (HS&P) in the mechanical trades. The objectives of this research are fourfold: (1) to identify industry needs, at-risk body regions, and working postures in mechanical-trade work; (2) to evaluate and classify low-cost wearable support devices; (3) to develop and validate a system that recommends worker-specific device combinations; and (4) to establish the conditions under which the framework applies to other trades. First, it identifies industry needs through a field survey of 13 owner organizations, examines worker injury trends to establish the back, legs, and shoulders as the at-risk body regions, and derives the working postures that load them. Second, it experimentally evaluates commercially available wearable support devices in laboratory and field settings by measuring various performance metrics to classify each device by the level of support (LOS) it provides. Third, it develops a decision support system (DSS) that uses machine learning to predict each worker's required LOS across the three regions from anthropometric, demographic, and health-related data, and then selects, in a single optimization spanning all at-risk regions, the combination of support devices that best matches those predicted requirements under a single budget constraint. The DSS is subsequently validated through field implementation involving real-world mechanical-trades work. Experiments with 44 participants, including 13 practitioners, showed that all 12 devices received the same LOS classification in the laboratory and the field (mean absolute percentage difference of 4.83% in the LOS index). The machine learning models predicted required LOS with 10-fold cross-validated accuracies of 77.8%, 78.4%, and 79.0% for the back, legs, and shoulders, and the recommended devices were generally well accepted by three additional practitioners in the field validation.

Fourth, the applicability of the framework beyond the mechanical trades is established. The worker injury and working-posture analyses are repeated for four further construction trades, demonstrating that the framework's targeted body regions and the postures under which its devices were evaluated recur beyond the trade group for which it was developed. These findings define the

conditions under which the framework applies, with application to a trade that meets those conditions requiring repetition of the industry data collection component alone.

The proposed framework offers a structured, systematic approach for matching individual mechanical-trade workers to the most suitable combination of wearable support devices for their specific needs. Because all at-risk body regions are optimized together rather than independently, the recommended set is tailored to the individual worker as a whole. The framework's significance is twofold: for research, it places device support and worker need on a common scale, the LOS index; for practice, it provides occupational health or procurement staff with a DSS that can be operated without programming expertise. By providing objective, data-driven, and worker-tailored recommendations, this research has the potential to reduce the substantial lost-time and compensation-cost burden of WMSDs in the mechanical trades while supporting the retention of an experienced and difficult-to-replace skilled workforce.

Acknowledgments

First and foremost, I thank ALLAH (SW) our Lord, the most Gracious and the most Merciful, for giving me the ability, the clarity, and the perseverance to complete this work.

I would like to convey my deepest thanks and appreciation to my supervisor, Dr. Tarek Hegazy, for his thoughtful guidance and vision throughout this research. His efforts sharpened this work at every stage, and it has been a genuine privilege to work under his supervision and to grow as a researcher under his mentorship.

I would like to extend my sincere appreciation and gratitude to my committee members, Prof. Tarek Zayed, Prof. Carl Haas, Prof. Nadine Ibrahim, and Prof. Ayman El-Hag, for their feedback and the time and effort they generously dedicated to this study.

Additional thanks to the Office of Plant Operations at the University of Waterloo for their cooperation and accommodation throughout the course of this research.

I would also like to thank my family, whose support has been essential to this work. To my mother, for her sacrifices and constant belief in me. To my father, for his steady encouragement and inspiration. Whatever I have accomplished, I trace back to what they instilled in me. To my brother and sister, for their unwavering presence and perspective.

Finally, to my wife, Yasmine, for her patience, her faith in me, and for standing beside me through every stage of this journey.

Table of Contents

Examining Committee Membership	ii
AUTHOR'S DECLARATION	iii
Abstract	iv
Acknowledgments	vii
List of Figures	xii
List of Tables.....	xv
Chapter 1: Introduction	1
1.1 General Problem Statement.....	1
1.2 Research Motivation	6
1.2.1 Productivity and cost impacts of WMSD-related injuries among mechanical trades	7
1.2.2 Significant potential of wearable devices for supporting construction tasks	10
1.2.3 Need for optimized worker-specific and body-region-targeted wearable selection	11
1.3 Research Scope and Objectives	12
1.4 Research Methodology	13
1.5 Thesis Organization	15
Chapter 2: Literature Review	17
2.1 Introduction	17
2.2 Traditional Industry Approaches to Reducing Worker Injuries.....	17
2.3 Research Efforts on Enhancing HS&P of Construction Workers.....	21
2.3.1 Studies to monitor and mitigate worker stress	22
2.3.2 Work schedule optimization.....	25
2.3.3 Computer vision	26
2.3.4 Intelligent robotics.....	27
2.3.5 Studies on ergonomic and physical stress analysis	28
2.3.6 Commercial wearable support devices to improve HS&P	32
2.4 Summary of Research Gaps.....	42
Chapter 3: Proposed Decision Support Framework	44
3.1 Introduction	44
3.2 Components of the Proposed Framework	44
3.2.1 Component 1 – Industry Data Collection	45
3.2.2 Component 2 – Experimental Evaluation and Classification of Wearable Devices	46

3.2.3	Component 3 – Decision Support System for Optimal Wearable Selection.....	46
3.3	Summary.....	50
Chapter 4:	Industry Data Collection	51
4.1	Introduction	51
4.2	Field Survey.....	52
4.2.1	Survey Methodology	52
4.2.2	Survey Results & Industry Gaps.....	52
4.3	Ergonomics Assessment.....	55
4.3.1	Mechanical-Trades Worker Injury Data.....	55
4.3.2	Identification of At-Risk Body Regions	59
4.3.3	Working Postures in Standard Mechanical-Trades Activities	59
Chapter 5:	Experimentation and Classification of Wearable Devices.....	63
5.1	Introduction	63
5.2	Experiment Design	63
5.2.1	Participant Recruitment	64
5.2.2	Tasks Performed	65
5.2.3	Wearable Support Devices	68
5.2.4	Performance Assessment Metrics	71
5.2.5	Measurement Instruments.....	76
5.3	Experiment Data Collection and Derived Measures	79
5.3.1	Participant Anthropometric, Demographic, and Physical Health Data	79
5.3.2	Participant Physical Performance Data	81
5.3.3	Questionnaire Data	85
5.4	Classification of Wearables’ Provided Level of Support	85
5.4.1	Dataset Preprocessing	85
5.4.2	Wearables Clustering Analysis.....	87
5.4.3	Wearables LOS Classification.....	98
5.4.4	Comparison of Laboratory and Field Wearable Classification Results	100
5.4.5	Cost-Benefit Analysis	105
5.4.6	Questionnaire Analysis.....	109
Chapter 6:	Decision Support System for Worker-Specific Optimal Wearable Selection.....	112
6.1	Introduction	112

6.2 Prediction of Worker Required Level of Support (DSS Phase #1).....	112
6.2.1 Dataset Augmentation	113
6.2.2 Calculation of Worker Required Level of Support	118
6.2.3 Predictive Model Architecture and Design	122
6.2.4 Predictive Model Results	129
6.3 Worker-Specific Selection of Wearable Device Set (DSS Phase #2).....	132
6.3.1 Inputs.....	133
6.3.2 Model Formulation	134
6.3.3 Solving Engine.....	135
6.3.4 Cost-Equivalence and Tie-Breaking	137
6.3.5 Outputs.....	139
6.4 DSS Visualization	140
6.5 DSS Mechanical Trades Field Validation	141
6.5.1 Worker Characterization	142
6.5.2 DSS Output and Device Recommendation	143
6.5.3 Mechanical Field Validation Results	144
6.6 Verification of the Optimization Model Against an Exact Solver	146
6.7 Summary of Validation	150
Chapter 7: Framework Generalization to Additional Construction Trades.....	152
7.1 Introduction	152
7.2 WMSD-Affected Body Regions Across Construction Trades	152
7.2.1 Injury Data Collection	153
7.2.2 Distribution of WMSD Claims by Body Region	154
7.2.3 Identification of Shared At-Risk Regions	156
7.3 Working Postures Across Construction Trades	157
7.3.1 Posture Data Collection	158
7.3.2 Posture Frequencies by Trade	158
7.3.3 Correspondence with the Evaluated Posture Set	159
7.4 Applying the Framework to Additional Trades.....	160
7.4.1 Component 1 – Industry Data Collection	161
7.4.2 Component 2 – Wearable Evaluation and LOS Classification	161
7.4.3 Component 3 – Decision Support System	163

7.5 Summary.....	164
Chapter 8: Conclusions and Future Research	166
8.1 Introduction	166
8.2 Research Summary and Conclusions	166
8.2.1 Research Summary	166
8.2.2 Key Conclusions	171
8.3 Research Contributions.....	173
8.3.1 Contributions to the Body of Knowledge	174
8.3.2 Contributions to Industry Practice	176
8.4 Limitations and Future Research	177
8.4.1 Future Research Related to Experimentation	177
8.4.2 Future Research Related to the Decision Support System	178
References	180
Appendices	195
Appendix A: Wearable Support Devices Considered	195
Appendix B: Mechanical-Trade Tasks – Field Images	200
Appendix C: Collected Experiment Data (Laboratory and Field)	203
Appendix D: Enumeration of the 60 Device Sets.....	229
Appendix E: Exact-Solver Verification Script	231
Appendix F: Field Survey Questionnaire	234

List of Figures

Figure 1.1: Leading injured body regions in mechanical & sheet metal workers, 2012-2016 (IHSA, 2017) .	5
Figure 1.2: Leading injury categories among mechanical & sheet metal workers, 2012-2016 (IHSA, 2017)	5
Figure 1.3: Mechanical construction claim costs and lost workdays, 2015-2024 (WorkSafeBC, 2026)	7
Figure 1.4: Mechanical trade injury claim costs by accident type, 2020-2024 (WorkSafeBC, 2026)	8
Figure 1.5: Mechanical trade lost workdays by accident type, 2020-2024 (WorkSafeBC, 2026).....	8
Figure 1.6: Most common injury causes for mechanical trades from 2015-2019 (IHSA, 2020).....	9
Figure 1.7: WMSD claim costs for mechanical trades (WorkSafeBC, 2026)	9
Figure 1.8: WMSD lost workdays for mechanical trades (WorkSafeBC, 2026).....	9
Figure 3.1: Framework for evaluation and optimal selection of wearable support devices	45
Figure 4.1: First component of decision support framework	51
Figure 4.2: Profile of survey respondents	52
Figure 4.3: Respondents' opinions on challenges encountered	53
Figure 4.4: Respondents' opinions on potential solutions/enhancements	53
Figure 4.5: WMSD claims and % of LTIs in mechanical trades, 2015-2024 (WorkSafeBC, 2026).....	57
Figure 4.6: WMSD claims by body region in mechanical trades, 2020-2024 (WorkSafeBC, 2026).....	57
Figure 4.7: WMSD injuries by body region for mechanical trades, 2015-2017 (WSIB, 2018)	58
Figure 4.8: WMSD injuries by body region for mechanical trades, 2015-2019 (IHSA, 2020).....	58
Figure 5.1: Second component of decision support framework.....	63
Figure 5.2: TuMeke pose overlay and joint-angle scoring: lifting (back)	74
Figure 5.3: TuMeke pose overlay and joint-angle scoring: overhead loading (shoulder)	74
Figure 5.4: TuMeke pose overlay and joint-angle scoring: squatting (leg)	74
Figure 5.5: TuMeke region-specific posture scores: squatting (leg) task	75
Figure 5.6: TuMeke overall MSD risk score and contribution: squatting (leg) task	75
Figure 5.7: WEKA clustering output for back under laboratory conditions.....	91
Figure 5.8: WEKA clustering output for legs under laboratory conditions.....	92
Figure 5.9: WEKA clustering output for shoulders under laboratory conditions	93
Figure 5.10: WEKA clustering output for back under field conditions.....	95
Figure 5.11: WEKA clustering output for legs under field conditions	96
Figure 5.12: WEKA clustering output for shoulders under field conditions	97
Figure 5.13: Comparison of laboratory and field LOS results.....	101
Figure 5.14: Correlation between wearable cost and provided LOS	106
Figure 5.15: Cost-LOS correlation for back wearables (laboratory)	107

Figure 5.16: Cost-LOS correlation for back wearables (field)	107
Figure 5.17: Cost-LOS correlation for shoulder wearables (laboratory)	107
Figure 5.18: Cost-LOS correlation for shoulder wearables (field)	107
Figure 5.19: Cost-LOS correlation for leg wearables (laboratory)	108
Figure 5.20: Cost-LOS correlation for leg wearables (field)	108
Figure 5.21: Correlation between LOS provided and user perception - Back (lab results)	110
Figure 5.22: Correlation between LOS provided and user perception - Back (field results)	110
Figure 5.23: Correlation between LOS provided and user perception - Leg (lab results)	110
Figure 5.24: Correlation LOS provided and user perception – Leg (field results)	110
Figure 5.25: Correlation between LOS provided and user perception - Shoulder (lab results)	110
Figure 5.26: Correlation between LOS provided and user perception - Shoulder (field results)	110
Figure 6.1: Third component of decision support framework	112
Figure 6.2: Age ECDF plot - original vs augmented sample	117
Figure 6.3: BMI ECDF plot - original vs augmented sample	117
Figure 6.4: BF% ECDF plot - original vs augmented sample	117
Figure 6.5: Age Q-Q plot - original vs augmented sample	117
Figure 6.6: BMI Q-Q Plot - original vs augmented sample	117
Figure 6.7: BF% Q-Q Plot - original vs augmented sample	117
Figure 6.8: Fatigue threshold ECDF plot - original vs augmented sample	117
Figure 6.9: HR Change ECDF plot - original vs augmented sample	117
Figure 6.10: Ergonomic risk score ECDF plot - original vs augmented sample	117
Figure 6.11: Fatigue Threshold Q-Q plot – original vs augmented sample	117
Figure 6.12: HR Change Q-Q plot – original vs augmented sample	117
Figure 6.13: Ergonomic risk score Q-Q plot - original vs augmented sample	117
Figure 6.14: Back - fatigue threshold Q-Q normality plot	119
Figure 6.15: Back - HR change Q-Q normality plot	119
Figure 6.16: Back - ergonomic risk score Q-Q normality plot	119
Figure 6.17: Leg - fatigue threshold Q-Q normality plot	119
Figure 6.18: Leg - HR change Q-Q normality plot	119
Figure 6.19: Leg - ergonomic risk score Q-Q normality plot	119
Figure 6.20: Shoulder - fatigue threshold Q-Q normality plot	119
Figure 6.21: Shoulder - HR change Q-Q normality plot	119
Figure 6.22: Shoulder - ergonomic risk score Q-Q normality plot	119
Figure 6.23: ANN for estimating required level of support (back)	128

Figure 6.24: ANN for estimating required level of support (leg)	128
Figure 6.25: ANN for estimating required level of support (shoulder)	128
Figure 6.26: Back ANN summary (WEKA).....	131
Figure 6.27: Leg ANN summary (WEKA).....	131
Figure 6.28: Shoulder ANN summary (WEKA)	131
Figure 6.29: Optimization model for worker-specific selection of wearable support devices	132
Figure 6.30: Optimization model output with shoulder region opted out.....	133
Figure 6.31: Solver parameters for optimization model	136
Figure 6.32: Optimization model output scenario #1 (feasible solution).....	139
Figure 6.33: Optimization model output scenario #2 (infeasible solution)	140
Figure 6.34: Decision support system for optimal wearable device selection.....	141
Figure 6.35: ANN prediction of LOS required for VP01 (back)	142
Figure 6.36: ANN prediction of LOS required for VP01 (leg).....	142
Figure 6.37: ANN prediction of LOS required.....	142
Figure 6.38: Optimization model recommended wearable devices.....	143
Figure 6.39: Output of the exact-solver verification script (HiGHS 1.15.1 through highspy)	148
Figure 7.1: WMSDs by body region across construction trades, 2021-2025 (WorkSafeBC, 2026)	155
Figure 7.2: Share of WMSDs affecting target body regions, by trade (WorkSafeBC, 2026)	155

List of Tables

Table 2.1: Approaches reviewed for the selection of wearable support devices	41
Table 3.1: Methods used in each framework component.....	47
Table 4.1: Key challenges faced in project and asset management	54
Table 4.2: Main desired enhancements in project and asset management.....	54
Table 5.1: Participant group characteristics (mean $\pm$ SD)	65
Table 5.2: Mapping of participant groups to experimental evaluations.....	65
Table 5.3: Simulated task design and relevant mechanical construction tasks	67
Table 5.4: Field task design for mechanical-trade work	68
Table 5.5: Wearable support devices selected for evaluation	70
Table 5.6: Participant questionnaire items	76
Table 5.7: Data recording schema for performance assessment metrics	82
Table 5.8: Percentage-change schema for performance assessment metrics	83
Table 5.9: Mean changes in performance metrics and associated p-values (laboratory results).....	83
Table 5.10: Mean changes in performance metrics and associated p-values (field results).....	84
Table 5.11: Questionnaire response schema (illustrative structure; values omitted)	85
Table 5.12: Proportion of HRC data points replaced via mean imputation	87
Table 5.13: Proportion of clustered instances for various clustering algorithms	88
Table 5.14: Laboratory data clustering results	90
Table 5.15: Field data clustering results	94
Table 5.16: Laboratory-based classification of wearable devices by level of support.....	99
Table 5.17: Field-based classification of wearable devices by level of support	100
Table 5.18: Comparison of laboratory and field classification results.....	101
Table 5.19: Spearman's rank correlation computation parameters.....	102
Table 5.20: Pearson's correlation computation parameters	103
Table 5.21: Wilcoxon test statistic computation parameters.....	104
Table 5.22: Coefficient of determination between wearable device LOS and cost	106
Table 5.23: Wearable performance testing vs user questionnaire feedback (laboratory results).....	109
Table 5.24: Wearable performance testing vs user questionnaire feedback (field results)	109
Table 5.25: R^2 values for wearables LOS provided and questionnaire outcomes	111
Table 6.1: Distributional similarity between original and augmented samples	115
Table 6.2: Normality assessment of participant performance dataset.....	120
Table 6.3: Participant group baseline performance (without wearable devices)	120

Table 6.4: Calculation of required level of support for sample participant	121
Table 6.5: Comparison of machine learning algorithms for prediction of required LOS	124
Table 6.6: Top ANN hyperparameter configurations and cross-validation performance	127
Table 6.7: Performance of the MLP ANNs for each body region	129
Table 6.8: Confusion matrices of the MLP ANNs for each body region.....	129
Table 6.9: Field validation worker characteristics and predicted required LOS.....	143
Table 6.10: DSS-recommended wearable devices by body region.....	144
Table 6.11: Worker questionnaire responses for DSS-recommended wearable devices	145
Table 6.12: Lowest-cost qualifying device set for each of the 27 combinations of required LOS	149
Table 6.13: Validation performed at each level of the framework	151
Table 7.1: Trades analyzed and their industry classification units (WorkSafeBC, 2026)	153
Table 7.2: WMSD claims by affected body region, 2021-2025 (WorkSafeBC, 2026)	155
Table 7.3: Working posture frequencies by trade, as percentage of workday (Alberta Construction Association, 2020a, 2020b, 2021a-f)	159
Table 7.4: Requirements for applying each framework component to a new trade.....	161
Table 8.1: Research gaps and the means by which this research addresses them.....	173

Chapter 1: Introduction

1.1 General Problem Statement

The construction industry is a major contributor to the Canadian and U.S. economies, supporting national infrastructure, housing, and employment. In Canada, the construction sector contributed approximately \$165 billion to real GDP in 2023, representing approximately 7.4% of the national economy (Statistics Canada, 2024). In the United States (U.S.), construction contributed approximately \$1.2 trillion in current-dollar value added, accounting for about 4.4% of national GDP in the same year (U.S. Bureau of Economic Analysis, 2024). Despite this economic importance, the sector continues to face persistent challenges related to worker attrition, productivity loss, and cost inefficiency. A major contributor to these challenges is the physical nature of construction work, which routinely exposes workers to demanding tasks, repeated exertion, and elevated injury risk.

Construction injuries are especially detrimental because they reduce labour capacity in a sector that depends on skilled workers who are difficult to replace. In 2024, the U.S. construction sector recorded 167,100 nonfatal occupational injuries and illnesses, corresponding to a total recordable case (TRC) rate of 2.2 cases per 100 full-time equivalent (FTE) workers (U.S. BLS, 2026). These injuries remove workers from their regular duties through days away from work, job transfers, or work restrictions. Among construction firms with open skilled-trade positions, 92% report difficulty filling them (Associated General Contractors of America [AGC] & National Center for Construction Education and Research [NCCER], 2025b), and 83% describe the positions as equally or more difficult to fill than one year earlier (AGC & NCCER, 2025a). Under these conditions, preventing avoidable injuries is essential for retaining the experienced workforce on which the industry depends.

Comparable trends are observed in Canada. In Ontario, the Workplace Safety and Insurance Board (WSIB) reported that Schedule 1 lost-time claim volume in 2023 was 3% higher than in 2022 and 2% higher than in 2019, with lost-time claims rising from 31% of total claim volume in 2019 to

35% in 2023 (WSIB, 2024). WSIB also reported that, across all Schedule 1 insured workers, the average compensated absence duration per accepted lost-time claim was 62.3 days as of year-end 2023, equivalent to approximately two months away from work per accepted claim (WSIB, 2024). Collectively, these data indicate that workplace injuries can impose substantial lost-time and productivity burdens across sectors, reinforcing the importance of injury prevention for both worker well-being and labour capacity.

Construction tasks routinely require workers to lift, carry, reach, kneel, bend, work overhead, and operate in confined or constrained spaces, placing repeated stress on the body's muscles, tendons, ligaments, joints, and nerves. In this research, musculoskeletal disorders (MSDs) refer to injuries and disorders affecting these soft-tissue and joint structures. In contrast, work-related musculoskeletal disorders (WMSDs) refer specifically to MSDs caused by work activities, particularly frequent and repetitive activities or activities performed in awkward postures (Canadian Centre for Occupational Health and Safety [CCOHS], 2024a). Common examples include muscle strains, lower-back injuries, shoulder rotator cuff injuries, knee disorders, and carpal tunnel syndrome.

Construction workers also face other health hazards, such as exposure to toxic chemicals and respiratory hazards from wood dust (CCOHS, 2025). However, WMSDs consistently represent one of the largest single categories of nonfatal lost-time injury in the industry, accounting for more than one-quarter (25.6%) of all nonfatal occupational injuries resulting in days away from work in U.S. construction over a 23-year surveillance period (Wang et al., 2017). The same study found that the rate of WMSDs in construction remained consistently higher than in all industries combined throughout the study period, with overexertion as the primary cause and back injuries accounting for more than 40% of all WMSDs in the industry (Wang et al., 2017). A more recent systematic review further established that WMSD prevalence is consistently elevated across construction trades and study settings, with strong evidence of associations between WMSDs and awkward

postures, manual material handling, prolonged work, high job demands, and psychosocial stressors (Anwer et al., 2021). A complementary science-mapping review of WMSDs among construction workers similarly confirms that WMSDs remain a sustained and active research priority in the sector (Antwi-Afari et al., 2023). Across the global construction workforce, a systematic review and meta-analysis of 35 studies spanning 15 countries and 303,384 workers (Umer, Antwi-Afari, et al., 2018) examined one-year musculoskeletal symptom prevalence in nine anatomical regions. The four highest rates were reported for the lower back (51.1%), knee (37.2%), shoulder (32.4%), and wrist (30.4%), indicating that these body regions bear the greatest musculoskeletal burden across the construction workforce broadly. Although workforce attrition in construction arises from a range of demographic and economic pressures, WMSDs represent a substantial yet largely preventable contributor, therefore motivating the targeted intervention proposed in this research.

This burden is particularly relevant to mechanical construction trades, including plumbers, pipefitters, steamfitters, welders, refrigeration technicians, and heating, ventilation, and air-conditioning (HVAC) technicians/mechanics. These trades combine many recognized WMSD risk factors within a single workday: overhead pipe and duct installation, kneeling and crouching in mechanical rooms and crawl spaces, lifting and carrying tools and fittings, repeated reaching, and prolonged work in constrained postures (Alwasel et al., 2017; Gonsalves et al., 2021; Zhang et al., 2019b). CCOHS identifies awkward and static postures, repetitiveness and pace of work, forceful movements and heavy loads, vibration, temperature, and high work demands as key WMSD risk factors (CCOHS, 2024b), exposures that are especially characteristic of mechanical-trade tasks.

The elevated risk facing these trades is reflected in U.S. occupational injury data. Based on 2011-2014 U.S. BLS data, heating and air-conditioning mechanics recorded a WMSD incidence rate of 98.9 per 10,000 FTE workers, 2.5 times the construction industry average of 39.5 per 10,000, while plumbers recorded a rate of 61.9 per 10,000 (1.6 times the average). Sheet metal workers recorded 86.2 per 10,000 (2.2 times the average) (Wang et al., 2017). More recent U.S. data confirm

that this pattern has persisted. An analysis of 2021-2022 injury data by the Center for Construction Research and Training (CPWR) reports that specialty trade contractors (NAICS 238), which encompass the mechanical, electrical, plumbing, and finishing trades, recorded the highest MSD rate of the three major U.S. construction subsectors, 28.4 per 10,000 FTE workers (Harris et al., 2025). This rate is nearly twice that of general building contractors (16.4 per 10,000) and of heavy civil infrastructure contractors such as road, bridge, and utility construction (15.3 per 10,000). Consistent with this risk profile, U.S. plumbing, heating, and air-conditioning contractors (NAICS 23822) recorded 3.0 total recordable injury and illness cases per 100 FTE workers in 2024, exceeding the U.S. construction sector average of 2.2 per 100 workers (U.S. BLS, 2026). These exposures are associated with measurable consequences for productivity and compensation costs among mechanical-trade workers. In British Columbia (BC), Canada, WMSD-related injuries in the mechanical trades from 2020 to 2024 resulted in approximately 69,800 lost workdays, representing 39% of all lost workdays for these trades, and \$39.5 million in claim costs, representing 28% of all claim costs for these trades (WorkSafeBC, 2026). For the purposes of this analysis, the mechanical trades include commercial refrigeration; plumbing, heating, ventilation, and air conditioning; pool, spa, and hot tub installation; commercial tank or boiler installation/removal; welding services or ornamental metal; and mechanical insulation. When viewed against the broader BC construction sector over the same period, the disproportionate scale of this impact is evident: mechanical-trade WMSD-related claim costs alone represent 23% of the total BC construction industry WMSD burden (WorkSafeBC, 2026).

In terms of the anatomical distribution of injuries among these mechanical workers, the Infrastructure Health & Safety Association (IHSA) reports that the three most commonly injured body regions among mechanical and sheet metal workers in Ontario are the back, fingers, and knees (IHSA, 2017). This uneven distribution is consistent with broader modelling of occupational injury data, which shows that injury susceptibility is concentrated in specific body regions rather than spreading uniformly across the body (Koc et al., 2023). The remaining body-region categories are

summarized in Figure 1.1, and Figure 1.2 shows that sprains, strains, and tears account for 36% of all injuries, the largest single nature-of-injury category for these workers (IHSA, 2017).

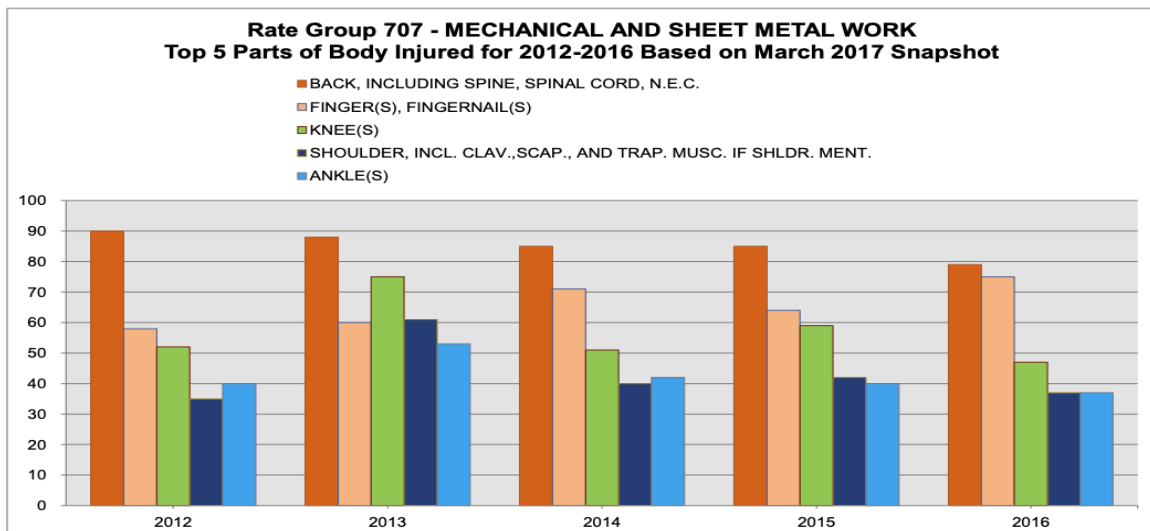


Figure 1.1: Leading injured body regions in mechanical & sheet metal workers, 2012-2016 (IHSA, 2017)

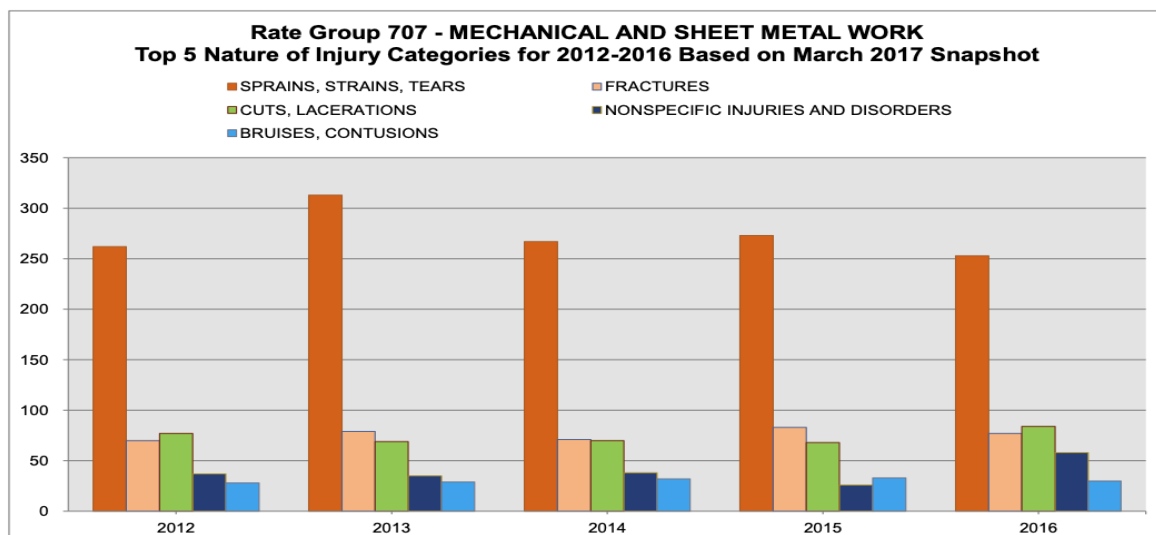


Figure 1.2: Leading injury categories among mechanical & sheet metal workers, 2012-2016 (IHSA, 2017)

The evidence discussed establishes the practical problem this research addresses: mechanical-trade workers are exposed to task- and body-region-specific WMSD risks that result in substantial lost time and claim costs, and there is a clear need for targeted, cost-feasible ergonomic interventions matched to the worker and the affected body region. In a labour-constrained industry,

targeted interventions may support retention of mechanical-trade workers by reducing injury-related absence and premature workforce exit.

1.2 Research Motivation

The General Problem Statement establishes that mechanical-trade workers experience task- and body-region-specific WMSD risks with measurable consequences for productivity and costs. This research addresses this problem by evaluating commercially available wearable devices for mechanical construction tasks and developing a decision support system (DSS) that recommends cost-effective, worker-specific combinations of low-cost wearable support devices intended to reduce WMSD risk exposure and support worker health, safety, and sustained participation in the mechanical trades (Attalla et al., 2026).

This research distinguishes wearable technologies by function, separating those that measure from those that intervene. Devices that collect worker physiological and ergonomic data during construction tasks are termed “physical sensing devices”, “sensing wearables”, or “wearable sensing devices”, used interchangeably throughout. Devices that physically support specific body regions and alleviate strain during tasks are termed “wearable support devices”, “support wearables”, or “support devices”. An “exoskeleton” falls within this second category, providing mechanical assistance to one or more body regions. Where an exoskeleton or “exosuit” assists multiple regions across the torso and limbs simultaneously, it is described here as “full-body”.

The motivation for this work rests on three points: (1) the productivity and cost severity of WMSD-related injuries in mechanical trades, (2) the potential, but constrained, adoption of wearable devices for reducing WMSDs, and (3) the absence of a structured, cost-effective method for selecting worker-specific, body-region-targeted combinations of low-cost wearable support devices, informed by the physical demands of mechanical-trade tasks. This chapter is organized as follows. Section 1.2.1 documents the productivity and cost impacts of WMSD-related injuries among mechanical trades. Section 1.2.2 reviews the potential of wearable devices for supporting

construction tasks. Section 1.2.3 identifies the need for an optimized, worker- and body-region-specific wearable-selection framework. The chapter concludes with the research scope, objectives, and methodology in Sections 1.3 and 1.4.

1.2.1 Productivity and cost impacts of WMSD-related injuries among mechanical trades

The preceding section established that WMSD-related injuries account for a substantial share of lost workdays and claim costs in the mechanical trades. This section examines how that burden has evolved over the past decade. Figure 1.3 shows that mechanical-trade lost workdays and paid claim costs increased from 2015 to 2024, demonstrating a persistent and worsening burden of productivity loss and compensation costs (WorkSafeBC, 2026). The mechanical-trade workforce was defined using the following WorkSafeBC occupational filters: commercial refrigeration; plumbing, heating, ventilation, and residential air conditioning; commercial tank or boiler installation and removal; welding services; mechanical insulation; and pool, spa, and hot tub installation.

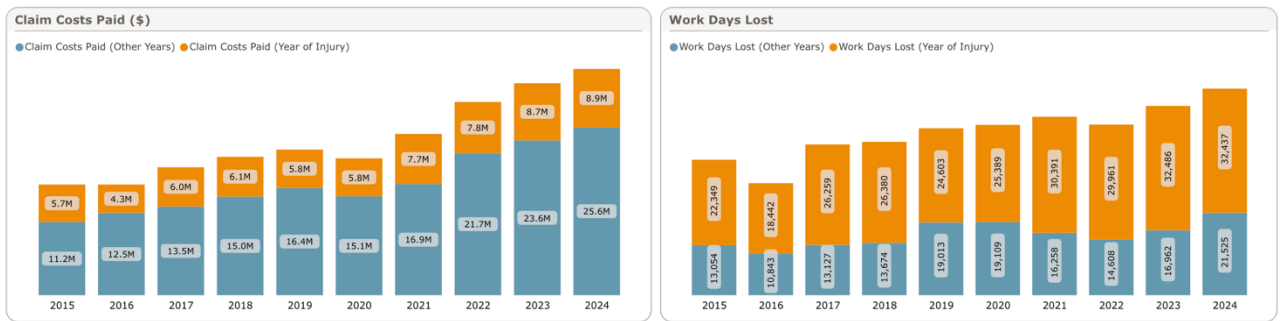


Figure 1.3: Mechanical construction claim costs and lost workdays, 2015-2024 (WorkSafeBC, 2026)

Furthermore, WorkSafeBC data from 2020-2024 reveal that, among injury mechanisms, overexertion and repetitive motion are the leading contributors to injury claim costs in the mechanical trades, collectively accounting for 28% of all recorded injury claim costs, as shown in Figure 1.4 (WorkSafeBC, 2026). This pattern aligns with biomechanical evidence that force and repetition interact to compound the risk of WMSDs, making high-force, high-repetition work especially hazardous (Gallagher & Heberger, 2013).

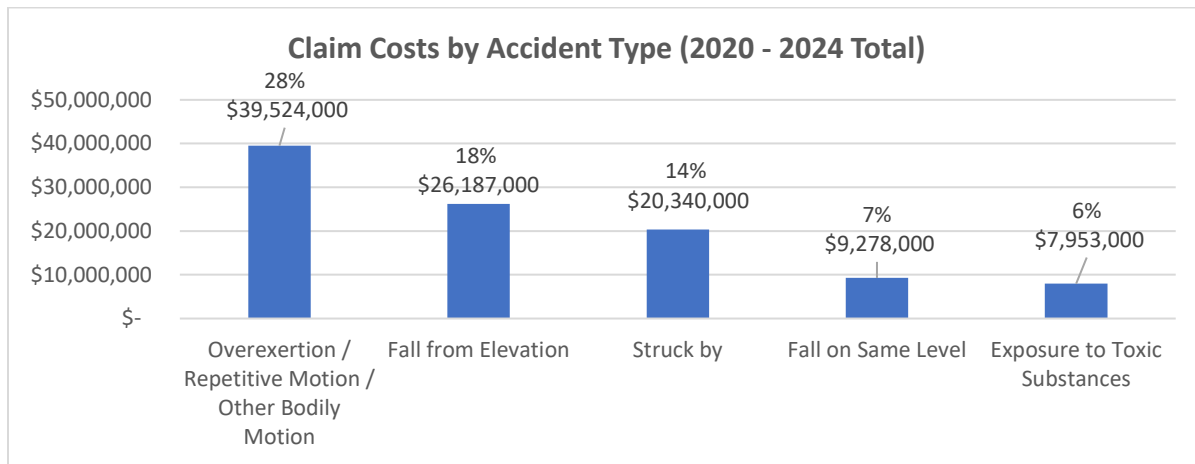


Figure 1.4: Mechanical trade injury claim costs by accident type, 2020-2024 (WorkSafeBC, 2026)

Figure 1.5 reveals that overexertion and repetitive motion are also the leading contributors to lost workdays among mechanical-trades workers, accounting for 39% of all lost workdays and exceeding the second-highest contributor by approximately 20%.

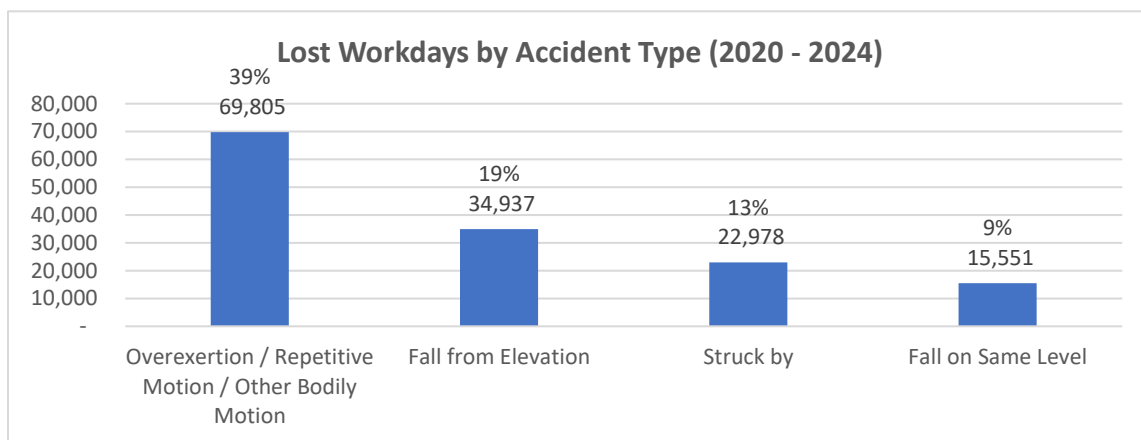


Figure 1.5: Mechanical trade lost workdays by accident type, 2020-2024 (WorkSafeBC, 2026)

These data indicate that WMSDs in the mechanical trades, caused by overexertion and repetitive motion, are associated with significant losses in workforce productivity and compensation costs. This is corroborated by IHSA data from 2015-2019, which found that the top three lost-time injury (LTI) categories for mechanical and sheet metal workers are overexertion/bodily reaction, contact with objects & equipment, and falls, as shown in Figure 1.6 (IHSA, 2020). Furthermore, the

percentage of injuries caused by overexertion / bodily reaction increased from approximately 30% to 35% over the study period.

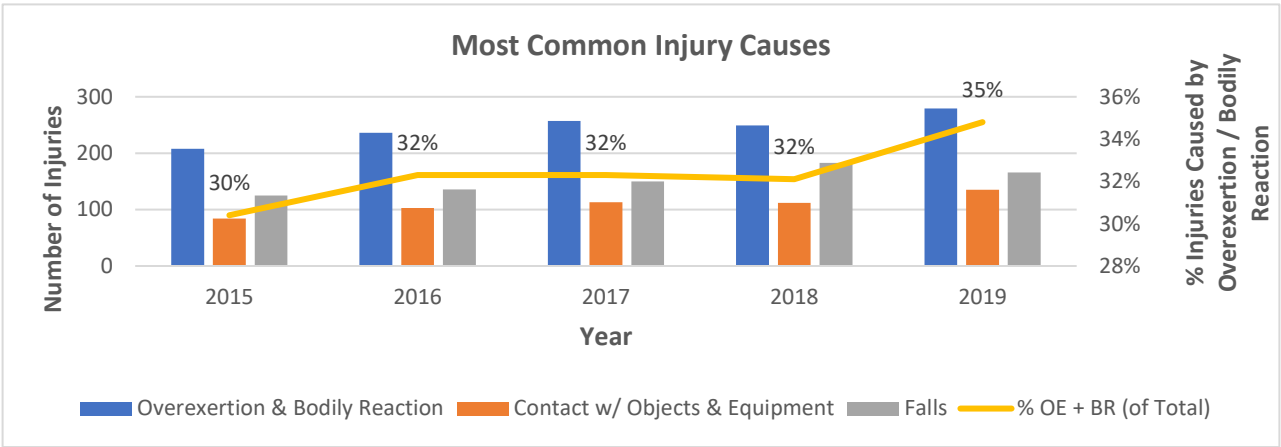


Figure 1.6: Most common injury causes for mechanical trades from 2015-2019 (IHSA, 2020)

Figure 1.7 and Figure 1.8 show that WMSD-related claim costs and lost workdays have steadily increased from 2015 to 2024 in the mechanical trades.

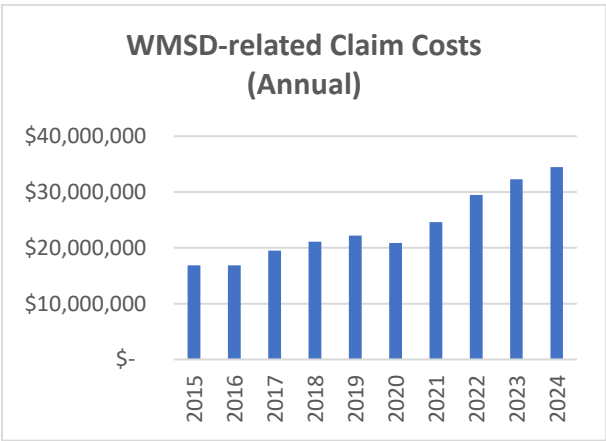


Figure 1.7: WMSD claim costs for mechanical trades (WorkSafeBC, 2026)

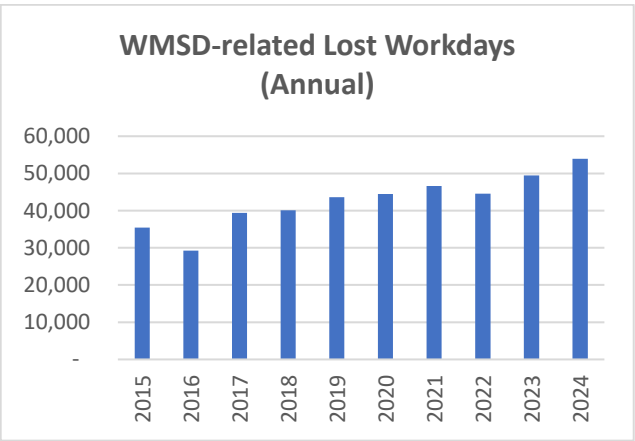


Figure 1.8: WMSD lost workdays for mechanical trades (WorkSafeBC, 2026)

A reduction in these workplace injuries would improve productivity by reducing lost workdays and claim costs. According to the National Safety Council, the cost per medically consulted work injury in 2023 was \$43,000, encompassing wage and productivity losses, medical expenses, and administrative expenses (National Safety Council, 2025). Applied to the mechanical-trade injury volumes documented above, this per-injury cost translates to substantial recoverable expense if

injury rates can be reduced. For employers operating in a constrained skilled-labour market, reducing injury-related lost time may also help preserve access to experienced workers whose skills and trade-specific knowledge are difficult to replace. These considerations motivate examination of intervention technologies in the next section.

1.2.2 Significant potential of wearable devices for supporting construction tasks

Affordable wearable devices are becoming increasingly available for occupational applications, including smartwatches, smart helmets, smart glasses, badges, wristbands, chestbands, and bionic suits. The market for these devices is growing rapidly, and many have direct potential for use on construction tasks. Contractor interest in wearable technology has grown substantially over the past decade. A Dodge Data & Analytics SmartMarket Brief reported that 60% of contractors viewed improved worker safety as the biggest benefit of wearable technology, and that 33% expected to use wearable technology by 2022, up from only 6% reporting current use at the time of the survey (Dodge Data & Analytics, 2018). This anticipated growth is reflected in more recent survey evidence: a 2025 EHS global corporate survey found that 45% of construction firms have already implemented industrial wearables either widely or partially across their organizations, with most expecting to expand that deployment further (Verdantix, 2025). The global construction wearable technology market, valued at \$4.6 billion in 2025, is projected to grow at a compound annual rate of 10.8% through 2029, driven primarily by heightened jobsite safety concerns and increased demand for real-time worker health monitoring (Business Research Company, 2025).

Mechanical-trade WMSD risk varies by task, worker, and affected body region; therefore, effective interventions must address specific physical demands rather than treat workers and tasks as uniform. Wearable technologies are well-suited to this context because they support two complementary functions: sensing, through measurement of physiological and ergonomic indicators such as heart rate, blood pressure, oxygen saturation, skin temperature, and muscular stress during work; and physical support, through reduction of loading on targeted body regions. A growing body of evidence indicates that wearables can produce meaningful reductions in musculoskeletal load

and exposure, with passive and active support devices yielding measurable decreases in muscle activation, perceived exertion, and ergonomic risk during representative construction tasks (reviewed in Chapter 2).

Collectively, these capabilities position wearable devices as a viable avenue for improving work safety, cost efficiency, and productivity in the mechanical trades. Sensing data can inform data-driven selection of optimal wearable support devices, while support devices can directly reduce the physical loading that drives WMSD onset. Their potential to address the WMSD burden documented in the preceding sections establishes wearable technologies as a meaningful and increasingly practical intervention for the mechanical trades.

1.2.3 Need for optimized worker-specific and body-region-targeted wearable selection

Individual workers differ in which body regions are most vulnerable, owing to factors such as age, sex, anthropometry, and baseline physical capacity. Two workers performing the same task can therefore differ substantially in the magnitude of support required.

Full-body exoskeletons and exosuits can mitigate physical loading across multiple regions simultaneously; however, they typically distribute support uniformly rather than concentrating it on the regions most affected for a given worker, and can therefore introduce unnecessary cost relative to more targeted alternatives. In addition, construction-focused research has identified bulky size, motion constraints, donning and doffing burden, and compatibility challenges with other personal protective equipment as important barriers to exoskeleton adoption, particularly when tasks require mobility, flexibility, and frequent task changes (Mahmud et al., 2022). Cost has likewise been identified as an obstacle to broader wearable adoption on construction sites (Mahmud et al., 2022). A more cost-effective and productivity-enhancing alternative is the targeted use of individual wearable support devices, combined into worker-specific configurations that address only the body regions a given worker requires support for.

Realizing this potential requires 1) an investigation of the efficacy of individual wearable support devices during representative mechanical tasks, and 2) a decision support system capable of accounting for worker-specific characteristics to select the optimal combination of wearable support devices to alleviate physical loading for a given worker. Such a selection must address all of a worker's at-risk body regions at once rather than one region at a time. Together, these two requirements define the practical and methodological motivation for the present research.

1.3 Research Scope and Objectives

The goal of this research is to reduce exposure to work-related musculoskeletal disorder (WMSD) risk factors among mechanical-trade workers through the targeted selection and use of wearable support devices. By supporting feasible, worker-specific ergonomic interventions, the research also seeks to contribute to reduced injury-related lost time and to the retention of skilled workers in the mechanical trades. This is achieved by developing a multi-criteria decision-support framework that recommends cost-effective combinations of wearable devices based on worker-specific characteristics and task demands (Attalla et al., 2026). The mechanical trades were selected because they bear a disproportionate share of the construction WMSD burden, as shown in Section 1.1. The conditions under which the framework applies to other construction trades are established in Chapter 7.

In this thesis, the terms “decision support framework”, “wearable device selection framework”, and “framework” refer to the comprehensive framework developed in this research, which encompasses the industry review, wearable device experimentation, and DSS development. Within this broader framework, the term “decision support system (DSS)” refers specifically to the predictive model and optimization-based selection tool developed to estimate the level of support required by workers and recommend cost-effective wearable support devices.

The objectives of this research are as follows:

1. Identify industry needs, mechanical-trade WMSD injury patterns, and at-risk body regions. Review representative mechanical-trade tasks and working postures to establish the basis for evaluating wearable support devices.
2. Measure worker physiological response, fatigue threshold, and ergonomic risk during representative mechanical-trade tasks; evaluate commercially available, low-cost, lightweight wearable support devices against these performance metrics; and classify the evaluated devices according to the level of support (LOS) they provide and compare their cost-benefit performance.
3. Develop a DSS that integrates a predictive model for estimating each worker's required LOS with an optimization model for selecting cost-effective, worker-specific combinations of wearable support devices across all at-risk body regions under a single budget constraint, and validate the DSS through field implementation with mechanical-trade workers.
4. Establish the conditions under which the framework may be applied to construction trades beyond the mechanical trades and determine whether the at-risk body regions and working postures on which it depends recur in other trades.

1.4 Research Methodology

The proposed research methodology to meet the research objectives is described in the following steps:

- **Literature Review:** Conduct a comprehensive review of (1) traditional industry approaches to reducing worker injuries; and (2) recent research efforts aimed at enhancing the health, safety, and productivity (HS&P) of construction workers
- **Industry Needs Survey:** Conduct a field survey of experienced practitioners across 13 construction-industry owner organizations to identify current industry practices and significant gaps related to worker health, safety, and productivity.

- **Mechanical-Trade Injury Analysis:** Review mechanical-trade worker injury data to identify the body regions most frequently affected by WMSD-related risks.
- **Mechanical-Trade Working-Posture Identification:** Review standard mechanical-trade activities and identify representative working postures for the targeted body regions using image-based review, field observations, and published Physical Demands Analyses.
- **Wearable Device Experimentation:** Identify recent commercial wearable support devices that are low-cost, lightweight, and well-suited to assisting workers during mechanical-trade tasks. Evaluate device performance in laboratory and field settings by measuring heart rate, fatigue threshold, and ergonomic risk while participants perform representative tasks.
- **Wearable Device Classification:** Apply clustering analysis to classify each device by the LOS it provides and conduct a cost-benefit comparison among the evaluated devices.
- **Worker Required-LOS Prediction:** Develop predictive models that estimate the LOS required by each worker based on their anthropometric, demographic, and health-related data.
- **Tailored Wearable Device Selection:** Develop an optimization model that considers each worker's predicted required LOS, the LOS provided by available wearable devices, device costs, and budget constraints to determine the device combination that best meets the worker's support requirements for all at-risk body regions simultaneously, and yields a tailored, worker-specific recommendation.
- **Field Validation:** Validate the DSS through field implementation in a mechanical-trade work setting.
- **Framework Generalization Assessment:** Repeat the injury data and working-posture analyses for a representative set of construction trades outside the mechanical group, and determine what the application of each framework component to a further trade requires.

1.5 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2 presents a literature review covering industry practices for reducing construction injuries, recent research on construction worker health, safety, and productivity (HS&P), and the use of ergonomic, physiological, cognitive, and wearable-based approaches to worker assessment and support. The chapter concludes by identifying the research gaps addressed in this thesis.

Chapter 3 introduces the proposed decision support framework for the optimal selection of wearable support devices. It presents the main components of the framework and explains how industry data collection, experimental evaluation, worker-specific LOS prediction, optimization-based wearable selection, and field validation are connected.

Chapter 4 presents the industry data collection and ergonomics assessment. It covers the field survey of construction-industry organizations, the analysis of mechanical-trade worker injury data, the identification of at-risk body regions, and the review of standard mechanical-trade activities and working postures.

Chapter 5 presents the experimental evaluation and classification of wearable support devices. It describes the laboratory and field experimental design, the collected participant anthropometric, demographic, health, and physical performance data, the assessment of wearable device performance, and the classification of devices by the LOS they provide.

Chapter 6 presents the proposed DSS. The system integrates a machine learning model trained on the experimental data to predict each worker's required LOS with an optimization model that selects the wearable-device combination best matched to that requirement. The chapter also presents the field validation of the DSS.

Chapter 7 examines the applicability of the framework to construction trades beyond the mechanical trades. It repeats the injury data analysis and working-posture review for four further trades,

compares the resulting profiles against those established for the mechanical trades, and establishes the conditions for applying each framework component to a further trade.

Chapter 8 summarizes the research, presents its main conclusions, highlights its contributions, discusses its limitations, and provides recommendations for future research.

Chapter 2: Literature Review

2.1 Introduction

This chapter critically reviews literature on worker physical stress, ergonomic assessment, wearable support technologies, and related decision-support approaches relevant to mechanical-trade work. It begins by examining traditional industry approaches for reducing worker injuries. It then reviews research on digital and data-driven methods related to worker-strain assessment, fatigue and posture monitoring, wearable sensing, wearable support devices, and intervention selection. Particular attention is given to studies that assess worker physical stress, evaluate wearable support technologies, or inform intervention decisions.

The chapter concludes by identifying the literature gap most relevant to this research: existing studies support worker monitoring, ergonomic assessment, and the general promise of wearable support technologies, but provide limited guidance on how suitable wearable support devices should be selected for mechanical-trade workers based on worker characteristics, task demands, body-region-specific support requirements, device capabilities, and implementation constraints.

2.2 Traditional Industry Approaches to Reducing Worker Injuries

To mitigate the risk of injuries, illnesses, or fatalities in the industry, preventative measures are implemented through safety processes, safety training, personal protective equipment (PPE), and best practices. Construction safety in Ontario is governed by the Occupational Health and Safety Act (OHSA), with sector-specific guidance and training support provided by the Infrastructure Health and Safety Association (IHSA). In the U.S., it is governed by the Occupational Safety and Health Act, administered by the Occupational Safety and Health Administration (OSHA), which sets and enforces construction-sector safety standards (OSHA, n.d.). The traditional methods for safety improvements are briefly discussed in the following subsections.

PPE is a layer of hazard control at the worker level, worn to reduce exposure to health and safety hazards that cause workplace injuries and illnesses (OHSA, 2025; CCOHS, 2025). For construction workers, this can include hard hats, safety boots, safety glasses, protective gloves, hearing protection, face shields, fall protection, and respiratory protection (IHSA, 2023a). Sections 25-27 of the OHSA establish employer and supervisor duties to ensure that required protective equipment and safety measures are provided and used. Section 28 establishes worker duties to use required PPE and comply with applicable safety requirements (OHSA, 2025).

Safety processes in the construction industry are implemented to reduce the risk of injury to construction workers and the public. These involve standard rules and procedures governing equipment usage, machinery lockout/tagout, working at heights, equipment and material storage, and manual material handling. For mechanical workers, health risks are most associated with ergonomic, respiratory, chemical, and fall hazards. For example, prolonged forward bending of the back during HVAC ductwork installation can result in muscle strain, ligament sprain, herniated discs, or other adverse back problems. Workers brazing in confined spaces may encounter oxygen depletion, and workers in older buildings may be exposed to asbestos. Workers performing furnace replacements are often required to change chimney venting on roofs, which poses a fall risk. Some refrigerants may also present toxicity risks, particularly if decomposition products are generated during hot work such as brazing (Johnson, 2017). To minimize the risk of injury from these hazards, mechanical workers must wear some or all of the following, depending on the job: hard hat, safety boots, full-coverage clothing, respirator, fall-arrest system, and earplugs (IHSA, 2022). They must also adhere to established lockout methods and procedures, use appropriate tools (e.g., refrigerant gauges, channel locks), inspect the condition of components (e.g., gas cylinders), store materials appropriately, and perform any other duties outlined in the OHSA (McMorrow, 2020a; McMorrow, 2020b). When air-conditioning and refrigeration mechanics perform work in an industrial establishment, either the Construction Projects regulation (OHSA O. Reg. 213/91, 2026) or the

Industrial Establishments regulation (OHSA O. Reg. 851, 2022) applies, depending on the nature of the work being performed (IHSA, 2021).

Proper safety training provides workers and supervisors with the knowledge and skills required to work safely and reduces the risk of accidents or injuries on site. Basic occupational health and safety awareness training is mandatory for all workers and supervisors in Ontario per the Occupational Health and Safety Awareness and Training Regulation, which states “an employer shall ensure that a worker who performs work for the employer completes a basic occupational health and safety awareness training program ... as soon as practicable” (OHSA O. Reg. 297/13, 2021). Additionally, Section 42 of the OHSA requires employers to provide prescribed instruction and training to workers who are exposed, or likely to be exposed, to hazardous materials or hazardous physical agents (OHSA, 2025, s. 42). Specialized training is also required for certain trades, based on the types of hazards they may be exposed to. For example, workers who engage in hot work, such as welding, cutting, soldering, or brazing, may be subject to additional fire-prevention and hot-work safety requirements, depending on the work environment and applicable site or regulatory requirements. Construction workers who require fall protection must also complete an approved Working at Heights training program (OHSA O. Reg. 297/13, 2021). In addition to the mandatory worker training per the OHSA, the IHSA offers a variety of interactive eLearning programs and courses to provide workers with additional knowledge to eliminate hazards further and reduce the risk of injuries. These include “Ergonomics – Manual Material Handling Workshop”, “Ergonomics for Skilled Trades”, “Ergonomics – How to Effectively Control MSD Hazards”, “Confined Space Hazard Awareness for Construction”, and “Lockout/Tagout: Electrical/Mechanical/Gaseous” (IHSA, 2023b). The IHSA also offers various manuals for specific trades, such as the “Refrigeration and Air-Conditioning Trade Health and Safety Manual” (IHSA, 2021), “Boilermakers Health and Safety Manual” (IHSA, 2015), and “Construction Health and Safety Manual” (IHSA, 2019).

Best construction practices refer to established procedures and recommended methods intended to improve safety and work performance. For example, the Construction Safety Association of Manitoba (CSAM) outlines best practices for various scenarios, such as construction site visits (CSAM, 2021a), drill operation (CSAM, 2021b), and COVID-19 prevention (CSAM, 2020). The IHSA outlines 8 best practices for independent operators in construction, including identification of all job-specific hazards (e.g., MSD hazards, repetitive strain, improper lifting), being informed on all rules and regulations (e.g., OHSA in Ontario or Canada Labour Code Part II for federally regulated businesses), and receiving adequate training (i.e., generic and job-specific training where applicable) (IHSA, 2023c). The Canadian Centre for Occupational Health and Safety (CCOHS) outlines various preventative measures for construction workers to minimize exposure to potential hazards. These include scanning the workplace for existing and potential hazards before work begins, inspecting equipment and machinery for defects, keeping tools and equipment in good working condition, and keeping work areas free of clutter (CCOHS, 2025). For manual material handling in particular, CCOHS recommends learning safe lifting techniques, avoiding awkward body positions, taking frequent breaks, and following a recommended shiftwork pattern (CCOHS, 2025).

Mechanical workers are exposed to additional hazards associated with handling, storing, and transporting chemicals. These workers must perform specific tasks and are exposed to unique hazards, necessitating specialized training and equipment. As such, they are required to receive specialized training, practice specialized safety procedures, wear role-specific PPE, and follow best practices for their work. Best practices for this type of work include removing gas cylinders from work vehicles on hot days (Peterson, 2018), avoiding use of damaged, rusted, or dented cylinders, and following manufacturer guidelines when servicing equipment (Harbin, 2006).

The mechanical trades are also governed by safety codes and standards that are periodically revised and adopted by authorities having jurisdiction. Relevant examples include CSA B51:24, Boiler, Pressure Vessel, and Pressure Piping Code; CSA B52:23, Mechanical Refrigeration

Code; and ASME A17.1-2025/CSA B44:25, Safety Code for Elevators and Escalators. These standards establish minimum safety requirements for the design, construction, installation, inspection, testing, operation, alteration, repair, and maintenance of covered equipment and systems.

As a result of the specialized tasks they perform, mechanical-trades workers are subjected to repetitive stresses, high workloads, awkward postures, and overexertion, often resulting in WMSDs. Work breaks are a commonly used injury mitigation measure, but they are often left to workers' or supervisors' discretion and are therefore not always optimally timed or consistently applied. WorkSafeBC identifies lifting, handling, or carrying objects as a source of musculoskeletal injuries, with risk increasing during bending, twisting, heavy loading, and awkward postures (WorkSafeBC, 2026). Accordingly, the literature on traditional controls indicates that mechanical-trade safety practices remain primarily oriented toward regulatory compliance, general hazard reduction, and procedural risk control, rather than toward measurement of worker-specific physical strain or task-specific support requirements.

Although these measures remain necessary for injury mitigation and compliance, they are generally broad or administrative in nature and do not consistently quantify task-specific physical strain. This motivates the need to examine more targeted, data-driven approaches to ergonomic assessment, worker-strain measurement, and intervention selection for WMSD risk mitigation.

2.3 Research Efforts on Enhancing HS&P of Construction Workers

Complementing the industry-level measures discussed in Section 2.2, recent research has increasingly explored digital and data-driven approaches for improving worker health, safety, and productivity in construction. These approaches include schedule optimization, computer vision, intelligent robotics, wearable sensing systems, and wearable support devices. Recent systematic reviews show that research on construction wearables has expanded across applications such as physiological monitoring, ergonomic assessment, hazard detection, activity recognition, location

tracking, fall detection, environmental sensing, worker-state evaluation, and data-analytics-enabled safety management (Kim et al., 2024; Fasoyinu et al., 2025). This broader literature is relevant to worker-strain assessment, intervention evaluation, and the growing use of data-driven methods to inform health and safety decisions in construction. Although these technologies differ in purpose and maturity, they collectively reflect a broader shift toward proactive and measurement-based management of worker injury risk.

2.3.1 Studies to monitor and mitigate worker stress

As noted in previous sections, unmanaged worker stress can contribute to fatigue and increase the risk of injury. One approach to controlling worker stress is to implement monitoring-based interventions that track physiological and physical indicators of strain. Park et al. (2023) and Bangaru et al. (2022) provide examples of fatigue-monitoring systems designed to assess worker fatigue with greater objectivity, while Aryal et al. (2017) showed under laboratory conditions that physiological measures, particularly heart rate and skin temperature, could be used to monitor fatigue in construction workers. Although much of this work remains laboratory-based, it suggests that real-time monitoring may help identify periods of elevated strain during physically demanding activities and support supervisory decisions regarding rest breaks, task rotation, or other controls. In addition to sensor-based measures, ratings of perceived exertion (RPE) provide a practical subjective indicator of physical strain and have long been used to characterize perceived work intensity (Borg, 1982). Recent construction research has also combined wearable heart rate sensing with worker fatigue perception surveys to monitor whole-body fatigue in field settings, further supporting the joint use of physiological and perceived exertion measures for strain assessment (Lee et al., 2024).

Heat-related illnesses (HRIs) are another important source of worker stress in construction. Li et al. (2016) conducted a case study of rebar workers to assess the impact of high-temperature conditions on construction labour productivity. The study found that each 1°C increase in on-site

Wet Bulb Globe Temperature (WBGT) resulted in a 0.57% decrease in direct work time and a 0.74% increase in idle time. The study also found that the period from 14:00 to 15:00 was the most hazardous for workers, while 07:00 to 09:00 was the least hazardous. These findings support the value of wearable sensing devices for monitoring workers' physiological measures, such as heart rate and skin temperature, to help mitigate the risk of injury.

Beyond physical strain and postural exposure, construction workers may also experience cognitive stress, mental fatigue, and reduced vigilance, which can affect safety performance in dynamic work environments. Early detection of these conditions can support preventative construction safety practices, such as optimized shift scheduling or worker break alerts, before reduced attention or impaired decision-making contributes to unsafe work. Historically, cognitive status assessment of construction workers relied mainly on self-reported surveys, which are subject to bias and may not provide objective or continuous data (Cheng et al., 2022b). Guo et al. (2017) conducted a field study in which construction workers' physical data were collected using wearable devices and psychological data were collected using a simplified PANAS questionnaire. While the study contributed to understanding the relationship between wearable-derived physical indicators and psychological status, the psychological assessment remained dependent on workers' self-reported emotional states. This reliance on subjective reporting limits the objectivity and consistency of cognitive-status assessment and supports the need for more continuous, sensor-based measurement approaches. More recently, Cheng et al. (2022b) reviewed 21 papers published between 2016 and 2021 on the use of electroencephalography (EEG) to measure and compute construction workers' cognitive statuses, including mental stress, mental fatigue, mental workload, vigilance, attention, and emotional state. Their review found that EEG-based computation models have shown reasonable accuracy under certain study conditions, demonstrating the potential of physiological sensing and computational models for construction safety applications. If this type of technology becomes practicable in construction settings, it could allow supervisors to use cognitive-

stress data to support proactive measures before reduced attention, impaired judgment, or fatigue contribute to hazardous situations.

Several studies have also examined optimization-based approaches for mitigating worker stress. Hsie et al. (2009) presented a theoretical genetic algorithm model implemented in MATLAB to create work-rest schedules for construction workers to minimize unnecessary energy expenditure from nonoptimal work arrangements and reduce job completion time. Under two case studies, the model efficiently located optimal solutions. In more recent work, Abuwarda et al. (2023) proposed a framework that uses wrist-worn wearable devices to continuously monitor construction workers' heart rate, energy expenditure, and location in real time, and then suggests efficient work-rest schedules to support recovery from fatigue. Cheng et al. (2018) developed a shiftwork optimization method that uses dynamic guiding, chaotic search, and particle swarm optimization to minimize evening and night shift work while meeting project duration and cost constraints. In the authors' case study, the method produced an 18-day schedule for \$148,900, \$7,400 (5%) less than a multi-objective genetic algorithm for the same duration. The authors also cite earlier field evidence that cycling two groups of workers every four days, instead of two 10-hour shifts five days per week, yielded 46% more work because of reduced cumulative fatigue. Collectively, these studies demonstrate that monitoring and optimization methods can leverage physiological, schedule, and task data to support proactive intervention decisions.

Job rotation has also been examined as an administrative control for reducing exposure to WMSD-related risk factors, although findings in this area remain equivocal (Comper et al., 2017; Padula et al., 2017). Some studies have found that job rotation may increase the risk of workplace injury in certain cases (Padula et al., 2017; Vinel et al., 2018). Mehdizadeh et al. (2020) reviewed the effects of job rotation on MSD risk. They concluded that its effectiveness depends strongly on the composition of the job pool, including the proportion of high-, medium-, and low-risk jobs, with higher-risk jobs receiving less benefit from rotation. These findings caution against treating

administrative controls as universally beneficial and reinforce the importance of accounting for work-specific and worker-specific risk profiles when selecting interventions.

The worker-stress literature indicates that physiological measures, perceived exertion, task demands, environmental conditions, and scheduling factors can support more objective assessments of worker strain and more proactive interventions. At the same time, limited guidance is available on how to translate such measures into decisions about the type of support a worker requires or the most appropriate wearable support device for that need. This leaves a critical gap between strain measurement and intervention selection. Addressing this gap requires selection approaches that connect physiological indicators, perceived exertion, ergonomic risk results, and affected body region to specific support requirements and, ultimately, wearable support device suitability.

2.3.2 Work schedule optimization

Poorly optimized or aggressively compressed work schedules can increase worker fatigue, stress, and exposure to hazardous conditions, especially when workers work excessive hours to compensate for project delays. Abuwarda and Hegazy (2019) addressed this issue at the planning level by developing a Constraint-Programming (CP) schedule fast-tracking model that integrates multiple acceleration strategies while accounting for worker overstress and site congestion risks. Abuwarda et al. (2023) extended this line of work toward real-time fatigue management by proposing a wearable-based framework that uses wrist-worn devices to collect worker heart rate, estimated energy expenditure, and location data to support work-rest scheduling, fatigue recovery, task sequencing, and reassignment of at-risk workers. These studies demonstrate that worker physiological data and optimization-based decision methods can support proactive health, safety, and productivity decisions in construction.

2.3.3 Computer vision

In recent years, computer vision (CV) technology has shown significant potential across several construction applications, including site inspection, progress monitoring, asset condition assessment, on-site material management, hazard identification, PPE compliance monitoring, and image-based ergonomic assessment. In the health and safety domain, CV is commonly used with artificial intelligence (AI) models to analyze construction-site images or videos, automatically detect hazardous conditions, and support timely warnings to workers or supervisors. For example, Zhang et al. (2019a) analyzed images from on-site cameras using Fast R-CNN to detect objects and identify hazardous zones; workers were also equipped with Bluetooth devices that would notify them if their location was detected within a hazardous area. This integration of CV-based hazard detection with wearable notification devices demonstrates the potential of incorporating wearable sensing in construction applications.

Other studies have used CV models to recognize construction workers, monitor PPE compliance, track moving entities, and detect accidents or unsafe conditions, with generally promising real-time performance, although smaller objects such as hardhats remain more difficult to detect reliably (Wang et al., 2019; Alateeq et al., 2023; Lo et al., 2023; Cheng et al., 2022a; Yang et al., 2022; Nath et al., 2020; Kim et al., 2016).

CV has also been applied to worker fatigue and ergonomic assessment. Such applications are valuable, given that WMSDs account for a large share of health issues among construction workers (Kim, 2017; Bangaru et al., 2022). Yu et al. (2019a) developed a fatigue assessment model that introduced a “fatigue index” based on changes in joint capacity during task performance, using CV-based 3D motion capture and biomechanical analysis of the resulting data. More recently, deep learning-based pose estimation has advanced considerably, enabling the automated computation of established ergonomic risk scores, such as REBA (Rapid Entire Body Assessment) and RULA (Rapid Upper Limb Assessment), directly from video data. Fan et al. (2024) introduced the ConstructionPose3D (CP3D) dataset, comprising approximately 421,000 annotated 3D construction

worker poses, and demonstrated that deep learning models trained on construction-specific data substantially outperform general-purpose models in estimating worker postures and generating ergonomic risk scores.

At the application level, CV-based ergonomic assessment tools are increasingly being used to automate posture-based risk assessment. For example, commercial software such as TuMeke uses smartphone video and computer vision-based joint tracking to extract 3D joint positions, calculate joint angles, and generate REBA, RULA, and NIOSH assessments (TuMeke, 2025). A recent reliability study found that TuMeke's REBA outputs showed strong reliability and useful agreement with trained human assessors, particularly for trunk, leg, and upper-arm scoring (Balogh et al., 2025). These developments suggest that CV-based tools can improve the consistency and efficiency of posture-related assessment.

Recent multimodal approaches have begun to combine CV with wearable pressure and inertial sensors to address occlusion and load-estimation limitations, thereby improving pose estimation accuracy in visually obstructed construction environments (Chen et al., 2025). Thus, CV-based assessment provides an accessible approach for identifying high-risk postures. At the same time, wearable sensing offers complementary data in conditions where camera-based methods face practical limitations, such as occlusion, viewpoint, or task conditions.

2.3.4 Intelligent robotics

Recent research on intelligent robotics has highlighted the potential of human-robot interaction to reduce worker physical demands and improve productivity, quality, and safety during construction tasks. Attalla et al. (2023) reviewed recent advancements in construction robotics. They described intelligent robotics as the integration of robotic systems with artificial intelligence, enabling robots to support perception, decision-making, and interaction in dynamic construction environments. Their review shows that robotics may support activities including automated installation and assembly, on-site fabrication, recognition or inspection, painting and printing, and additive manufacturing.

Related work has also examined simplified robotic programming approaches aimed at lowering the barrier to adopting construction robotics (Attalla et al., 2024). However, widespread implementation remains constrained by cost, complexity, site variability, and deployment practicality. Aparicio et al. (2020) similarly identified high implementation cost as a major barrier.

Accordingly, the robotics literature reinforces the broader need for feasible, cost-effective methods to reduce workers' physical stress in construction. Because many robotic systems require substantial capital investment, fixed installation, and specialized operation, wearable support devices offer a more practical, scalable, and economically accessible ergonomic intervention for many mechanical-trade applications, particularly when supported by a structured selection framework. Their comparatively lower cost, portability, and deployability at the individual-worker level make them a more feasible entry point for small and mid-sized contractors.

2.3.5 Studies on ergonomic and physical stress analysis

Historically, occupational ergonomics and fatigue assessment methods were limited in effectiveness because they relied heavily on manual observation by staff and on self-reporting by workers, such as through surveys or interviews (Matthews & Desmond, 2002; Neumann et al., 2001; Zhang et al., 2015). These methods were subjective, incomplete, and labour-intensive (Park et al., 2023; Valero et al., 2016; Yu et al., 2019a). To improve objectivity and scalability, researchers investigated the use of video recordings analyzed using established observational tools such as REBA, RULA, and OWAS, in which worker postures captured on camera are systematically evaluated for ergonomic risk (Yan et al., 2017; Yu et al., 2019b). This body of research has since supported the development of software tools that automate ergonomic risk scoring from video recordings, enabling more efficient and consistent assessment of worker postures than traditional observational methods.

More recently, wearable sensing systems have been investigated as a complementary approach for measuring worker condition, physical strain, posture, and exposure to safety-related risks. Systematic reviews indicate that these systems can support monitoring by detecting postures,

physical loads, physiological states, and biomechanical exposures, although practical validation and implementation remain variable across devices and settings (Donisi et al., 2022; Stefana et al., 2021; Kim et al., 2024; Fasoyinu et al., 2025). Kim et al. (2024) reviewed studies on wearable physiological technology in construction safety and health. They emphasized the importance of data preprocessing, feature extraction, statistical modelling, and prediction algorithms when using physiological signals to assess workers' physical and mental states. Fasoyinu et al. (2025) further investigated wearable sensing-device research in construction. They identified major application areas, including health monitoring, fatigue monitoring, hazard identification, activity recognition, location tracking, fall detection, environmental sensing, and communication/training, while also highlighting barriers related to cost, device durability, connectivity, privacy, and worker acceptance. Park et al. (2023) developed a fatigue assessment framework to measure and analyze workers' physical and mental fatigue in real time. Physiological features such as heart rate, skin temperature, and surface electromyography (EMG) were collected with a Samsung Galaxy Watch Active 2, and data were exported using LAsoR software. An ecological momentary assessment (EMA) application was also used. In a field test involving 100 workers on a construction site, the study reported that physical, or objective, fatigue was positively associated with early work start times, high workload intensity, poor work conditions, and changing or demanding schedules.

Bangaru et al. (2022) developed a continuous fatigue-monitoring system that predicts workers' aerobic fatigue threshold (AFT) using forearm muscle activity and motion data acquired via wearable EMG and IMU sensors. The proposed system comprised five modules: data acquisition, activity recognition, oxygen uptake prediction, maximum aerobic capacity estimation, and continuous AFT monitoring. The system was evaluated on participants performing fourteen scaffold-building activities and achieved a fatigue assessment accuracy of 92.31% using AFT features, compared to 51.28% using heart rate alone. This approach builds on earlier work by Aryal et al. (2017), who demonstrated that physiological measurements, including heart rate, skin

temperature, and galvanic skin response, could be used to monitor and predict fatigue levels in construction workers under laboratory conditions.

Valero et al. (2016) developed a system for real-time automated ergonomic assessment of construction workers, named “AT-BAN” (Activity Tracking with Body Area Network). AT-BAN uses wearable, wireless IMUs distributed over the body to measure acceleration, angular velocity, and heading, from which limb movements, joint angles, and working postures such as stooping and squatting are derived. The IMU devices contain sensors, including an accelerometer, gyroscope, and magnetometer, as well as a microprocessor, wireless transmission components, and built-in storage and power supply. The system was tested in a laboratory setting, with future work aimed at assessing it in real construction environments.

Complementarily, Yu et al. (2021) conducted a systematic review of posture-related data collection methods for construction workers and found that IMU-based wearables were the most frequently adopted sensing modality. However, inconsistencies in sensor placement, sampling frequency, and task scope limited cross-study comparability. Umer, Li, et al. (2018) developed a worker static balance-monitoring tool for proactive fall prevention using wearable IMUs to detect fatigue-induced changes in static balance after construction tasks. The tool was tested in laboratory simulations of rebar tying performed in stooping, stool-sitting, and squatting postures. Stooping and squatting significantly impaired post-task postural stability, and the tool detected these subtle post-task changes in static balance. If implemented in a practical setting, this technology could support informed decision-making on construction sites and minimize the risk of falls.

Antwi-Afari et al. (2018) similarly used a wearable insole pressure system to automatically detect and classify awkward working postures among construction workers, demonstrating that plantar pressure patterns could reliably distinguish high-risk from low-risk postures during repetitive construction tasks. Mohapatra et al. (2022) developed a lifting capacity prediction model for construction workers using physical performance and body measurements, including age, height,

weight, muscle strength, and endurance. The model recorded workers' core strength and endurance, grip strength, and lower-limb flexibility in 65 construction workers, and stepwise multiple linear regression was used to assess lifting capacity. The study found that age, BMI, grip strength, flexibility, and prone plank and trunk lateral flexor endurance tests had a significant influence on lifting capacity, and the resulting model was proposed for use in pre-placement and return-to-work evaluations to reduce the risk of low back disorders.

Suresh and Narwade (2022) proposed a lightweight smart PPE tool for monitoring construction workers and health and safety protocol adherence through a standard safety helmet equipped with an MQ-135 smoke sensor, MQ-3 gas sensor, DS18B20 temperature sensor, sound sensor, and infrared sensor, along with a Bluetooth module, buzzer, and Arduino Nano board. The device was designed to notify the construction site supervisor if a worker failed to adhere to health and safety protocols, such as intoxication or drowsiness on the job, and to warn the worker via buzzer upon exposure to safety hazards such as toxic fumes, high temperatures, or loud noises. This illustrates that smart, lightweight wearable devices have the potential to enhance health and safety performance on construction sites and suggests that future devices incorporating additional sensing capabilities could extend such monitoring to other safety-relevant indicators.

Collectively, these studies demonstrate that worker posture, fatigue, physical strain, balance, lifting capacity, and safety exposure can be quantified with increasing objectivity using video-based tools, wearable sensors, physiological measurements, and predictive models. However, much of this literature remains focused on monitoring or assessment rather than on translating the resulting information into practical intervention decisions. For mechanical-trade applications, wearable sensing and assessment methods can identify physical demands and risk exposure. However, additional decision-support methods are needed to determine which wearable support devices are most appropriate for specific workers, tasks, and work conditions. Recent reviews reinforce this limitation by noting the need for stronger field validation, larger and more

diverse samples, multi-sensor integration, and better translation of wearable-derived data into practical safety-management actions (Donisi et al., 2022; Stefana et al., 2021; Yu et al., 2021; Kim et al., 2024; Fasoyinu et al., 2025).

2.3.6 Commercial wearable support devices to improve HS&P

Wearable support devices and exoskeletons have become an increasingly active area of research in construction ergonomics, particularly as potential interventions to reduce physical demands in high-exertion, repetitive trade tasks. These assistive devices may support construction workers by reducing musculoskeletal loading, providing joint support, redistributing physical load, and promoting improved working posture (Monica et al., 2021; Zhu et al., 2021; Pomerleau, 2022). The need for such interventions is especially evident given the prevalence of WMSDs among construction workers, with Zingman et al. (2017) reporting a 16% higher rate of occurrence in construction than across all other industries combined. Butler (2016) field-tested a wearable support device with welders and electrostatic painters, reporting productivity gains of 86% for welders and 26.79% and 53.13% for the two painters, sustained work quality, relief of existing shoulder discomfort, and a significantly lower %MVC (muscle activation) while wearing the device. Bosch et al. (2016) further found that support wearables used during forward-bending tasks reduced lower-back muscle activity by approximately 35-38%. Da Costa and Vieira (2010) also identified posture-related and physical-load-related occupational exposures as important contributors to musculoskeletal outcomes. However, the suitability of wearable support devices depends on the task being performed, the target body region, worker characteristics, and the implementation context, indicating that device selection should not be treated as a universal or one-size-fits-all decision (Drees et al., 2023; Okunola et al., 2024; Qu et al., 2025).

Zhu et al. (2021) reviewed existing wearable support device technologies across 85 relevant articles and analyzed their potential for use in construction manual-handling tasks. Their review found that most existing device assessments had been conducted in laboratory settings with healthy

participants aged 20-30, indicating a need for stronger evidence from practical construction environments. The review also noted that previous efforts had focused mainly on physical performance improvements from exoskeleton use, with less attention given to user comfort and applicability across different trades. Consistent with these concerns, Bennett et al. (2023) conducted a field-based pilot study in which four professional construction workers performed a range of construction tasks while using exoskeletons and exosuits. Participants reported mixed usability experiences; some identified task-related benefits, whereas others reported movement restrictions and discomfort from tight arm and leg straps. Recent construction-specific adoption research has similarly emphasized that exoskeleton implementation is shaped by both technical and organizational factors, including task suitability, training requirements, user adjustment, maintenance, cost, and stakeholder acceptance (Okunola et al., 2024; Gonsalves et al., 2023). Collectively, these studies indicate that wearable support devices offer meaningful potential for reducing physical stress during labour-intensive work. However, their practical value depends on task-level applicability, user acceptance, field conditions, and organizational constraints.

Mahmud et al. (2022) reviewed facilitators and barriers to exoskeleton adoption in construction and identified key challenges, including ownership and maintenance costs, logistical requirements such as staffing and training, movement restrictions, and limited empirical evidence given the technology's novelty. Broader occupational-exoskeleton research has similarly mapped the methodological and organizational challenges of large-scale workplace adoption, framing it as a multi-stakeholder process rather than a purely technical one (Crea et al., 2021). Consistent with these barriers, Drees et al. (2023) proposed a systematic framework for selecting occupational exoskeletons for specific use cases, consolidating 99 selection criteria into seven dimensions spanning task and workplace, user, human-machine interface, technological, economic, socio-cultural, and political factors. Drees et al. (2025) extended this work into a knowledge-based methodology that proposes integrating task simulation, biomechanical (musculoskeletal and physiological) simulation, and multi-criteria decision analysis to rank candidate exoskeletons by their

fitness for a given user and task. These methodologies demonstrate that structured, criteria-based selection can link worker characteristics and physical strain to device-provided support. However, that linkage is established using modelled strain derived from biomechanical simulation rather than strain measured directly on workers, and both methodologies remain oriented toward manufacturing and industrial-production settings and are explicitly theoretical: Drees et al. (2023) note that their framework has yet to be proven in practice, while Drees et al. (2025) present an unvalidated simulation methodology. This underscores the remaining need for worker-specific matching of measured strain to device-provided support for real-world mechanical-trade construction tasks.

Recent review work by Qu et al. (2025) further indicates that back-support exoskeletons show meaningful potential to reduce work-related musculoskeletal loading, but that their effectiveness varies with device type, driving mode, mechanical structure, task conditions, human-machine interaction, and evaluation method. The review also notes that performance indicators and evaluation approaches remain heterogeneous, reinforcing the need for structured, task-specific assessments rather than generalized assumptions about back-support benefits.

Golabchi et al. (2022) systematically reviewed industrial exoskeletons for injury prevention and found that evaluations have relied on a range of objective and subjective measures, with electromyography and motion capture being most common, but also including force measurement, heart rate, ratings of perceived exertion, discomfort ratings, and task-performance outcomes. Their review emphasized that exoskeleton evaluation should consider both objective and subjective indicators, as well as the target task and supported body posture. This indicates that readily available measures such as heart rate, perceived exertion, discomfort, and task performance are already recognized in exoskeleton evaluation, supporting their relevance for assessing the suitability of wearable support devices. A remaining limitation is the lack of guidance on translating such measures into practical, task-specific device-selection decisions for construction work.

Construction-specific field evidence further supports this task-dependent interpretation. In a field study with fourteen pipe workers, Gonsalves et al. (2023) found that a passive back-support

exoskeleton was generally rated as easy to use and did not appear to reduce perceived productivity, while workers also reported lower-back support benefits. However, workers identified important adoption barriers, including increased discomfort at the chest, thigh, and shoulder, compatibility issues with safety harnesses, and reduced suitability in confined spaces. These findings show that the suitability of wearable support devices depends not only on support benefit but also on task conditions, worker acceptance, and compatibility with site constraints.

Beyond perceived usability, a growing body of controlled and field experiments now quantifies the biomechanical effects of these devices on the targeted body regions and consistently shows that the benefits are task- and region-specific. For back-support devices, both passive and active designs reduce the demand on trunk extensors during lifting and forward-bending work. Antwi-Afari et al. (2021) reported that a passive back-support exoskeleton significantly reduced lower-back muscle activity and improved subjective responses during repetitive manual material handling among construction workers, while Walter et al. (2023) found that an active exoskeleton reduced erector spinae muscle activity during lifting. Powered and soft-exosuit designs have produced comparable results in construction-relevant protocols: Lei et al. (2024) demonstrated that a lightweight active soft back exosuit reduced lumbar muscular effort during lifting tasks, and Chung et al. (2024) showed that a lightweight active back exosuit reduced muscular effort across an hour-long order-picking task, which shares the sustained repetitive lifting demands relevant to mechanical-trade work and suggests that benefits can persist over realistic work durations. Okunola et al. (2025) extended this evidence to a specific trade, reporting that an active back-support exoskeleton reduced physical demand during carpentry framing tasks.

However, the back-support literature shows that exoskeleton effects are task- and outcome-specific, reinforcing the need for task-specific selection rather than assumed benefit. Some studies report benefits across all measured outcomes without observed costs. Ojha et al. (2024) found that powered back-support exoskeletons significantly reduced back and abdominal muscle activity

(~60%), metabolic cost (~17%), and ergonomic risk (~40–50%) during construction material-handling and rebar-tying tasks, without compromising postural stability. Other work, however, documents more complex trade-offs. Ratke et al. (2025) reported that a passive back-support exoskeleton reduced perceived exertion and lumbar erector spinae activity (asymmetrically) during a complex repetitive lifting task, yet also altered movement coordination. Specifically, trunk (thorax–pelvis) coordination variability decreased while shoulder-lumbar variability increased. Biomechanical-modelling work by Madinei & Nussbaum (2023) further showed that estimated lumbar spine loading is task-specific and device-dependent: the BackX and Laevo reduced peak L5/S1 compression and shear by roughly 8–15%, but the Laevo's reductions occurred only during the lowering phase, and reductions in trunk muscle activity did not always correspond to reductions in spinal loading.

For overhead and arm-elevation work, upper-limb and shoulder-support devices show region-specific benefits. Kong et al. (2023) found that two passive upper-limb exoskeletons significantly reduced muscle activity during overhead drilling, with reductions of roughly 29–58% in the targeted upper-limb muscles. Reductions in the non-targeted back and leg muscles were smaller (roughly 3–42%), and rectus femoris activity was unchanged. Mänttari et al. (2023) reported reduced muscle activity (on average about 22.5%, up to ~38% in the deltoid) in tasks requiring arm elevation. Ojelade et al. (2023) compared three passive arm-support exoskeletons and found that they generally reduced or maintained perceived exertion during overhead tasks, with the magnitude of the effects varying across devices and task demands. In construction-specific evaluations, Musso et al. (2024) reported that an upper-limb exoskeleton influenced muscle activity during construction tasks, reducing shoulder flexor activity while modestly increasing extensor activity when work was performed below shoulder level. Pinho & Forner-Cordero (2022) found that a commercial upper-limb exoskeleton reduced shoulder muscle activity while maintaining or improving perceived comfort during simulated tasks. Zheng et al. (2024) found that passive shoulder-assist exoskeletons provided more limited muscle-activity benefit during a block-laying task on a simulated mast climber

and were accompanied by changes in whole-body balance, suggesting that stability is an important consideration when selecting devices for this kind of construction setting. Active and power-assist designs have also been explored for handling tasks, with Yoon et al. (2024) presenting an upper-limb power-assist wearable robot for repetitive weight handling, and Yan et al. (2021) developing and testing a passive lower-limb support exoskeleton to support industrial workers during sustained postures.

A recurring methodological theme in this experimental literature is that laboratory-measured effectiveness may not transfer directly to the field. Shakourislim et al. (2024) compared biomechanical assessments of manual material handling with exoskeletons in laboratory and field settings and found meaningful differences between the two settings, reinforcing the importance of realistic test conditions. Consistent with this, efforts toward realistic and standardized evaluation have emerged: Dunson-Todd et al. (2024) implemented a realistic, controlled, repeatable test of a passive back-support exoskeleton for rebar workers and observed significant reductions in lower-back muscle activity across lifting, carrying, placing, and tying, while also documenting that effects varied with working posture. Di Natali et al. (2024) applied an equivalent-weight assessment method to a real task performed by railway workers wearing a back-support exoskeleton, finding that the device reduced the NIOSH Lifting Index by 54-64% in targeted lifting, lowering, and carrying sub-tasks. Together, these studies confirm that 1) wearable support devices can deliver measurable physical support benefits, and 2) those benefits are conditional on task, body region, device type, and evaluation setting, precisely the factors that a structured selection method must account for.

Beyond physical-support devices, smart wearable technologies have also expanded across sectors such as healthcare, warehousing, distribution, and sport, reflecting broader advances in sensing, monitoring, and assistive systems. In construction, the literature reviewed in this chapter points to benefits of wearable devices such as smart hard hats, safety vests, boots, wristbands, inertial sensors, physiological sensors, and eye-tracking systems for worker stress monitoring,

ergonomic analysis, hazard detection, and worker-state assessment (Kim et al., 2024; Fasoyinu et al., 2025). Abuwarda et al. (2022) reviewed 173 papers on wearable devices across the healthcare and construction domains and found substantial potential for construction applications, particularly in ergonomic and fatigue analysis. Awolusi and Sulbaran (2021) proposed a decision-support framework using a TOPSIS multi-criteria approach for selecting wearable Internet of Things devices for construction safety management, demonstrating the growing need for structured selection methods as the number and diversity of wearable technologies expand. However, their framework addresses construction wearable IoT devices more broadly rather than the selection of wearable support devices for body-region-specific physical support. Therefore, although prior work has proposed promising structured selection approaches for occupational exoskeletons and construction wearable IoT devices, existing frameworks do not fully address the combined influence of task demands, worker characteristics, affected body regions, device support capabilities, and implementation constraints in real-world mechanical-trade applications.

Several recurring methodological limitations further motivate a structured, worker-specific selection approach. First, samples are often small and demographically narrow, drawn from young, healthy participants who may not represent the age range, conditioning, or sex distribution of the working population (Ratke et al., 2025; Dunson-Todd et al., 2024). Second, as noted above, much of the evidence comes from controlled laboratory or simulated conditions, and biomechanical effects measured in such settings do not always transfer to the field (Shakourisalim et al., 2024). Third, exposure durations are frequently short, so longer-duration evidence such as Chung et al.'s (2024) hour-long protocol remains comparatively rare, and the persistence of benefits over a full shift is not well established. Fourth, reductions in one outcome can coincide with costs in another. A back-support device can alter movement coordination, increasing coordinative variability at the shoulder while constraining it at the trunk, or require compensatory antagonist-muscle activation (Ratke et al., 2025), and reductions in muscle activity do not necessarily correspond to reductions in spine loading, with benefits proving task- and design-specific (Madinei & Nussbaum, 2023). Collectively,

these limitations indicate that device benefit cannot be assumed from biomechanical performance alone, and that selection must jointly account for worker-, task-, and context-specific factors.

These benefits are also unevenly accessible. Much of the strongest evidence relies on relatively high-cost, logistically demanding assessment tools: Golabchi et al. (2022) found that 33 of 42 reviewed studies used electromyography, 18 used motion capture, 8 used heart rate, and 7 used metabolic measures. A systematic review of the quality, productivity, and economic implications of occupational exoskeletons further found that evidence on cost-effectiveness and productivity outcomes remains limited and mixed, reinforcing the need to weigh economic feasibility alongside biomechanical benefit (Fournier et al., 2023). Similarly, many evaluated support devices are higher-cost powered exoskeletons. This points to an underexplored opportunity around lower-cost wearable devices and accessible measures, such as heart rate, perceived exertion, ergonomic risk scores, and task completion time, that are more feasible for use on real construction sites (Attalla et al., 2025).

Overall, the literature demonstrates that wearable support devices can reduce physical loading, improve posture, and mitigate the risk of WMSDs during construction work. However, the reported benefits are not universal and depend strongly on the specific task, target body region, worker characteristics, usability or procurement constraints, and implementation setting. Existing studies therefore support the potential value of wearable support devices, while also indicating that effective deployment requires a structured selection process. This need is more pronounced in mechanical-trade applications, where tasks vary substantially in posture, force demands, duration, access constraints, and the anatomical regions affected. Accordingly, the literature supports the need for a decision-support method that matches workers, work activities, and wearable support devices based on multiple factors.

The selection and decision-support tools cited in this chapter rest on different techniques. Drees et al. (2023) consolidated 99 selection criteria into seven dimensions, Drees et al. (2025)

proposed combining task and biomechanical simulation with multi-criteria decision analysis to rank candidate exoskeletons, and Awolusi and Sulbaran (2021) proposed a TOPSIS-based framework for selecting wearable IoT devices. The two Drees methodologies link worker characteristics and strain to device-provided support but neither measures strain on workers (the 2025 methodology simulates it) and both remain oriented toward manufacturing settings, while the IoT framework does not address body-region-specific physical support. The schedule-oriented studies of Sections 2.3.1 and 2.3.2 rest on search and optimization techniques, from a genetic algorithm and particle swarm optimization to constraint programming (Hsie et al., 2009; Cheng et al., 2018; Abuwarda & Hegazy, 2019), later extended with wearable data for real-time work-rest scheduling (Abuwarda et al., 2023), and a third group applies prediction models to monitoring or assessment rather than selection (Mohapatra et al., 2022; Bangaru et al., 2022; Fan et al., 2024; Cheng et al., 2022b). None of these tools combines strain measured directly on workers, a prediction of the support each worker requires, and a constrained choice among candidate devices within a single method. Table 2.1 summarizes the strengths and limitations of the approaches reviewed in Section 2.3 for the selection of wearable support devices.

Table 2.1: Approaches reviewed for the selection of wearable support devices

Approach (Section)	Strengths	Limitations
Wearable physiological monitoring and self-report measures (2.3.1, 2.3.5)	Objective indicators of strain (heart rate, skin temperature, EMG and IMU signals) and perceived exertion for assessing or predicting fatigue; heart rate and perceived exertion are feasible to collect on construction sites	Limited guidance on translating measured strain into the type of support a worker requires; research-grade EMG and IMU systems are high-cost and logistically demanding for routine field use
EEG-based cognitive-state assessment (2.3.1)	Sensor-based measures of mental stress, mental fatigue, mental workload, vigilance, attention, and emotional state, with reasonable accuracy under certain study conditions	Addresses cognitive rather than physical strain; practicability in construction settings not yet established
Work-schedule optimization (work-rest, shift, and fast-tracking schedules) and job rotation (2.3.1, 2.3.2)	Scheduling decisions that account for worker fatigue or overstress, using physiological, schedule, and task data (genetic algorithm, particle swarm optimization, constraint programming, wearable data); job rotation as an administrative control	Outputs are schedules or rotations, not support-device selections; job-rotation findings are equivocal
Computer vision for hazard detection and PPE compliance (2.3.3)	Automatic detection of hazardous zones, PPE compliance, moving entities, and unsafe conditions from site imagery, with generally promising real-time performance	Addresses hazards rather than physical strain; small objects such as hardhats remain more difficult to detect reliably
Video-based and automated ergonomic risk scoring (2.3.3, 2.3.5)	Posture-risk scores (REBA, RULA, OWAS, NIOSH) and a joint-capacity fatigue index from video; automation improves the consistency and efficiency of assessment; available through commercial software using smartphone video	Assesses posture risk without indicating an intervention
Intelligent robotics and human-robot interaction (2.3.4)	Potential to reduce worker physical demands and improve productivity, quality, and safety; may support installation, fabrication, inspection, painting, and additive manufacturing	Substantial capital investment, fixed installation, and specialized operation; implementation cost identified as a major barrier
Body-worn sensing for posture, balance, and exposure; prediction of physical capacity (2.3.5)	Objective measurement of posture, joint angles, balance, and hazard exposure with IMUs, insole pressure sensors, and sensor-equipped helmets; regression-based prediction of lifting capacity	Focused on monitoring and assessment rather than intervention selection; inconsistent sensor placement limits cross-study comparability; research-grade IMU systems are high-cost and logistically demanding for routine field use
Wearable support devices: passive and active exoskeletons and exosuits (2.3.6)	Reported reductions in muscle activity, metabolic cost, and perceived exertion, and modelled reductions in lumbar spine loading; productivity and usability benefits reported in some field studies	Benefits are task-, body-region-, and device-specific and may not transfer from the laboratory to the field; many evaluated devices are higher-cost powered exoskeletons assessed with EMG and motion capture; discomfort and compatibility issues reported
Structured selection frameworks and decision-support tools (2.3.6)	Criteria-based selection: Drees et al. (2023, 2025) link worker characteristics and physical strain to device-provided support; Awolusi and Sulbaran (2021) propose a TOPSIS-based framework for selecting wearable IoT devices	Strain not measured on workers (simulated in 2025 methodology), oriented toward manufacturing settings, not validated in practice (Drees et al.); does not address body-region-specific physical support (Awolusi and Sulbaran)

Note. EEG = electroencephalography; EMG = electromyography; IMU = inertial measurement unit; IoT =

Internet of Things; NIOSH = National Institute for Occupational Safety and Health; OWAS = Ovako Working Posture

Analysis System; PPE = personal protective equipment; REBA = Rapid Entire Body Assessment; RULA = Rapid Upper

Limb Assessment; TOPSIS = Technique for Order of Preference by Similarity to Ideal Solution.

2.4 Summary of Research Gaps

Based on the preceding literature review, the following research gaps can be summarized:

- **Absence of device-level selection in conventional controls:** Traditional safety approaches, including PPE, training, and best practices, address workplace risk broadly but operate at the program level. As such, they do not facilitate the selection of a wearable support device suited to a specific worker, task, and body region, offering limited basis for effective device-level intervention.
- **Promising technologies require translation into intervention:** A substantial body of promising research exists on wearable sensing, computer vision-based ergonomic assessment, wearable support devices, exoskeletons, schedule optimization, and robotic systems for improving worker health, safety, and productivity. These technologies demonstrate the ability to assess worker conditions, evaluate ergonomic risks, and reduce physical demands. However, the literature remains more developed in demonstrating these capabilities than in guiding practical, worker- and task-specific intervention decisions.
- **Task- and worker-dependent device suitability:** Smaller, lower-cost wearable support devices targeting specific body regions may offer practical benefits for mechanical-trade applications, yet a significant gap remains in their appropriate selection across different trades and worker needs. Because support requirements can vary with the trade, the affected body region, and the individual worker profile, suitability cannot be judged on biomechanical benefit alone; it must also account for these factors.
- **Insufficient field validation:** Much of the published evaluation of wearable support devices has been conducted under controlled or simulated laboratory conditions. Although these findings remain relevant, further evidence from practical field settings is needed to capture task variability, environmental constraints, worker acceptance, and implementation barriers.
- **Reliance on high-cost support devices and assessment tools:** Much of the reviewed literature centers on high-cost, logistically demanding wearable support devices and

assessment tools. This reveals an underexplored opportunity to leverage more accessible alternatives, including heart rate monitoring, perceived exertion, ergonomic risk scores, and low-cost wearable support devices, that are not only better suited to active construction sites but also implementable more broadly across trades, sites, and larger worker populations.

- **Disconnect between strain measurement and device selection:** Research on wearable sensing and fatigue monitoring demonstrates that physiological measures, such as heart rate, and worker-reported measures, such as perceived exertion, can support the assessment of worker strain. However, limited guidance exists on how to incorporate these measures into a structured selection process for wearable support devices, leaving a gap between measuring worker strain and translating those measurements into the support device a worker requires.
- **Incomplete coverage in existing selection frameworks:** Existing decision-support work has addressed related problems, such as occupational exoskeleton selection and wearable IoT device selection for construction safety. However, these frameworks rely on modelled rather than directly measured strain, remain oriented toward manufacturing settings, and have not been validated in practice. Therefore, the literature does not adequately address the appropriate selection of wearable support devices for mechanical-trade workers, considering the combined influence of task demands, worker characteristics, body-region-specific support requirements, device capabilities, and implementation constraints.

Therefore, the primary research gap is the limited availability of an integrated decision-support approach for matching wearable support devices to mechanical-trade workers based on worker, device, and task fit. Addressing this gap requires a structured method that integrates physiological and ergonomic indicators, affected body region, device-provided support, and implementation constraints, so that device selection is based on measurable worker, task, and device characteristics rather than generalized assumptions about wearable benefit.

Chapter 3: Proposed Decision Support Framework

3.1 Introduction

This chapter presents the proposed framework for the evaluation and optimal selection of wearable support devices for mechanical-trade workers. The framework spans the identification of industry needs and the body regions most at risk in mechanical-trade work, the experimental evaluation and classification of low-cost commercially available wearable devices, and the development of a decision support system that generates worker-specific device recommendations under budget constraints. Its outputs are therefore twofold: an evidence-based classification of the support that low-cost wearables provide, and a means of selecting, for an individual worker, the combination of devices best suited to their needs. The following sections present each component of the framework.

3.2 Components of the Proposed Framework

As illustrated in Figure 3.1, the framework comprises three sequential components:

- **Component 1:** Industry data are collected and analyzed to identify the body regions most affected by WMSDs among mechanical-trade workers and the working postures that load them.
- **Component 2:** A range of low-cost wearable support devices is experimentally evaluated to investigate the extent to which each device provides support for the identified body regions.
- **Component 3:** Experimental results are used to train predictive models to estimate each worker's required level of support (LOS) for each body region. The predictive models are then integrated with an optimization model to form a decision support system (DSS) that provides tailored wearable device recommendations for mechanical-trade workers.

In Figure 3.1, Component 1 corresponds to the Industry Data Collection input and to the Industry Findings of the Analysis stage; Component 2 to the Experimentation column and to the Classification of Wearable Devices' Provided Level of Support in the Model Development stage; and Component 3 to DSS Phases #1 and #2 (prediction of the worker's required LOS, and

optimization of device selection). The outputs of each component serve as inputs to the next. The at-risk body regions and working postures identified in Component 1 determine which devices are catalogued and which tasks are performed in Component 2. Component 2 then supplies two inputs to Component 3: the classified device catalogue, and the experimental measurements used to determine each worker's required LOS, which the predictive models are trained to estimate. The predicted worker requirements, together with the classified device catalogue, are the inputs to the optimization model, which outputs the body-region-specific wearable support device combination that satisfies the worker's requirements within budget.

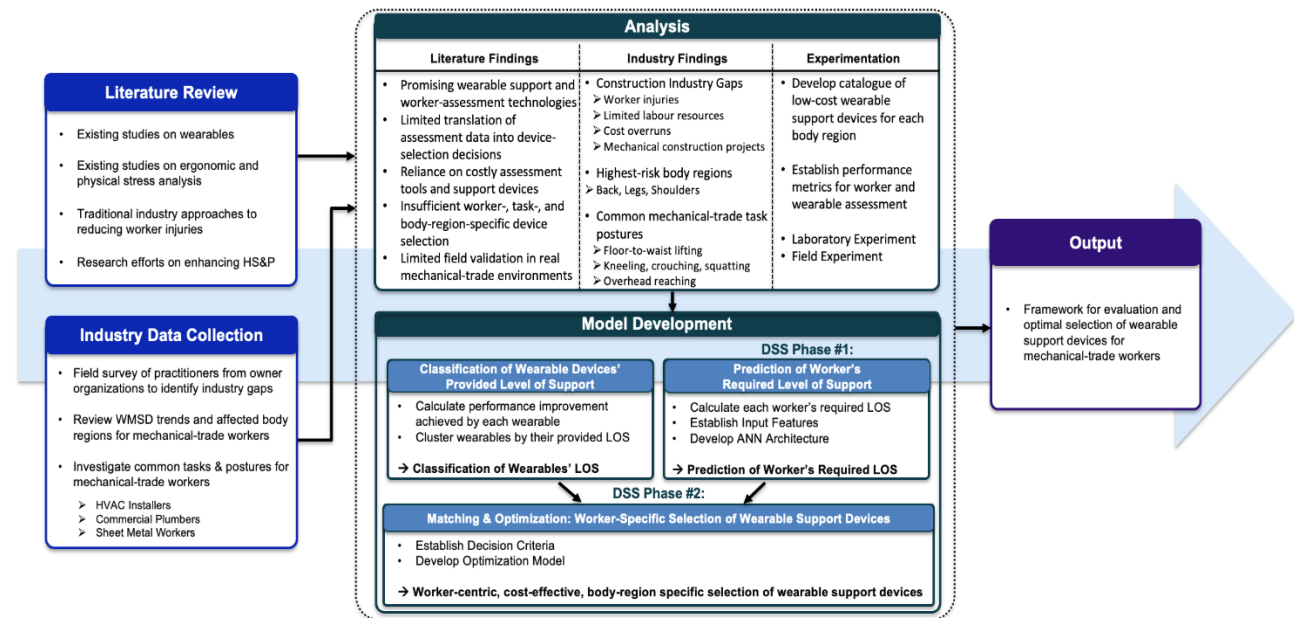


Figure 3.1: Framework for evaluation and optimal selection of wearable support devices

3.2.1 Component 1 – Industry Data Collection

In this component of the research, a field survey is administered to project managers, field engineers, and executive staff to investigate the primary challenges currently faced by the construction industry and to identify key industry gaps. The survey serves to ground the research problem in current practitioner priorities rather than in the literature alone. Publicly available worker injury databases are then examined to understand the body regions most frequently affected by WMSDs within the targeted mechanical trades. These findings inform the selection of body regions

for subsequent experimental evaluation. Finally, commonly performed mechanical-trade tasks are investigated to identify the postures most frequently adopted by workers in the field, thereby informing the design of experimental tasks in subsequent sections. Together, these analyses establish the body regions requiring the greatest support and the working postures responsible for loading them, thereby guiding wearable device selection and defining the experimental scope.

3.2.2 Component 2 – Experimental Evaluation and Classification of Wearable Devices

This research component comprises four steps. First, a catalogue of low-cost commercially available wearable support devices targeting the identified body regions is compiled, spanning a range of costs and anticipated levels of support. Second, performance metrics are established for the assessment of both wearable devices and workers. Third, the catalogued devices are evaluated in a laboratory setting using simulated tasks and in a field setting using real mechanical-trade tasks. Fourth, the performance improvement achieved by each device is calculated, and the devices are clustered by the LOS they provide. The resulting classification is then examined in three ways: a comparison of laboratory and field results is performed to validate the laboratory findings and confirm their applicability in the field; a cost-benefit analysis is conducted to investigate the relationship between wearable device cost and the LOS provided; and questionnaire results are analyzed to assess correlations between objectively classified support levels and user-perceived outcomes, further corroborating the classification results. The output of this component is a classified catalogue of wearable devices, each with an assigned LOS value.

3.2.3 Component 3 – Decision Support System for Optimal Wearable Selection

The third component of this research involves the development of a decision support system for recommending wearable support devices to mechanical-trade workers. The DSS consists of two sequential and integrated phases: (1) prediction of a worker's required LOS, and (2) optimization of device selection based on the predicted requirement.

In the first phase of the DSS development, experimental data collected without wearable devices are used to determine participants' required LOS for each body region. Participant performance is assessed using the performance metrics established in the previous component, which are combined to classify workers into required-LOS categories. These classifications are subsequently used as the target outcomes for machine-learning predictive models. Using workers' anthropometric, demographic, and general health characteristics as inputs, the predictive models estimate the required LOS of individual workers for each body region.

In the second phase, an optimization model recommends a set of wearable devices across the worker's at-risk body regions, matching the predicted required LOS for each region against the LOS provided by the catalogued devices, subject to device cost and the worker's available budget. The budget allocation is optimized across all regions simultaneously, rather than region by region, such that the recommended wearable device set satisfies the worker's overall support requirements. Finally, the proposed DSS is tested through a field validation in which recommended devices are assigned to mechanical-trade workers performing real-world tasks, and feedback on device performance is collected and evaluated.

Table 3.1 summarizes the methods used in each component of the framework: for each step, its inputs, the method or tool applied, the rationale for its selection, its output, and the section in which it is detailed. The table also shows how the components are connected, since the output of each component is an input to the next.

Table 3.1: Methods used in each framework component

Step	Inputs	Method/Tool	Rationale	Output	Section
<i>Component 1 – Industry data collection (Chapter 4)</i>					
Field survey	Practitioners in executive, project-management, and field roles (13 owner organizations)	Online questionnaire; descriptive analysis of counts, ratings, and open-ended responses	Grounds the research problem in practitioner priorities rather than the literature alone	Industry challenges and opportunities (Tables 4.1 and 4.2)	4.2

Step	Inputs	Method/Tool	Rationale	Output	Section
Injury data analysis	WMSD claim records from IHSA, WSIB, and WorkSafeBC	Tabulation of claims, costs, and lost workdays by age group, body region, and injury mechanism	Authoritative multi-year records that indicate where support is most required	At-risk body regions: back, legs, and shoulders	4.3.1-4.3.2
Working-posture review	Field images, site observations with practitioner input, and published physical demands analyses	Frequency review of postures across mechanical-trade tasks	Derives realistic postures that load the at-risk regions	Posture set for the experimental tasks	4.3.3
<i>Component 2 – Experimental evaluation and classification of wearable devices (Chapter 5)</i>					
Device catalogue	Commercially available low-cost wearables for the three regions	Market review across a range of cost and anticipated support	Affordability is a documented barrier to adoption	12 catalogued devices (5 back, 4 leg, 3 shoulder)	5.2.3
Performance metrics and instruments	Each participant-task-device trial	Fatigue Threshold, Heart Rate Change (Apple Watch Ultra 2), and Ergonomic Risk Score (TuMeke video analysis); five-point questionnaire	Accessible, validated measures of complementary dimensions of strain; sEMG excluded for cost, worker burden, and limited accessibility	Metric values per trial and user ratings	5.2.4-5.2.5
Laboratory and field experiments	44 participants in the laboratory (31 non-practitioners and 13 practitioners); the 13 practitioners in the field	Baseline and with-device trials on simulated (laboratory) and real (field) mechanical-trade tasks; two-tailed paired t-tests of with-device against baseline values for each device and metric (Tables 5.9 and 5.10)	Laboratory control with field realism; the field experiment tests laboratory-to-field transfer; pairing makes each participant their own control	Percentage change in each metric per participant-device trial	5.2.1-5.2.2, 5.3
Device clustering	Percentage change in each metric for every participant-device observation (laboratory and field)	EM clustering in WEKA with three clusters, compared with K-means, Farthest First, and Canopy	Balanced clusters across regions and settings; three levels correspond to the worker LOS scale	Low, Medium, and High cluster shares per device	5.4.2
LOS classification	Cluster shares per device	Level of Support Index with equal-width thresholds	Fixed, sample-independent partition that is comparable across studies	LOS provided (1 to 3) for each device	5.4.3

Step	Inputs	Method/Tool	Rationale	Output	Section
Classification verification	Laboratory and field LOS indices; device prices; questionnaire ratings	Classification agreement, MAPD, Spearman, Pearson, and Wilcoxon tests; R ² of cost against LOS; rating-by-LOS comparison	Tests laboratory-to-field transfer, the cost-support relationship, and agreement with user perception	Laboratory-field agreement of the classification; cost-LOS relationship by region; relationship between LOS and user ratings	5.4.4-5.4.6
Component 3 – Decision support system (Chapter 6)					
Dataset augmentation	44 baseline (no-device) records per region	Gaussian noise with a standard deviation of 10% of each feature's standard deviation	A sample of 44 is small for a robust model and risks overfitting	Augmented dataset (n = 176 per region)	6.2.1
Required LOS of workers	Baseline (no-device) performance records for each region	Percentile of the composite baseline score within the approximately normal sample distribution (analytical method), preferred over a clustering alternative	Consistent, predefined criterion on the same three-level scale as the devices	Required LOS (1 to 3) per participant and region	6.2.2
Predictive model	Age, sex, BMI, body fat percentage, and health score	MLP ANN in WEKA, compared with Random Forest, SVM, and J48	Highest Kappa in every region and highest or near-highest F-Measure; suited to small tabular datasets	Predicted required LOS per region	6.2.3-6.2.4
Optimization	Predicted required LOS, device catalogue, budget, and opt-outs	Excel Solver (Evolutionary engine): cost minimization with a 1% cost-equivalence tie-breaker; exact MILP verification with HiGHS	Solves the lookup-based model as constructed, without programming expertise; solutions verified against an exact solver (Section 6.6)	Recommended worker-specific device set, or the minimum budget required	6.3, 6.6
Field validation	Practitioners from outside the model-development cohort	End-to-end application of the DSS and an eight-item questionnaire after real tasks	Independent test of the complete workflow	Recommended device sets and worker feedback (Tables 6.10 and 6.11)	6.5

Note. ANN = artificial neural network; EM = expectation maximization; EMG = electromyography; IHSA = Infrastructure Health and Safety Association; LOS = level of support; MAPD = mean absolute percent difference; MILP = mixed-integer linear programming; MLP = multilayer perceptron; SVM = support vector machine; WEKA = Waikato Environment for Knowledge Analysis; WSIB = Workplace Safety and Insurance Board.

3.3 Summary

This chapter has presented the proposed framework for the evaluation and optimal selection of wearable support devices. The first component draws on industry data to establish the body regions most at risk in mechanical-trade work and the postures responsible for loading them. The second component develops a catalogue of low-cost commercial devices targeting those regions, establishes the performance metrics used to assess both devices and workers, and evaluates the devices in laboratory and field settings; the resulting measurements are then used to classify the devices by their provided LOS. The third component draws on the same experiments, using each worker's unassisted baseline performance to determine their required LOS and training a predictive model to estimate it from individual worker characteristics. This predictive model is paired with an optimization model that returns a worker-specific, body-region-specific device selection satisfying the predicted requirements for all at-risk regions simultaneously, within the worker's available budget. The development and validation of each component are detailed in the chapters that follow.

Chapter 4: Industry Data Collection

4.1 Introduction

This chapter corresponds to the first component of the proposed framework, as shown in Figure 4.1, establishing the industry context that motivates and informs the research direction. A field survey is conducted to identify the most significant challenges currently faced in the construction industry. Worker injury data is then analyzed to determine the body regions and age groups most frequently affected by work-related musculoskeletal disorders (WMSDs) among mechanical-trades workers, thereby informing the selection of target body regions for subsequent experimentation. Common mechanical trade task postures are subsequently identified through a review of field images, worker discussions, and published physical demands analyses for relevant mechanical trades, providing the basis for experimental task design in subsequent sections.

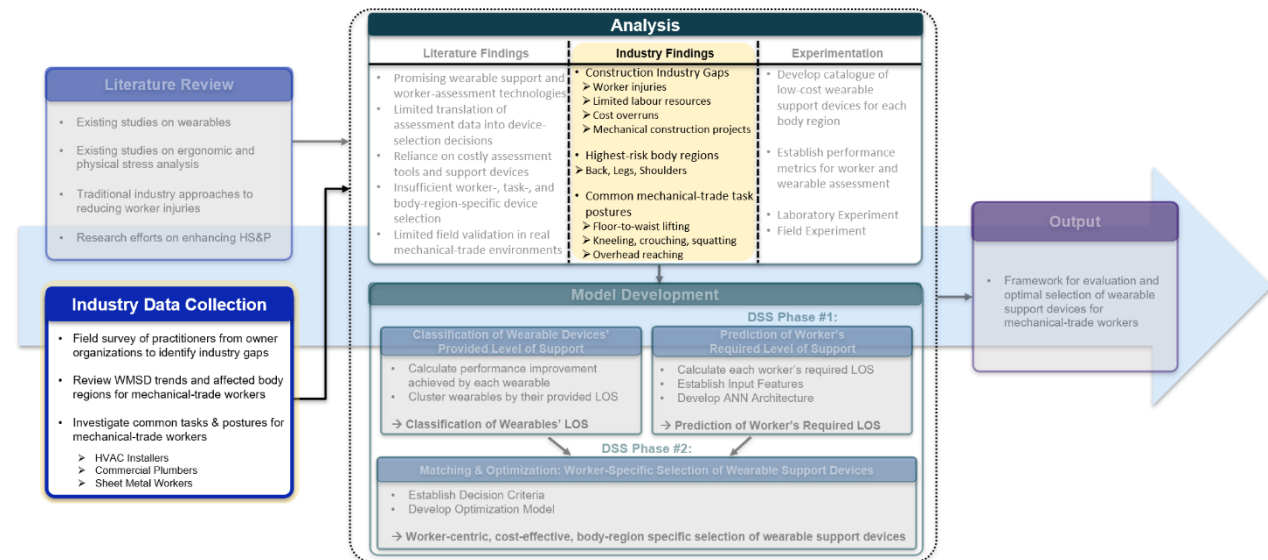


Figure 4.1: First component of decision support framework

4.2 Field Survey

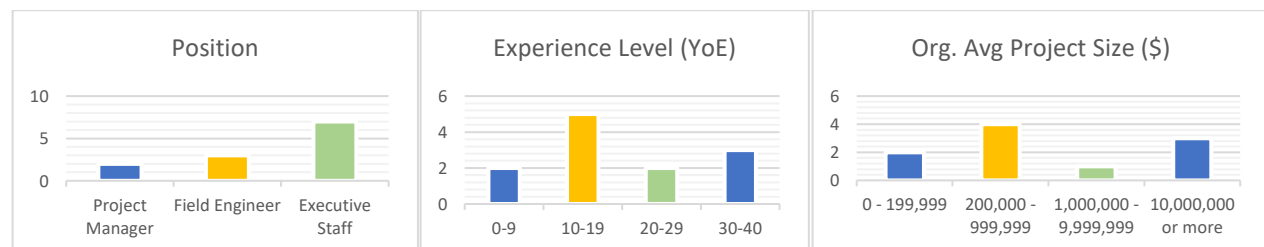
Prior to analyzing worker ergonomics and commercial wearable devices, a field survey was conducted to identify challenges, needs, and priorities from owner organizations regarding safety, productivity, automation, and project controls.

4.2.1 Survey Methodology

The survey was distributed to experienced industry practitioners across 13 organizations, targeting experienced staff within owner organizations involved in managing building and power plant infrastructure rehabilitation and replacement projects. The questionnaire comprised three sections (Part A, managing a portfolio of assets; Part B, a portfolio of projects; Part C, individual projects), and respondents completed the sections relevant to their role; the responses to the individual-projects section are summarized in Figure 4.3-c, Figure 4.4-a, and Figure 4.4-b. The questionnaire, as administered online, is shown in Appendix F; this chapter reports the responses most relevant to the present research. Given the survey's exploratory purpose, its results are reported descriptively. Key findings from the survey are presented in Section 4.2.2. This survey study received approval from the University of Waterloo Office of Research Ethics (#44301).

4.2.2 Survey Results & Industry Gaps

Figure 4.2 to Figure 4.4 summarize the survey responses: the respondents' profile (Figure 4.2), the challenges they reported (Figure 4.3), and their opinions on potential solutions and enhancements (Figure 4.4).

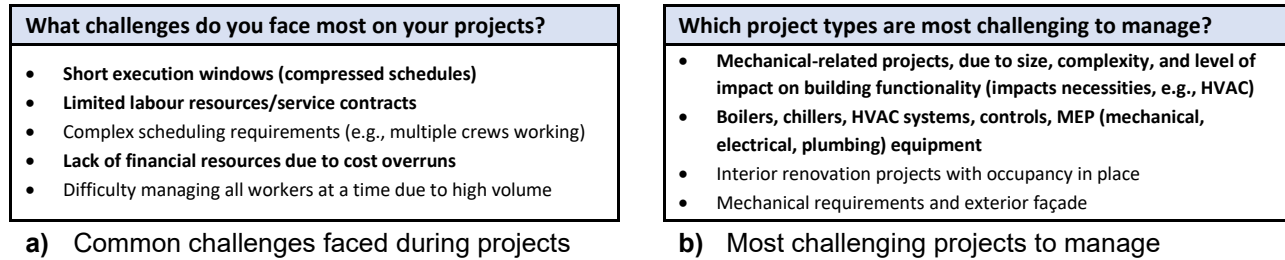
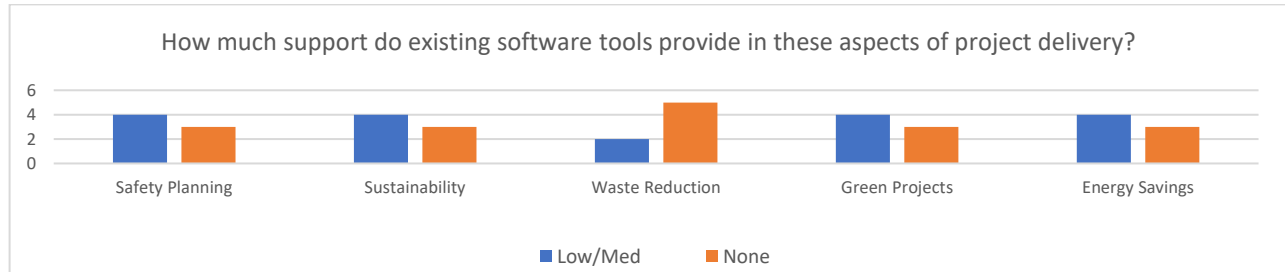


a) Respondent position

b) Respondent experience level

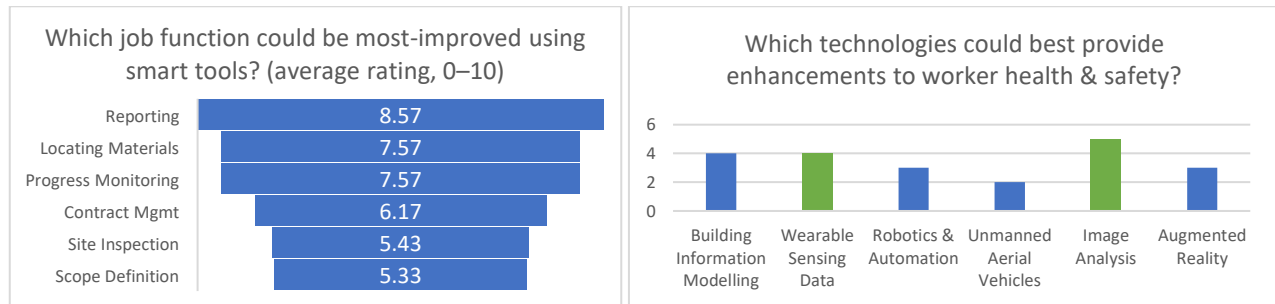
c) Organization average project size

Figure 4.2: Profile of survey respondents



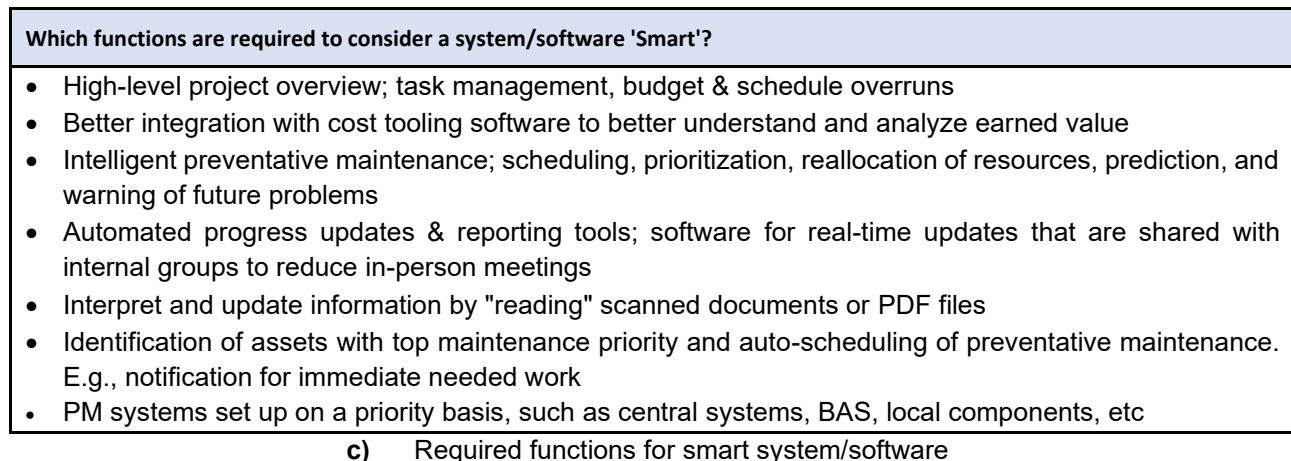
c) Level of existing software tool support

Figure 4.3: Respondents' opinions on challenges encountered



a) Potential job functions for improvement

b) Technologies for worker health and safety



c) Required functions for smart system/software

Figure 4.4: Respondents' opinions on potential solutions/enhancements

Respondents were mostly executive staff, followed by field engineers and project managers, with 6 to 38 years of experience (Figure 4.2-a and Figure 4.2-b). Their organizations' average project size

ranged from less than \$200,000 to \$10 million or more (Figure 4.2-c). Those managing individual projects reported no more than medium support from existing software tools for safety planning, sustainability, waste reduction, green projects, and energy savings (Figure 4.3-c). They rated reporting, locating materials, and progress monitoring as the job functions that smart tools could improve most (Figure 4.4-a), and most often selected image analysis, wearable sensing, and building information modelling as technologies that could support the management of worker health and safety (Figure 4.4-b). Across the survey sections, respondents' requirements for a smart system included high-level project overviews, integration with cost tools, preventative-maintenance prioritization, and automated progress reporting (Figure 4.4-c). The challenges and project types reported in Figure 4.3-a and Figure 4.3-b are discussed following Table 4.2.

Table 4.1 and Table 4.2 summarize the key challenges and opportunities identified by the respondents, with regards to project controls, automation, and safety and productivity.

Table 4.1: Key challenges faced in project and asset management

Project Management	Asset Management
<ul style="list-style-type: none"> • Time/resource requirements for monitoring progress of multiple concurrent projects • Lack of ability to predict future project performance (e.g., schedule delays) based on existing performance issues (e.g., safety or productivity) 	<ul style="list-style-type: none"> • Prediction of asset deterioration and optimization of spending • Accuracy and frequency of asset performance inspections (lack of adequate resources) • Lack of resources (i.e., workers) • Lack of funding, exacerbated by cost overruns

Table 4.2: Main desired enhancements in project and asset management

Project Management	Asset Management
<ul style="list-style-type: none"> • Automation of site monitoring (e.g., image analysis) and project status/progress reporting • Prediction of project performance based on current performance (e.g., worker injuries) • Improved project reporting (e.g., more informative performance metrics) 	<ul style="list-style-type: none"> • Optimization of asset management (i.e., prioritization based on multiple criteria such as criticality) • Automation of asset performance inspections • More resources or more effective resource cycling (e.g., via enhanced work-rest scheduling) • Preventative measures for cost overruns (e.g., via reduced worker injuries)

The survey identifies limited labour resources and insufficient financial capacity, further strained by cost overruns, as among the most prevalent challenges reported by respondents, with mechanical projects being particularly challenging due to their scale, complexity, and direct impact

on critical building functionality (e.g., HVAC systems). These challenges are compounded by the high prevalence of WMSDs among mechanical-trades workers, with overexertion- and repetitive motion-related injury claims accounting for approximately 28% of total claim costs and 39% of lost workdays in the mechanical trades (WorkSafeBC, 2026). These findings highlight a critical need to simultaneously address worker safety and the ongoing skilled labour shortage, as injury-related absences directly exacerbate existing workforce constraints. Furthermore, the survey identifies wearable sensing as one of the most promising technologies for advancing worker health and safety.

In response, this research leverages wearable sensing data to develop a framework for the evidence-based, automated selection of wearable support devices for mechanical-trades workers, allowing workers to be equipped with wearables suited to their specific tasks and physical profiles, with the aim of reducing exposure to overexertion- and repetitive motion-related injury risk. By serving as a preventative measure, this framework has the potential to: 1) reduce worker WMSD frequency, thereby mitigating lost workdays, lowering injury claim costs, and reducing cost overruns on mechanical projects, and 2) help alleviate skilled labour shortages among mechanical trades in the construction industry.

4.3 Ergonomics Assessment

This stage of the research follows a two-stage process. First, injury data were analyzed to identify the body regions most frequently affected by WMSDs among mechanical-trades workers. Second, common mechanical-trade tasks were reviewed to derive realistic working postures that load these at-risk body regions, thereby informing the experimental design presented in Chapter 5.

4.3.1 Mechanical-Trades Worker Injury Data

Data Collection Methodology: The dataset for this study was compiled from a range of authoritative sources dedicated to occupational health and safety. Specifically, injury records were obtained from the Infrastructure Health and Safety Association (IHSA), the Workplace Safety and

Insurance Board (WSIB), and WorkSafeBC, a provincial agency dedicated to promoting safe and healthy workplaces across B.C. These organizations have systematically tracked and recorded worker injuries across various trades, providing a robust basis for analysis. The scope of this study encompassed WMSD-related injury records for mechanical-trades workers of all age groups over a ten-year period. This trade group encompasses a wide variety of specialties, including HVAC technicians, plumbers, pipefitters, and welders. Data were extracted on the frequency of WMSD-related injuries, associated claim costs, and lost workdays, thereby gauging the economic and operational impacts of such injuries on the workforce and industry. The collected data were then categorized by age group, affected body region, and injury mechanism.

Data Analysis: The analysis aimed to identify the key drivers of WMSDs among mechanical-trades workers and to quantify their economic and operational impact on the industry, to inform the wearable device solution framework proposed in this research. Specifically, the following objectives were addressed: 1) identifying the age groups most frequently affected by WMSDs, 2) determining the body regions most affected by WMSDs, and 3) determining the types of incidents most frequently contributing to WMSD occurrence.

1 – WMSD Claim Count

According to data from WorkSafeBC, WMSD-related claims among mechanical-trades workers have remained relatively stable over the past decade, with little indication of a downward trend. Furthermore, WMSDs have consistently constituted approximately one-third of all lost time injuries (LTIs) (WorkSafeBC, 2026). This is illustrated in Figure 4.5. These trends underscore their persistent and significant contribution to the occupational injury burden within this trade group.

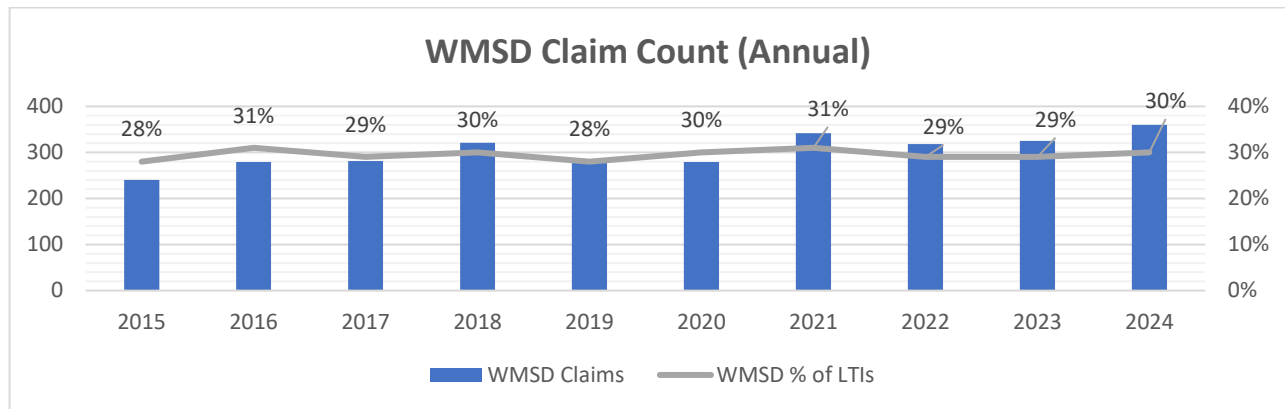


Figure 4.5: WMSD claims and % of LTIs in mechanical trades, 2015-2024 (WorkSafeBC, 2026)

Furthermore, IHSA data shows that WMSD claims in mechanical trades are consistently concentrated in the 25-34 and 35-44 year age groups. The 2015 to 2019 study indicates that total annual WMSD claim counts remained relatively stable, but the proportion of claims involving workers aged 44 and younger increased from approximately 65% to 71% over the study period (IHSA, 2020). This pattern indicates that relatively younger workers account for a growing share of WMSDs in this trade group.

2 – WMSDs by Body Region

Figure 4.6 illustrates the distribution of WMSD claims across the most affected body regions among mechanical-trade workers. The back emerges as the most frequently affected region, accounting for nearly half of all recorded WMSD claims, followed by the legs and shoulders (WorkSafeBC, 2026).

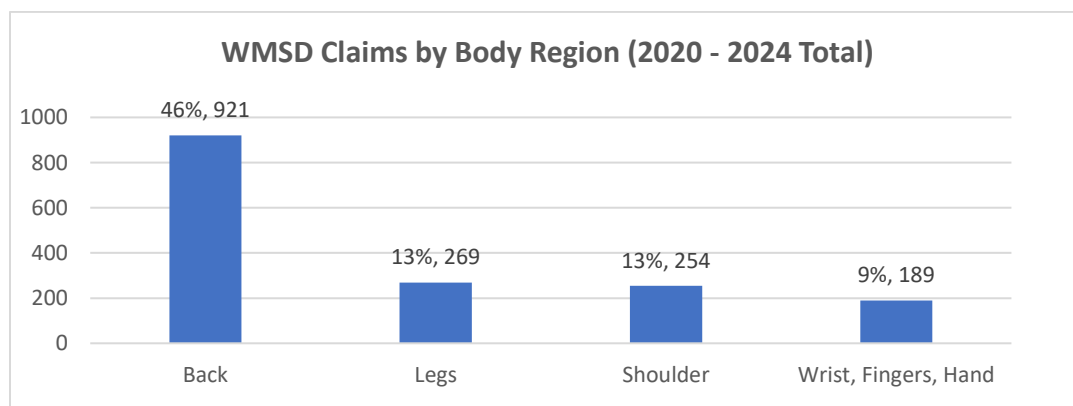


Figure 4.6: WMSD claims by body region in mechanical trades, 2020-2024 (WorkSafeBC, 2026)

Data from the WSIB demonstrates that these three body regions have consistently accounted for approximately 80% of all WMSD-related claims over the study period, as shown in Figure 4.7 (WSIB, 2018). Their relative proportions have remained largely stable, with little indication of a downward trend in either the frequency or the share of the total WMSD burden.

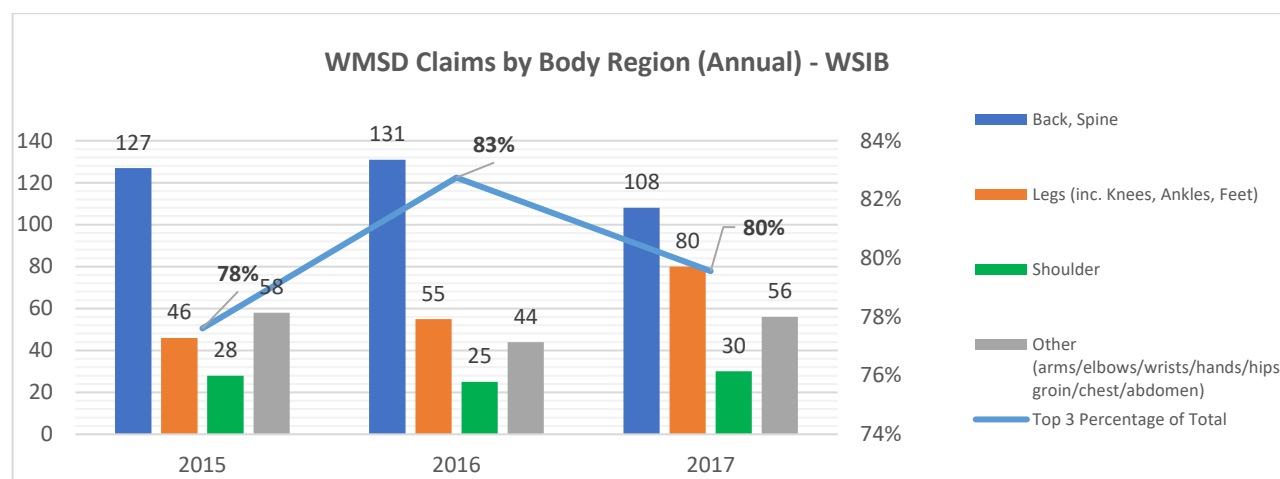


Figure 4.7: WMSD injuries by body region for mechanical trades, 2015-2017 (WSIB, 2018)

Data from the IHSA corroborates these findings, identifying the back as consistently the most frequently affected body region among the mechanical trades, with the back and legs collectively accounting for approximately two-thirds of all WMSD-related claims, as shown in Figure 4.8 (IHSA, 2020).

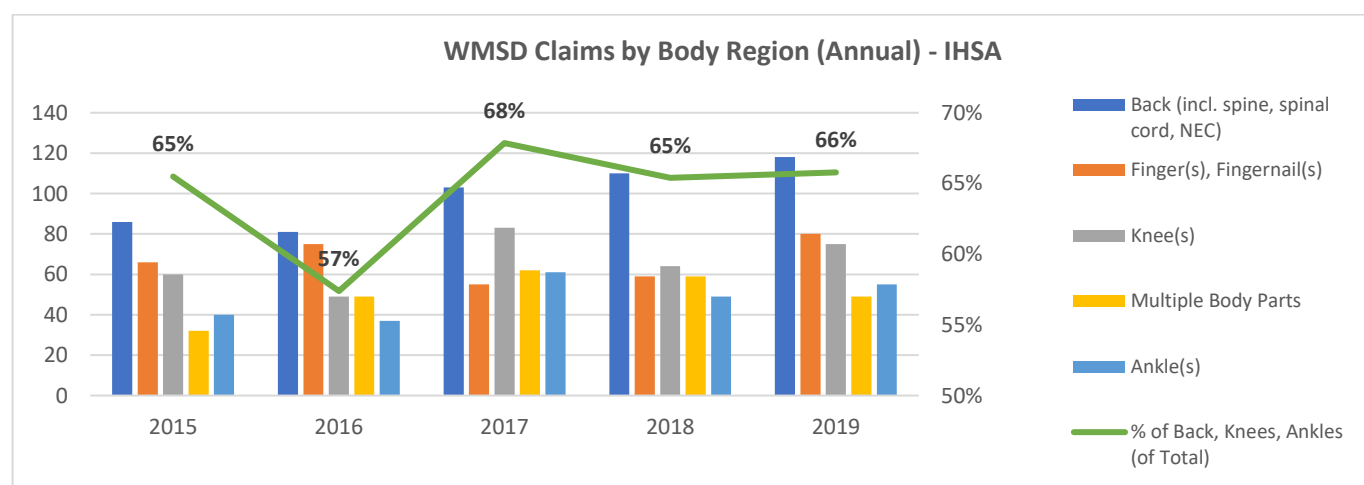


Figure 4.8: WMSD injuries by body region for mechanical trades, 2015-2019 (IHSA, 2020)

4.3.2 Identification of At-Risk Body Regions

The preceding analysis of worker injury data provided the foundation for selecting target body regions for experimentation. Building on those injury records, this section identifies the body regions most frequently affected by WMSDs among mechanical-trades workers and designates them as the primary focus of subsequent testing.

Based on WSIB data from 2015 to 2017, the back, shoulders, and legs collectively accounted for approximately 80% of all WMSD-related claims among mechanical-trades workers. This trend is corroborated by WorkSafeBC data from 2020 to 2024, in which these three body regions constituted approximately 72% of all WMSD-related claims, and by IHSA data from 2015 to 2019, in which the back and legs alone accounted for approximately 64%. Analyzed together, these findings, drawn from multiple provinces and spanning approximately a decade, consistently identify the back, legs, and shoulders as the body regions most frequently affected by WMSDs among mechanical-trades workers.

On this basis, the back, legs, and shoulders were selected as the primary targets for experimentation, directly informing both the selection of tasks that systematically engage these regions and the choice of wearable support devices intended to reduce associated muscular loading. Accordingly, the experimental design was structured to evaluate the efficacy of commercial wearable devices in providing support to the three highest-risk body regions among mechanical-trades workers, thereby establishing a well-founded basis for experimentation and interpretation of results while addressing a significant source of lost-time injuries and claim costs within the mechanical trades.

4.3.3 Working Postures in Standard Mechanical-Trades Activities

To accurately derive realistic body postures representing common mechanical tasks for experimentation, this section reviews tasks typically performed by mechanical-trade workers, with a focus on the three targeted body regions: back, legs, and shoulders. Working postures were

identified through: 1) image-based review, 2) field observations and discussions with workers, and 3) published Physical Demands Analyses (PDAs) for the relevant trades.

Field Images: Publicly available images depicting real-world mechanical-trades workers performing tasks in situ (e.g., equipment maintenance, assembly, overhead work) were compiled, with a focus on the back, legs, and shoulders. The inclusion criteria were workers performing common mechanical-trade tasks, with clear visibility of the torso and limbs, and in representative work environments. These images, drawn from trade association materials, manufacturer resources, and other public repositories, were reviewed to identify common task configurations such as overhead work, forward-bent trunk postures, and floor-level activities. Patterns were observed, and an initial set of representative postures was established based on frequency across the different tasks and work environments. This provided a visual basis for identifying realistic body positions for subsequent experimentation. Examples of these mechanical-trade field images across the three targeted body regions are provided in Appendix B.

Field Observations of Mechanical-Trades Tasks and Practitioner Input: Further to the image review, field observations were conducted in active mechanical-trade work settings to document how tasks were realistically performed in the field. Workers were observed performing routine tasks, and situations were noted that required sustained exertion of the back, legs, and shoulders, such as overhead reaching during pipe and duct installation, kneeling at low-level connections, and trunk flexion while handling components at or near floor level. Discussions with workers were used to confirm which tasks they perceived as physically demanding and to verify that the identified postures reflected typical aspects of their work. This input supported the validation of the final posture set, ensuring relevance from a practitioner perspective.

Physical Demands Analysis: Published PDAs provided by the Alberta Construction Association (ACA), in collaboration with the Alberta Construction Safety Association (ACSA), were reviewed as an independent reference for the physical requirements of the mechanical trades. These documents

summarize key job tasks, associated postures, typical load levels, posture frequencies, as well as photos of the tasks and work environments. The following subsections summarize the findings from the ACA PDAs for various mechanical occupations.

1 – HVAC Installer

The PDA for HVAC Installers indicates that workers regularly perform heavy material-handling tasks. Specifically, floor-to-waist-level and knee-to-waist-level lifting of 40+ lbs. (e.g., 52 lbs. funnel elbows, 40 lbs. snap locks) is performed for 6-33% of the workday (25 min to 2 hours 40 min/day). Similar lifting postures for 11-22 lbs. items (e.g., hole saw, drill, crimper) are performed for 34-66% of the workday (2 hours 41 min to 5 hours 17 min/day). Overhead reaching tasks (e.g., hammering or drilling overhead pipe) are performed for 34-66% of the workday. Trunk flexion (bending), trunk rotation (twisting), kneeling, and crouching (e.g., installing duct, marking holes) are each performed 6-33% of the workday (Alberta Construction Association, 2020b).

2 – Plumber (Commercial)

The PDA for commercial plumbers documents that workers regularly perform floor-to-waist level and knee-to-waist level lifting of varying weights: 44+ lbs. for 6-33% of the workday, 22-44 lbs. for 34-66% of the workday, and 11-22 lbs. for 67-100% of the workday. Overhead reaching tasks are performed for 34-66% of the workday. Squatting, kneeling, and crouching (e.g., groundwork, installing fixtures/fittings, low-level rough-in) are each performed for 34-66% of the workday (Alberta Construction Association, 2020a).

3 – Sheet Metal Worker

The PDA for sheet metal workers documents that workers perform floor-to-waist-level and knee-to-waist-level lifting tasks of 12-40 lbs. (e.g., insulation, fall-arrest equipment, tool bags) for 6-33% of the workday. Overhead-reaching tasks (e.g., pulling a rope to transfer materials or equipment onto a roof, installing clipping/flashing/insulation overhead, securing a ladder) are performed for 6-33% of the workday. Squatting (e.g., picking up materials, pulling rope for material transfer) is performed

for 6-33% of the workday. Kneeling (e.g., installation of flashing or insulation) is performed for 67-100% of the workday (Alberta Construction Association, 2021f).

Collectively, the image-based review, field observations, and PDAs provided a basis for defining a set of representative working postures that prominently engage the back, legs, and shoulders. These postures were then incorporated into the experimental design for subsequent evaluation.

Chapter 5: Experimentation and Classification of Wearable Devices

5.1 Introduction

This section corresponds to the second component of the proposed framework, as shown in Figure 5.1, presenting a systematic evaluation of lightweight, low-cost wearable support devices through laboratory and field-based experimentation. The objective is to assess the efficacy of each device in supporting key body regions during physically demanding work. Machine learning is then used to classify each wearable by the level of support (LOS) it provides. A statistical comparison between laboratory and field results is conducted to validate the representativeness of laboratory findings in a real-world context. Additionally, a cost-benefit analysis examines the relationship between device cost and LOS provided. Lastly, a participant questionnaire analysis investigates associations between objectively classified level of support provided and self-reported comfort, range of motion, and perceived fatigue reduction.

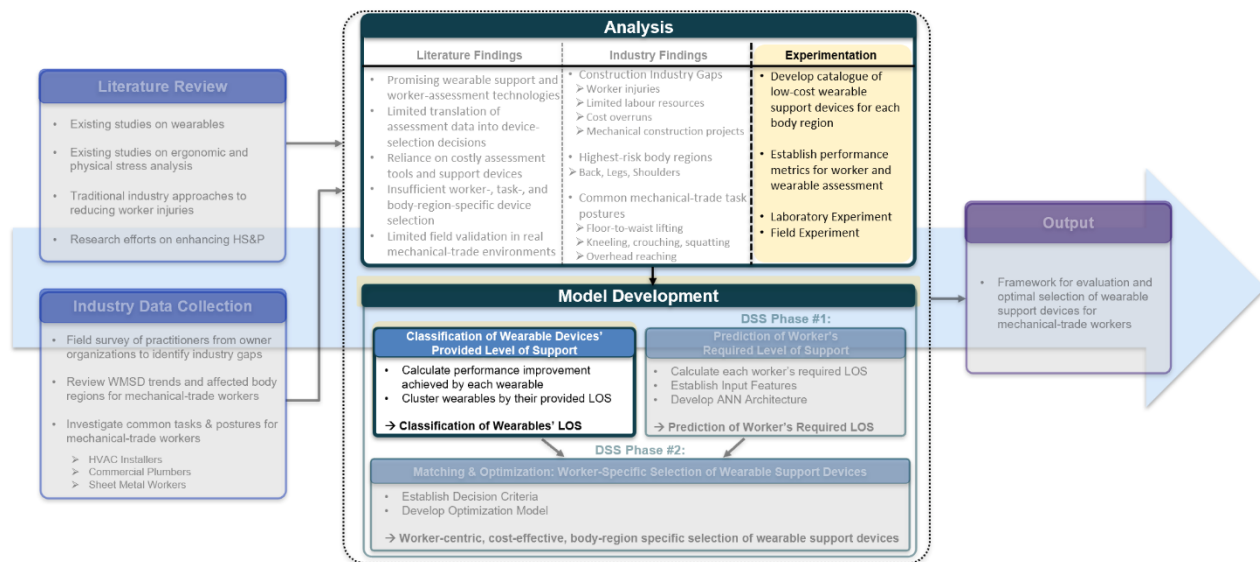


Figure 5.1: Second component of decision support framework

5.2 Experiment Design

As demonstrated by the literature and industry data review, musculoskeletal injuries are prevalent among workers in the mechanical trades, including plumbing, HVAC, insulation, fireproofing, welding, and metal installation. These occupations, performed by tradespeople such as HVAC

technicians, plumbers, welders, and sheet metal workers, routinely involve physically demanding actions such as lifting heavy materials, bending, stooping, squatting, and overhead reaching. This study involved participants performing representative tasks while a range of biomechanical and physiological metrics were measured and recorded. The objective was to evaluate the efficacy of various wearable support devices in reducing the physical demands placed on the back, legs, and shoulders during these activities. All study procedures were approved by the University of Waterloo Office of Research Ethics (#47511).

5.2.1 Participant Recruitment

Non-Practitioner Participant Group: A total of 31 non-practitioner participants were recruited for this study. This group had a mean age of 33 years (range: 22-65), with 65% aged between 25 and 44, which closely aligns with the age group most affected by WMSDs, as reported by the Infrastructure Health & Safety Association (2020). Of these participants, 21 (68%) were male, and 10 (32%) were female, closely reflecting the demographic composition of Ontario's construction workforce (86% male, 14% female; Statistics Canada, 2024). Participants had a mean height of 172 cm (range: 136-190 cm) and a mean weight of 77.1 kg (range: 55-108 kg). These ranges were deliberately selected to capture variability in body type and physical condition, ensuring a diverse sample for evaluating the effectiveness of wearables.

Practitioner Participant Group: A total of 13 mechanical-trades practitioners were recruited from the University of Waterloo Plant Operations team and other private organizations, primarily plumbers, steamfitters, and millwrights. This group had a mean age of 47 years (range: 34-60), with 46% aged 25-44. All 13 participants (100%) were male. Participants had a mean height of 180 cm (range: 172-190) and a mean weight of 93 kg (range: 79-107).

Across both groups, 44 participants were recruited. Table 5.1 summarizes the demographic and anthropometric characteristics of each participant group.

Table 5.1: Participant group characteristics (mean $\pm$ SD)

Participant Group	Sample Size	Age (years)	Sex (M/F)	Height (cm)	Weight (kg)
Non-Practitioners	31	32.9 $\pm$ 12.2	68% M 32% F	172.0 $\pm$ 12.6	77.1 $\pm$ 15.3
Practitioners	13	47.3 $\pm$ 8.8	100% M 0% F	179.7 $\pm$ 5.7	92.5 $\pm$ 8.4
Total	44	37.2 $\pm$ 13.0	77% M 23% F	174.3 $\pm$ 11.5	81.6 $\pm$ 15.2

The combined sample of 44 participants was selected to support an initial implementation and feasibility evaluation of the proposed framework, providing sufficient variability in age, sex, body type, and physical condition to expose the developed models to a diverse range of participant profiles. Consistent with established practice in feasibility and pilot studies, the sample was intended to demonstrate whether meaningful patterns could be identified and to generate preliminary evidence, rather than to produce population-level findings generalizable to the broader mechanical-trade workforce. It is therefore appropriate for establishing the framework's viability and for informing sample-size planning in subsequent larger-scale studies. This preliminary scope is acknowledged as a limitation of the present study and is discussed in Section 8.4 (Limitations and Future Research).

5.2.2 Tasks Performed

Two sets of experimental evaluations were conducted: laboratory (simulated) and field. All 44 participants completed the laboratory experiment, while the 13 practitioner participants also completed the field experiment. Table 5.2 summarizes this mapping.

Table 5.2: Mapping of participant groups to experimental evaluations

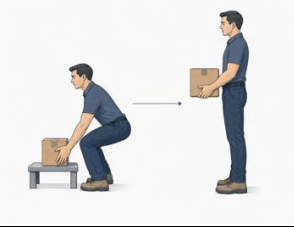
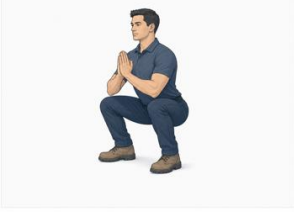
Experiment	Participant Group	Sample Size
Laboratory	Non-Practitioners and Practitioners	44
Field	Practitioners	13

The general experimental procedure was as follows: for each body region (back, legs, shoulders), participants first performed the tasks without a wearable device to establish a baseline condition. They then repeated each task while wearing the device under evaluation. Baseline was established once per body region, prior to any device trials for that region. Trial duration ranged from 1 to 5 minutes, depending on the participant, the specific task performed, and individual fatigue threshold. A standard 3-minute seated rest interval was provided between tasks to mitigate fatigue carryover and preserve data integrity. The order in which the three body regions were tested was randomized across participants, and the order in which devices were tested within each body region was also randomized per participant to reduce potential order effects, such as participants becoming more practiced with the task or progressively more fatigued over successive trials. Furthermore, where time constraints prevented a participant from testing all 12 devices, the omitted devices varied across participants due to the imposed randomization protocol.

Both experiments were subsequently used to evaluate each wearable device, and the laboratory and field results were compared to validate the applicability of the laboratory findings in a real-world context (Section 5.4.4).

Laboratory (Simulated) Tasks: For laboratory testing, three experimental tasks were designed to impose mechanical loading on the back, legs, and shoulders. These tasks were intended to simulate the identified occupational activities while prioritizing generalizability and procedural simplicity, minimizing participant learning curves and ensuring consistent performance across trials. Table 5.3 presents the tasks designed for the laboratory experiment.

Table 5.3: Simulated task design and relevant mechanical construction tasks

Body Region	Simulated Task Steps	Related Mechanical Construction Tasks	Task Image
Back	<ul style="list-style-type: none"> Lift and lower a 4 kg box from a height of 30 cm, keeping back straight and knees bent Repeat until onset of muscle fatigue, counting repetitions 	<ul style="list-style-type: none"> Lift AC compressors onto platforms Lift boxes of material 	
Leg	<ul style="list-style-type: none"> Squat with both hands together Hold until onset of leg muscle fatigue, counting seconds 	<ul style="list-style-type: none"> Inspect refrigerant line Install plumbing fixtures 	
Shoulder	<ul style="list-style-type: none"> Hold right arm up at 90° with a 2 kg object Hold until onset of shoulder muscle fatigue, counting seconds 	<ul style="list-style-type: none"> Weld overhead pipes Drill overhead holes 	

Field Tasks: For the field testing, real-world tasks for experimentation were selected based on a review of standard mechanical-trade activities in Section 4.3.3 and are well supported by the analysis of ACA PDAs for HVAC installers, commercial plumbers, and sheet metal workers.

For the back, lifting materials such as pipe or ductwork sections (for transportation from staging area to installation location) was selected as the most relevant mechanical-trade activity for experimentation. This aligns with floor-to-waist and knee-to-waist material handling tasks documented across all three ACA PDAs (Section 4.3.3). Ductwork and pipe sections are representative of the types of materials routinely handled on mechanical-trade job sites. For the legs, floor-level plumbing rough-in installation (installing connections such as drain assemblies or shutoff valves) was selected due to the sustained squatting and/or kneeling postures involved. The ACA PDAs document squatting at 34-66% of the workday for commercial plumbers (Alberta Construction Association, 2020a), and kneeling at 67-100% of the workday for sheet metal workers (Alberta Construction Association, 2021f). For the shoulders, overhead drilling to fasten pipe

strapping or duct hangers to an overhead structure (e.g., ceiling joists) was selected. Overhead drilling was identified as a high-frequency demand in both the HVAC installer (Alberta Construction Association, 2020b) and commercial plumber (Alberta Construction Association, 2020a) PDAs (34-66% of the workday). Table 5.4 presents the designed tasks for the field experiment.

Table 5.4: Field task design for mechanical-trade work

Body Region	Mechanical-Trade Task	Experiment Steps	Task Image
Back	<ul style="list-style-type: none"> Lift pipe/ductwork sections 	<ul style="list-style-type: none"> Lift and lower using standard jobsite form Repeat until muscle fatigue, counting repetitions 	
Leg	<ul style="list-style-type: none"> Floor-level plumbing rough-in installation 	<ul style="list-style-type: none"> Adopt required position for task, using standard jobsite form Hold until leg muscle fatigue, counting seconds 	
Shoulder	<ul style="list-style-type: none"> Overhead drilling of pipe or duct hangers 	<ul style="list-style-type: none"> Adopt required position for task, using standard jobsite form Hold until shoulder muscle fatigue, counting seconds 	

5.2.3 Wearable Support Devices

This section identifies a range of wearable support devices suitable for deployment among mechanical-trades workers during occupational tasks. In recent years, a growing number of commercially available wearables have been developed to support various body regions and mitigate the musculoskeletal stresses that workers encounter in the field. As established in the preceding literature review, such devices represent a promising avenue for WMSD prevention within the construction industry.

To identify suitable candidates, the selection process began with a broad search of commercially available wearable support devices spanning the targeted body regions (back, legs, and shoulders) (Appendix A). This initial pool was narrowed using two criteria: affordability and the availability of sufficient manufacturer/product information to assess design and support

characteristics.

Since affordability is a well-documented barrier to adoption, the framework prioritizes low-cost wearables, with affordability applied as a selection filter during device procurement. Most selected devices were priced below \$250 CAD, a threshold that reflects the typical upper end of the price range for back, leg, and shoulder support devices commonly available through mainstream online retailers. A small number of higher-priced devices (specifically devices 4, 5, and 12) were also included because their support capabilities were notably superior while their cost remained competitive relative to comparable market options. Importantly, affordability served as a selection filter rather than a priority over efficacy; whether each device delivered a meaningful support benefit was left to be determined through the subsequent experimentation and analysis.

Beyond cost, the narrowed device pool was further refined based on expected support level, with the aim of obtaining a diverse set of devices spanning varying levels of support across the targeted body regions, reflecting the reality that different workers require different degrees of physical support. An initial assessment of device support level was informed by supplier-provided marketing data and an evaluation of each device's design features, including pulleys, straps, and compression mechanisms.

This combined narrowing process, first by cost, then by support-level diversity, ensured that the final selection was both: 1) affordable enough for realistic adoption by mechanical construction firms, and 2) representative of the diverse support needs across the targeted body regions. Based on this selection process, 12 commercial wearable support devices were procured for experimentation, as shown in Table 5.5.

Table 5.5: Wearable support devices selected for evaluation

Body Region	Wearable Support Device	Device Code	Cost (\$ CAD)	Device Image
Back	BraceUP Back Brace	1	\$31	
	CopperFit Elite Back Brace	2	\$50	
	BraceAbility Back Brace	3	\$146	
	Mediaid Textile Exoskeleton Suit	4	\$465	
	Herowear Apex	5	\$2500	
Leg	NEENCA Knee Brace	6	\$32	
	TIMTAKBO Hinged Knee Brace	7	\$100	
	Z1 K6 Deziire Hinged Knee	8	\$216	
	WRUIOY Wearable Chair	9	\$145	
Shoulder	Suptrust Shoulder Brace	10	\$29	
	Kuangmi Double Shoulder	11	\$48	
	Hilti EXO-S	12	\$1999	

5.2.4 Performance Assessment Metrics

To evaluate participant performance across baseline and intervention conditions, a set of assessment metrics was established prior to experimentation and collected for each trial. These metrics were selected for their widespread use and established validity in the literature for quantifying wearable device efficacy. In a systematic review of 42 studies, Golabchi et al. (2022) found that ratings of perceived exertion (RPE), motion capture, and heart rate were among the most commonly employed measures for this purpose. Beyond their prevalence, the three performance metrics, Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score, were selected to capture complementary dimensions of wearable support efficacy. Fatigue Threshold reflects muscular endurance, Heart Rate Change reflects cardiovascular demand, and Ergonomic Risk Score, computed using standardized ergonomic assessments, captures posture-related musculoskeletal risk based on the degree of deviation from neutral working postures. While direct biomechanical instrumentation such as electromyography may offer greater physiological detail, it is costly, requires specialized expertise, and would be impractical within the accessible, field-deployable framework this research aims to develop. These metrics were therefore selected as accessible, validated indicators, capturing distinct dimensions of physical strain and providing a more comprehensive representation of support efficacy than any single metric alone. The statistical comparison of these metrics across the evaluated wearables is presented in Section 5.3.2.

Fatigue Threshold: For each trial, participants performed the task continuously until they first perceived slight fatigue. Fatigue Threshold was defined as the point at which the participant first reported perceiving slight fatigue and was computed as elapsed time (in seconds) for the shoulder and leg tasks and as the total number of completed repetitions for the back task. Fatigue Threshold is a participant-perceived measure and may therefore be influenced by inter-individual variability in fatigue tolerance. Therefore, to ensure consistency across participants, standardized instructions were provided, defining “slight fatigue” as a noticeable increase in perceived effort or mild muscular discomfort that would prompt participants to voluntarily cease the activity. This corresponds

approximately to a rating of 2, “weak (light)”, on the Borg CR10 scale, which was explained and displayed to participants (Borg, 1982).

Because participants performed tasks both with and without a wearable device, Fatigue Threshold values are expected to differ between the baseline and intervention conditions, with wearable devices potentially extending the Fatigue Threshold by reducing muscular loading in the relevant body region. These quantified differences will be used in the subsequent analyses to support the assessment of each wearable support device.

Heart Rate Change: Heart Rate Change (HRC) is an indicator of acute physiological stress, calculated as the difference between a participant’s post- and pre-task heart rates. Pre-task heart rate was recorded immediately prior to task commencement, and a second measurement was taken immediately upon task completion. Standardized 3-minute seated rest intervals were provided between tasks to mitigate fatigue carryover and to ensure that pre-task HR measurements were not confounded by residual cardiovascular elevation from preceding tasks.

For a given task, t , HRC is defined in Equation 1:

$$HRC_t = HR_{post,t} - HR_{pre,t} \quad (1)$$

Where:

$HR_{pre,t}$ is the heart rate recorded immediately prior to task commencement (bpm).

$HR_{post,t}$ is the heart rate recorded immediately upon task completion (bpm).

A positive HRC indicates a measurable cardiovascular response to physical exertion. During the wearable support device testing, HRC magnitudes are expected to be lower than those observed in the no-wearable baseline, reflecting the reduction in physical strain that the wearables are intended to provide. While this measurement approach does not capture intra-task heart rate variability, the sustained, continuous nature of the designed tasks suggests that post-task HR is a reasonable indicator of immediate cardiovascular response to task performance, with the pre-to-post difference providing a valid measure of task-induced physiological exertion.

Ergonomic Risk Score: The ergonomic risk score for each trial was derived from video recordings analyzed using TuMeke Risk Suite, the video-based ergonomic assessment platform used in this study. The selection of TuMeke and the smartphone-video recording procedure are described in Section 5.2.5. As discussed in Section 2.3.5, traditional manual and observation-based ergonomic assessment methods have long been recognized in the literature as subjective, incomplete, and labour-intensive (Park et al., 2023; Valero et al., 2016; Yu et al., 2019a). These limitations motivated the use of video-based tools that automate the implementation of established ergonomic assessment methods, such as REBA (Rapid Entire Body Assessment), RULA (Rapid Upper Limb Assessment), and NIOSH (National Institute for Occupational Safety and Health), to improve the objectivity and consistency of posture assessment.

REBA and RULA are ordinal scoring systems that classify posture into a limited number of risk categories rather than continuous measurements (Schwartz et al., 2019; Kee, 2022). These methods remain widely used in validated tools for posture-related MSD risk assessment in occupational and industrial settings and are routinely employed to guide ergonomic interventions (Kee, 2022; Hita-Gutiérrez et al., 2020; Halek et al., 2025). Posture-assessment tools that implement REBA and RULA have also demonstrated strong reliability and agreement with trained human assessors, supporting their use to improve the consistency and efficiency of posture-related assessment (Schwartz et al., 2019; Widyanti, 2020). Accordingly, TuMeke's video-based implementation of established ergonomic assessment algorithms was used to derive the Ergonomic Risk Score for each experimental condition. TuMeke's NIOSH output was used to assess ergonomic risk for the lifting (back) and overhead loading (shoulder) tasks, and its REBA output was used for the squatting (leg) task.

During each trial, participants were video recorded while performing the experimental tasks. The recorded videos were then input into TuMeke, which processed the inputs using its integrated ergonomic assessment algorithms to generate numerical risk scores. Higher scores indicate

increasingly hazardous postures and a greater need for ergonomic investigation or corrective intervention.

Figure 5.2, Figure 5.3, and Figure 5.4 present sample output frames from the TuMeke Risk Suite platform, illustrating how the software identifies anatomical landmarks, constructs body-segment vectors, and computes joint angles to generate ergonomic risk scores across the targeted body regions. In each frame, the estimated skeletal linkage is overlaid on the participant, and body segments are colour-coded according to their assessed posture-related risk. Green indicates postures within acceptable, low-risk angular ranges, whereas yellow, orange, and red indicate progressively greater deviations toward potentially hazardous ranges. The selected frames capture task postures from each of the three designed laboratory tasks for the targeted body regions: lifting (back), overhead loading (shoulder), and squatting (leg). Together, they demonstrate the TuMeke platform's capacity to provide region-specific risk information under varied biomechanical demands.

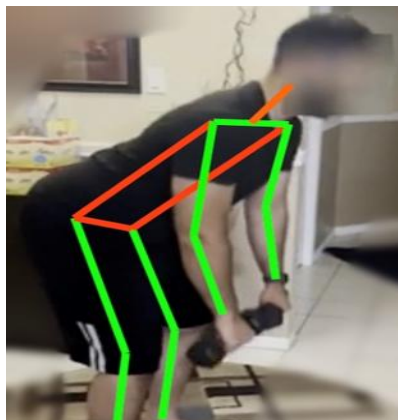


Figure 5.2: TuMeke pose overlay and joint-angle scoring: lifting (back)

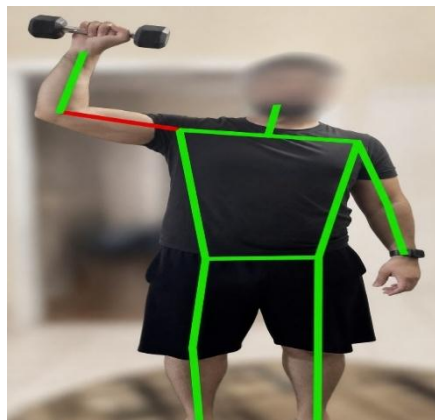


Figure 5.3: TuMeke pose overlay and joint-angle scoring: overhead loading (shoulder)



Figure 5.4: TuMeke pose overlay and joint-angle scoring: squatting (leg)

Figure 5.5 presents the Posture panel from TuMeke's Risk Suite for the squatting (leg) task shown in Figure 5.4. While Figure 5.4 presents a pose-overlay frame from the recorded squatting (leg) task video, Figure 5.5 reports TuMeke's posture scores derived from the full assessed video. As shown in Figure 5.5, TuMeke reports the regional posture scores for the squatting (leg) task, with a leg posture score of 3/4 consistent with the pronounced knee flexion visible in Figure 5.4.

Because Figure 5.5 is based on the full assessed video, its regional posture scores may not align directly with the overlay colours in the single frame shown in Figure 5.4.

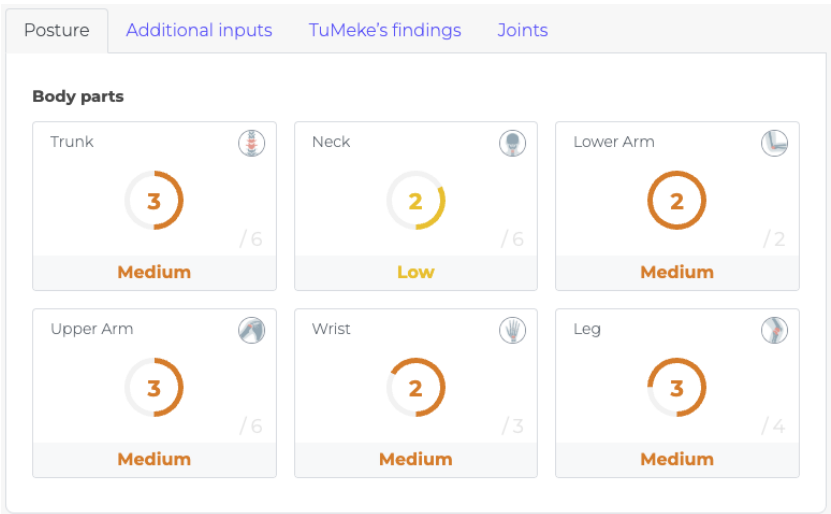


Figure 5.5: TuMeke region-specific posture scores: squatting (leg) task

The regional posture scores in Figure 5.5 inform the overall MSD risk score reported by TuMeke. This is shown in Figure 5.6, which presents TuMeke’s MSD Risk Score panel for the same squatting (leg) task shown in Figure 5.4. The panel reports an overall MSD risk score of 8, classified as “High.” This classification is based on the REBA action-level framework, where scores of 8 to 10 indicate “High” risk and require investigation and timely corrective action.

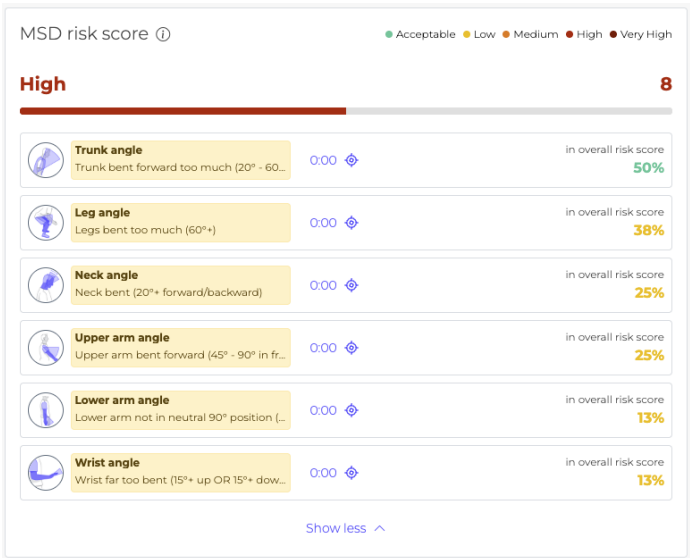


Figure 5.6: TuMeke overall MSD risk score and contribution: squatting (leg) task

Participant Questionnaire: A questionnaire was developed to assess each participant's experience with each wearable device. The purpose of this questionnaire is to capture perceived physical support and overall willingness to use the device in an occupational context. Responses were recorded on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher aggregate scores therefore indicate a more favourable user experience. Table 5.6 summarizes the questionnaire items.

The first three items (Q1-Q3) were administered immediately following each task in the laboratory and field experiments, as these capture the primary dimensions of device usability. The full set of eight items (Q1-Q8) was administered during the subsequent DSS field validation in Chapter 6, to obtain more comprehensive feedback from the validation practitioners.

Table 5.6: Participant questionnaire items

Item No.	Questionnaire Item
Q1	The device was comfortable to wear during task performance.
Q2	The device reduced muscle fatigue.
Q3	The device did not restrict my range of motion (ROM).
Q4	I was able to perform job tasks effectively while wearing the device.
Q5	The device did not add difficulty, distraction, or anxiety to task completion.
Q6	The device was compatible with other equipment or clothing.
Q7	I would recommend this device to other workers.
Q8	I would use this device again in a work setting.

5.2.5 Measurement Instruments

Digital Stopwatch (Fatigue Threshold): Given that fatigue threshold was quantified differently depending on the task, two measurement approaches were employed. For the shoulder and leg tasks, the fatigue threshold was expressed in seconds and recorded with a smartphone digital stopwatch, capturing the elapsed time from task initiation to the moment the participant voluntarily ceased the activity upon perceiving fatigue. For the back task, fatigue threshold was expressed as the total number of repetitions completed, which a designated observer tallied.

Wearable Sensor (Heart Rate): To measure participant heart rate during experimental trials, several commercially available sensing devices were evaluated. An Apple Watch Ultra 2, a wrist-worn fitness watch employing photoplethysmography (PPG) technology, was ultimately selected for its non-invasiveness, ease of use, affordability, and established suitability for monitoring heart rate during physical tasks. Existing literature demonstrates that wrist-worn PPG-based devices provide acceptable heart-rate accuracy across low-, moderate-, and high-intensity physical activity, with mean absolute percentage errors remaining below 10% when validated against ECG chest-strap technology in both construction-field and laboratory settings (Hwang et al., 2016; Schweizer & Gilgen-Ammann, 2025). This level of accuracy supports the use of affordable wrist-worn device monitoring to assess construction workers' physical demands through heart rate measurements (Hwang & Lee, 2017).

TuMeke Software (Ergonomic Risk Score): Ergonomic analysis was conducted using commercially available ergonomic assessment software. The majority of current software tools available for worker ergonomic assessment incorporate established ergonomic assessment methods, such as REBA, RULA, and NIOSH. Many of these tools also incorporate artificial intelligence (AI)-enabled computer vision to automate posture measurement, thereby enhancing measurement accuracy and reducing reliance on manual observation. Using video-derived anatomical landmark positions and joint angles, they generate ergonomic risk outputs that quantify posture-related risk across relevant body regions.

Following a review of various ergonomic assessment tools, TuMeke Risk Suite was selected as the most suitable option for several reasons. It enables field-deployable ergonomic assessment using standard video recordings, without requiring body-worn sensors or specialized motion-capture equipment. Its AI-driven computer-vision analysis tracks key anatomical landmarks and estimates three-dimensional joint angles from video recordings, reducing the subjectivity and inter-observer variability associated with manual posture assessment and supporting more consistent scoring

across trials (Balogh et al., 2025). These joint-angle outputs are then processed through standardized algorithms such as REBA, RULA, and NIOSH, making the resulting scores interpretable and comparable to the broader ergonomics literature. Accordingly, TuMeke was selected as an accessible, non-invasive, and scalable video-based platform for implementing established ergonomic assessment algorithms to quantify posture-related risk across the experimental conditions.

TuMeke is designed to accept smartphone video as its sole input and process the footage to generate a quantitative ergonomic risk score. Therefore, to compute each participant's ergonomic risk score, participant movements were recorded using a smartphone camera during each experimental trial. The camera was positioned to keep the body region relevant to the assessed task (back, leg, or shoulder) clearly visible throughout the movement. This smartphone-based setup reduced data-collection complexity while providing the standardized video input required for TuMeke analysis. Furthermore, markerless pose estimation using smartphone-captured video can yield joint-angle estimates with accuracy comparable to laboratory-grade motion-capture systems (Uhlrich et al., 2023; Turner et al., 2024).

Surface EMG (Considered and Excluded): Surface electromyography (sEMG) devices were also considered as a means of quantifying localized muscle activation with and without wearable support devices (Bosch et al., 2016). Devices such as the Shimmer3 and TeleMyo EMG units were evaluated for this purpose. However, electrode application requires partial removal of clothing, precise anatomical placement over the target muscles, and careful management of electrode-skin contact to minimize signal interference (Alcan & Zinnuroğlu, 2023; Bosch et al., 2016). These requirements could introduce participant discomfort and likely reduce the attainable sample size of the study (Milosevic et al., 2017). Furthermore, the placement of sEMG electrodes on the targeted muscle sites could conflict with donning and operating the wearable devices, potentially compromising both fit and measurement integrity. In addition, research-grade multichannel sEMG

systems entail a substantial unit cost. For instance, complete commercial systems are priced at approximately \$24,000-\$55,000 CAD (Motion Lab Systems, 2026), consistent with the \$10,000-\$40,000 USD range reported for clinical-grade equipment (Campanini et al., 2020). Moreover, leading research vendors such as Delsys and Noraxon disclose pricing only via custom quotation, indicating that such systems are not readily accessible as off-the-shelf instruments. Accordingly, sEMG was excluded from this study, as its cost, worker burden, and limited accessibility would constrain the reproducibility and scalability of the proposed framework.

5.3 Experiment Data Collection and Derived Measures

This section describes the data recorded during experimentation and the measures derived from them. Three data streams were captured for each participant: individual characteristics collected prior to testing, physical performance measured during task execution under baseline and wearable intervention conditions, and user perception recorded after task completion.

5.3.1 Participant Anthropometric, Demographic, and Physical Health Data

Prior to task performance, three categories of participant data were recorded: anthropometric, demographic, and physical health-related. Anthropometric data included each participant's height and weight, while demographic data captured age and sex. Physical health-related data consisted of self-reported, body-region-specific information for the three targeted body regions (back, legs, and shoulders), including relevant musculoskeletal health history. These variables are intended to support the development of predictive patterns for personalized support levels, as prior research has demonstrated associations between such characteristics and both musculoskeletal disorder (MSD) risk and biomechanical demands in occupational settings (Ji et al., 2023).

Following data collection, three measures were derived from the recorded variables: Health Score, Body Mass Index (BMI), and Body Fat Percentage (BFP). These variables subsequently serve as inputs to the proposed predictive model to estimate participants' required level of support.

Health Score: For each body region, participants' self-reported health information was converted into a numerical health score on a three-point scale (1 = Poor, 2 = Normal, 3 = Good), quantifying current functional status across the three targeted body regions. The score reflects a participant's current physical condition, with all participants performing the tasks within their comfortable capacity. For example, a participant who exercises regularly and reports no current limitations would receive a score of 3 for a given region, whereas a participant reporting minor, non-limiting discomfort or reduced conditioning in that region would receive a lower score.

Body Mass Index: BMI is a simple numerical index calculated from a person's height and weight, widely used as a population-level screening tool to broadly categorize individuals as underweight, normal weight, overweight, or obese.

For a given participant, p , BMI is estimated via Equation 2:

$$BMI_p = \frac{W_p}{H_p^2} \quad (2)$$

Where:

W_p is participant weight (kg).

H_p is participant height (m).

While BMI is practical due to its ease of calculation, it does not distinguish between fat mass and muscle mass, limiting its value as a standalone indicator of body composition. To address this limitation, BMI was utilized to estimate body fat percentage in this research, providing a more complete characterization of each participant's body composition.

Body Fat Percentage: BFP represents the proportion of a person's total body weight that is composed of fat mass, expressed as a percentage. It provides a more precise indicator of body composition by accounting for the amount of fat tissue relative to total body mass, including lean mass (muscle, bone, and organs). In this research, BFP was estimated using the CUN-BAE (Clínica Universidad de Navarra - Body Adiposity Estimator) equation, a clinically validated predictive

formula based on BMI, age, and sex, which has been tested in large adult cohorts (Gómez-Ambrosi et al., 2012). A key advantage of CUN-BAE is that it requires no additional measurements beyond these basic anthropometric and demographic inputs, making it straightforward to apply in field settings.

For a given participant, p , BFP is estimated via Equation 3:

$$BFP_p = -44.988 + (0.503 \times A_p) + (10.689 \times S_p) + (3.172 \times BMI_p) - (0.026 \times BMI_p^2) + (0.181 \times BMI_p \times S_p) - (0.02 \times BMI_p \times A_p) - (0.005 \times BMI_p^2 \times S_p) + (0.00021 \times BMI_p^2 \times A_p) \quad (3)$$

Where:

A_p is participant age (years).

S_p is participant sex (Male = 0, Female = 1).

BMI_p is participant body mass index.

Because CUN-BAE requires no direct body composition measurement, it can be applied in contexts where advanced body composition techniques, such as DEXA scanning or hydrostatic weighing, are unavailable or impractical. While approaches that incorporate physical measurements such as neck and waist circumference are known to improve BFP prediction accuracy by capturing regional fat distribution more directly (e.g., the U.S. Navy Body Fat formula), such methods would require a more invasive data collection process, with the potential to reduce participant recruitment and affect the reproducibility of the study.

5.3.2 Participant Physical Performance Data

Each body region (shoulders, back, and legs) was assessed through a separate task, during which three performance assessment metrics (Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score) were recorded without a wearable device (baseline condition) and with each of the twelve wearable devices (intervention condition). Table 5.7 illustrates the recording schema for a sample participant, with symbolic entries denoting the recorded variables.

Table 5.7: Data recording schema for performance assessment metrics

Participant	Body Region	Device Code	Without Wearable Device (baseline condition)					With Wearable Device (intervention condition)				
			Fatigue Thr.	HR _{pre}	HR _{post}	HRC	Erg. Risk Score	Fatigue Thr.	HR _{pre}	HR _{post}	HRC	Erg. Risk Score
Sample	Back	1						<i>FT</i> ₁	<i>HR</i> _{pre,1}	<i>HR</i> _{post,1}	<i>HRC</i> ₁	<i>ERS</i> ₁
		2						<i>FT</i> ₂	<i>HR</i> _{pre,2}	<i>HR</i> _{post,2}	<i>HRC</i> ₂	<i>ERS</i> ₂
		3	<i>FT</i> ₀	<i>HR</i> _{pre,0}	<i>HR</i> _{post,0}	<i>HRC</i> ₀	<i>ERS</i> ₀	<i>FT</i> ₃	<i>HR</i> _{pre,3}	<i>HR</i> _{post,3}	<i>HRC</i> ₃	<i>ERS</i> ₃
		4						<i>FT</i> ₄	<i>HR</i> _{pre,4}	<i>HR</i> _{post,4}	<i>HRC</i> ₄	<i>ERS</i> ₄
		5						<i>FT</i> ₅	<i>HR</i> _{pre,5}	<i>HR</i> _{post,5}	<i>HRC</i> ₅	<i>ERS</i> ₅
	Leg	6						<i>FT</i> ₆	<i>HR</i> _{pre,6}	<i>HR</i> _{post,6}	<i>HRC</i> ₆	<i>ERS</i> ₆
		7						<i>FT</i> ₇	<i>HR</i> _{pre,7}	<i>HR</i> _{post,7}	<i>HRC</i> ₇	<i>ERS</i> ₇
		8	<i>FT</i> ₀	<i>HR</i> _{pre,0}	<i>HR</i> _{post,0}	<i>HRC</i> ₀	<i>ERS</i> ₀	<i>FT</i> ₈	<i>HR</i> _{pre,8}	<i>HR</i> _{post,8}	<i>HRC</i> ₈	<i>ERS</i> ₈
		9						<i>FT</i> ₉	<i>HR</i> _{pre,9}	<i>HR</i> _{post,9}	<i>HRC</i> ₉	<i>ERS</i> ₉
	Shoulder	10						<i>FT</i> ₁₀	<i>HR</i> _{pre,10}	<i>HR</i> _{post,10}	<i>HRC</i> ₁₀	<i>ERS</i> ₁₀
		11	<i>FT</i> ₀	<i>HR</i> _{pre,0}	<i>HR</i> _{post,0}	<i>HRC</i> ₀	<i>ERS</i> ₀	<i>FT</i> ₁₁	<i>HR</i> _{pre,11}	<i>HR</i> _{post,11}	<i>HRC</i> ₁₁	<i>ERS</i> ₁₁
		12						<i>FT</i> ₁₂	<i>HR</i> _{pre,12}	<i>HR</i> _{post,12}	<i>HRC</i> ₁₂	<i>ERS</i> ₁₂

Note. Subscript 0 denotes the baseline (no-device) measurement, and subscripts 1-12 denote measurements with each of the twelve wearable devices. Each body region is assessed through a separate task; therefore, the baseline (subscript 0) values differ across body regions. This table presents an illustrative structure, with values omitted.

Following data collection across baseline and intervention conditions, percentage change values were computed for each participant-wearable combination for the three performance assessment metrics (Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score). The percentage change for each performance assessment metric was calculated using Equation 4.

$$\text{Percent Change} = \frac{\text{Intervention Condition} - \text{Baseline Condition}}{\text{Baseline Condition}} \times 100 \quad (4)$$

These percentage changes represent the magnitude of performance improvement attributable to each wearable device and serve as the primary indicators of the evaluated wearables' support efficacy. Table 5.8 illustrates the percentage-change schema for a sample participant, with symbolic entries denoting the computed percentage change for each device.

Table 5.8: Percentage-change schema for performance assessment metrics

Participant	Body Region	Device Code	Percentage Change		
			Fatigue Threshold	Heart Rate Change	Ergonomic Risk Score
Sample	Back	1	$\% \Delta FT_1$	$\% \Delta HRC_1$	$\% \Delta ERS_1$
		2	$\% \Delta FT_2$	$\% \Delta HRC_2$	$\% \Delta ERS_2$
		3	$\% \Delta FT_3$	$\% \Delta HRC_3$	$\% \Delta ERS_3$
		4	$\% \Delta FT_4$	$\% \Delta HRC_4$	$\% \Delta ERS_4$
		5	$\% \Delta FT_5$	$\% \Delta HRC_5$	$\% \Delta ERS_5$
	Leg	6	$\% \Delta FT_6$	$\% \Delta HRC_6$	$\% \Delta ERS_6$
		7	$\% \Delta FT_7$	$\% \Delta HRC_7$	$\% \Delta ERS_7$
		8	$\% \Delta FT_8$	$\% \Delta HRC_8$	$\% \Delta ERS_8$
		9	$\% \Delta FT_9$	$\% \Delta HRC_9$	$\% \Delta ERS_9$
	Shoulder	10	$\% \Delta FT_{10}$	$\% \Delta HRC_{10}$	$\% \Delta ERS_{10}$
		11	$\% \Delta FT_{11}$	$\% \Delta HRC_{11}$	$\% \Delta ERS_{11}$
		12	$\% \Delta FT_{12}$	$\% \Delta HRC_{12}$	$\% \Delta ERS_{12}$

Note. Each entry is the percentage change of the corresponding metric for a given device, relative to the no-device baseline. This table presents an illustrative structure, with values omitted.

Laboratory-based Wearable Performance Results: Table 5.9 presents the mean percentage change values for the wearable assessment metrics for the laboratory results. Additionally, to evaluate the statistical significance of each wearable device's performance, p-values were computed for each device with a two-tailed paired t-test comparing each participant's with-device and baseline values ($\alpha = 0.05$) and are presented in the same table. The collected laboratory and field measurements from which Tables 5.9 and 5.10 are derived are provided in Appendix C.

Table 5.9: Mean changes in performance metrics and associated p-values (laboratory results)

Body Region	Device Code	Fatigue Threshold		Heart Rate Change		Ergonomic Risk Score	
		Mean % Change	P-Value	Mean % Change	P-Value	Mean % Change	P-Value
Back	1	10.44%	0.0590	-4.37%	0.5324	3.79%	0.0003
	2	10.75%	0.2599	-4.45%	0.7859	3.21%	0.0006
	3	17.38%	0.0001	8.32%	0.0492	6.63%	0.0000
	4	26.55%	0.0000	18.72%	0.0002	15.66%	0.0000
	5	58.58%	0.0000	36.49%	0.0000	26.88%	0.0000
Leg	6	13.91%	0.0666	-4.53%	0.7785	0.19%	0.6615
	7	27.81%	0.0001	19.44%	0.0000	5.71%	0.0001
	8	42.41%	0.0000	19.27%	0.0006	8.14%	0.0000
	9	228.09%	0.0000	42.34%	0.0000	14.40%	0.0000

Shoulder	10	3.81%	0.6049	-0.15%	0.2729	2.04%	0.0802
	11	6.14%	0.2297	1.78%	0.0573	4.93%	0.0022
	12	68.63%	0.0000	37.28%	0.0000	36.03%	0.0000

Field-based Wearable Performance Results: Table 5.10 presents the mean percentage change values by wearable device along with the corresponding p-values for the field results.

Table 5.10: Mean changes in performance metrics and associated p-values (field results)

Body Region	Device Code	Fatigue Threshold		Heart Rate Change		Ergonomic Risk Score	
		Mean % Change	P-Value	Mean % Change	P-Value	Mean % Change	P-Value
Back	1	-1.37%	1.0000	-0.08%	1.0000	-0.90%	0.2311
	2	3.42%	0.7388	5.20%	0.0780	1.48%	0.0269
	3	18.70%	0.0024	12.46%	0.0010	3.65%	0.0064
	4	34.01%	0.0001	24.51%	0.0002	8.73%	0.0042
	5	66.28%	0.0000	33.58%	0.0001	25.11%	0.0000
Leg	6	6.06%	0.0775	3.28%	0.0876	2.31%	0.0821
	7	13.27%	0.0407	8.52%	0.0082	3.06%	0.1039
	8	34.66%	0.0002	15.59%	0.0010	7.09%	0.0019
	9	180.10%	0.0000	38.10%	0.0000	17.65%	0.0000
Shoulder	10	2.96%	0.8815	0.98%	0.4504	4.19%	0.0542
	11	3.99%	0.3461	1.67%	0.4043	5.62%	0.0156
	12	81.93%	0.0003	36.70%	0.0015	38.77%	0.0000

Table 5.9 and Table 5.10 show that many devices produced statistically significant improvements ($p < 0.05$) across both laboratory and field conditions, indicating that the effects of the more supportive wearables were large enough to be detected despite the modest sample size. Furthermore, the tables show that the three performance metrics are consistent across laboratory and field conditions. In general, a wearable that produces a large, statistically significant improvement in one metric also improves the other two metrics (e.g., wearables 5, 9, and 12). Conversely, a wearable with little effect shows no significant change in any of them (e.g., wearable 10). This pattern holds in both the laboratory (Table 5.9) and field (Table 5.10) datasets, indicating that the three metrics collectively provide a comprehensive indication of wearable support efficacy. At the same time, the three metrics are not redundant. The occasional small, non-significant negative mean percentage change values observed for certain devices reflect their complementary coverage of separate endurance, cardiovascular, and postural dimensions.

5.3.3 Questionnaire Data

Following task completion, participants completed the questionnaire items Q1-Q3 from Table 5.6, with responses recorded on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), as established in Section 5.2.4. Table 5.11 illustrates the questionnaire response schema for a sample participant, with symbolic entries denoting the recorded Likert responses.

Table 5.11: Questionnaire response schema (illustrative structure; values omitted)

Participant	Body Region	Device Code	Q1	Q2	Q3
			Comfort	Fatigue Reduction	ROM Preservation
Sample	Back	1	$L_{Q1,1}$	$L_{Q2,1}$	$L_{Q3,1}$
		2	$L_{Q1,2}$	$L_{Q2,2}$	$L_{Q3,2}$
		3	$L_{Q1,3}$	$L_{Q2,3}$	$L_{Q3,3}$
		4	$L_{Q1,4}$	$L_{Q2,4}$	$L_{Q3,4}$
		5	$L_{Q1,5}$	$L_{Q2,5}$	$L_{Q3,5}$
	Leg	6	$L_{Q1,6}$	$L_{Q2,6}$	$L_{Q3,6}$
		7	$L_{Q1,7}$	$L_{Q2,7}$	$L_{Q3,7}$
		8	$L_{Q1,8}$	$L_{Q2,8}$	$L_{Q3,8}$
		9	$L_{Q1,9}$	$L_{Q2,9}$	$L_{Q3,9}$
	Shoulder	10	$L_{Q1,10}$	$L_{Q2,10}$	$L_{Q3,10}$
		11	$L_{Q1,11}$	$L_{Q2,11}$	$L_{Q3,11}$
		12	$L_{Q1,12}$	$L_{Q2,12}$	$L_{Q3,12}$

Note. Q1-Q3 correspond to the questionnaire items shown in the column headers. Each entry denotes a participant's Likert response for the respective question and device.

5.4 Classification of Wearables' Provided Level of Support

Following data collection and calculation of derived measures, this section establishes the level of support provided by each wearable device from the collected performance data. The percentage-change measures were grouped through unsupervised clustering and converted into an ordinal support classification, which was then examined for laboratory-field consistency and assessed against device cost and user-reported perceptions.

5.4.1 Dataset Preprocessing

The dataset was first preprocessed to identify and address outliers and improve the accuracy of subsequent analyses. Outlier detection and data imputation are established approaches in

preparing such data for machine-learning analysis (Ortiz et al., 2024). Two outlier detection and imputation approaches were applied.

First, negative HRC values, indicating that post-task heart rate was lower than the pre-task baseline, were identified as outliers. A negative HRC value contradicts cardiovascular physiology and indicates measurement error or external stressors affecting participants prior to task initiation. Heart rate increases during physical exertion due to sympathetic activation, whereas recovery occurs after exercise cessation rather than during the task itself. Because these values reflect measurement error rather than a true physiological response to the task, they were treated as outliers on physiological grounds rather than by a statistical threshold, consistent with recommended practice for wearable data (Ortiz et al., 2024). These values were then replaced with the mean of all positive HRC values recorded for the corresponding body region, a mean-substitution imputation strategy documented across comparable wearable-sensor studies (Ortiz et al., 2024). This approach preserves the sample size while limiting the influence of physiologically implausible measurements on subsequent analyses. This adjustment was applied to both “without wearable” observations and “with wearable” observations.

Second, the z-score method was applied to the percentage change values for Fatigue Threshold, HRC, and Ergonomic Risk Score, with values exceeding three standard deviations from the mean for a given wearable device flagged as potential outliers. This z-score approach is a widely used technique for detecting outliers (Jamshidi et al., 2022). Each flagged value was then reviewed for physiological plausibility rather than removed on a statistical basis alone. This review confirmed that the flagged values reflected genuine, physiologically plausible responses, including the large yet valid improvements achieved by the most effective devices. As such, all values were retained; therefore, the only values treated were the negative HRC measurements identified in Table 5.12, which were replaced using mean imputation.

Table 5.12 summarizes the number of data points/observations that were replaced via mean imputation. Each value represents the number of individual HRC measurements collected, where each measurement corresponds to a single participant completing a single task for a single body region under the specified condition. The number of wearables evaluated varied by body region (back = 5, leg = 4, shoulder = 3), for a total of 12. Baseline (without wearable) measurements were collected once per participant per body region, whereas with-wearable measurements were collected once for each wearable a participant tested. In the field study, every participant tested all available wearables, yielding complete coverage; in the laboratory study, a subset of participant-wearable combinations was not completed, so the laboratory with-wearable total reflects the measurements collected (460) rather than the maximum of 528.

Table 5.12: Proportion of HRC data points replaced via mean imputation

Heart Rate Change	Laboratory (44 participants)	Field (13 participants)
Without Wearable	4.55% (6/132) ^a	0% (0/39) ^c
With Wearable	3.04% (14/460) ^b	0% (0/156) ^d

^a 132 = 44 participants × 3 body regions × 1 baseline

^b 460 = laboratory participant–wearable measurements performed (of 44 × 12 = 528 possible)

^c 39 = 13 participants × 3 body regions × 1 baseline

^d 156 = 13 participants × 12 wearables

5.4.2 Wearables Clustering Analysis

Following data preprocessing, clustering analysis was performed to support the classification of wearables based on the level of support efficacy they provide. The resulting dataset, comprising wearable device code and percentage changes in Fatigue Threshold, HRC, and Ergonomic Risk Score, was input into WEKA© (Waikato Environment for Knowledge Analysis) machine learning software. Percentage change values were used as inputs for the clustering analysis because they quantify the performance improvement directly attributable to each wearable device, thereby serving as meaningful indicators of the devices' support efficacy. Table 5.9 and Table 5.10 present the average percentage change values for each of the three quantitative performance metrics across

the twelve wearable devices, summarizing the dataset used as input to the WEKA clustering analysis. WEKA was selected for its comprehensive library of standardized, well-validated machine learning algorithms, which facilitates rapid prototyping and enhances reproducibility across studies. Since no pre-existing labels for wearable support efficacy levels existed prior to experimentation, unsupervised clustering was employed to derive these categories directly from the observed performance data, allowing for natural groupings without imposing predefined classifications.

To evaluate the suitability of the various candidate clustering algorithms, clustering was performed (with WEKA's default settings) using four considered algorithms: Expectation Maximization (EM), Farthest First (FF), K-means, and Canopy. The data were grouped into three clusters representing Low, Medium, and High levels of support efficacy. These three clusters were deliberately chosen to align the clustering output, which represents the provided level of support of each wearable device, with the calculated required level of support for each participant. This alignment is critical for the wearable device selection optimization model proposed in this research. Additionally, three groupings were selected for their practical balance between granularity and simplicity, providing more detail than a simple High/Low classification while remaining easy to interpret. Table 5.13 presents the proportion of instances assigned to each cluster across the four candidate clustering algorithms.

Table 5.13: Proportion of clustered instances for various clustering algorithms

Body Region	Cluster	Laboratory				Field			
		EM	FF	K-means	Canopy	EM	FF	K-means	Canopy
Back	1	56%	17%	51%	77%	18%	68%	22%	40%
	2	18%	16%	31%	15%	28%	5%	29%	25%
	3	25%	67%	18%	8%	54%	28%	49%	35%
Leg	1	53%	94%	23%	93%	21%	79%	50%	81%
	2	17%	2%	35%	4%	27%	8%	35%	10%
	3	31%	4%	42%	3%	52%	13%	15%	10%
Shoulder	1	63%	96%	63%	66%	36%	67%	36%	36%
	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	3	37%	4%	37%	34%	64%	33%	64%	64%

As shown in Table 5.13, notable differences in cluster distribution were observed across the four algorithms. Farthest First (FF) consistently produced highly skewed distributions, concentrating the majority of instances into a single cluster across all body regions and both experimental conditions, for example, assigning 94% of leg instances to Cluster 1 in the laboratory dataset and 79% in the field dataset. Canopy similarly produced uneven distributions, particularly for the back and leg regions, with one cluster capturing the majority of instances. K-means yielded more balanced distributions than FF and Canopy in some regions, though it still exhibited inconsistencies across body regions and between the laboratory and field conditions. In contrast, EM generally produced balanced distributions across all three body regions in both datasets. The relatively even partitioning produced by EM across body regions and experiment settings suggests that it is better able to capture the underlying structure of the data. This behaviour is consistent with the probabilistic nature of the EM algorithm, which models cluster assignment as a continuous probability rather than a hard assignment. Based on this superior class balance, EM was identified as the most appropriate clustering algorithm for this application and was selected for subsequent analysis.

Laboratory Clustering Results: The clustering process was performed separately for each body region (shoulders, back, and legs). For each wearable device i , the clustering analysis produced the percentage of observations classified into each cluster, denoted as p_i^L , p_i^M , and p_i^H , for Low, Medium, and High support, respectively (columns 3, 4, and 5 in Table 5.14). Figure 5.7, Figure 5.8, and Figure 5.9 present the WEKA clustering outputs under laboratory conditions for the back, legs, and shoulders, respectively.

Table 5.14: Laboratory data clustering results

Body Region	Device Code	Cluster Percentage (%)		
		Low	Med	High
Back	1	100	0	0
	2	84	3	13
	3	71	17	12
	4	29	44	27
	5	0	22	78
Leg	6	82	18	0
	7	78	7	15
	8	54	22	24
	9	2	20	78
	10	100	0	0
Shoulder	11	95	0	5
	12	0	0	100

Preprocess Classify **Cluster** Associate Select attributes Visualize

Clusterer

Choose **EM** -I 100 -N 2 -X 10 -max 2 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Cluster mode

☐ Use training set

☐ Supplied test set Set...

☐ Percentage split % 66

☒ Classes to clusters evaluation

(Nom) Device Code v

☒ Store clusters for visualization

Ignore attributes

Start Stop

Result list (right-click for options)

14:49:51 - EM

Clusterer output

Scheme: weka.clusterers.EM -I 100 -N 3 -X 10 -max 3 -ll-cv 1.0E-6

Relation: Back -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Instances: 179

Attributes: 4

 Fatigue Threshold

 Heart Rate Change

 Ergonomic Risk Score

Ignored: Device Code

Test mode: Classes to clusters evaluation on training data

=== Clustering model (full training set) ===

EM

==

Number of clusters: 3

Number of iterations performed: 42

Attribute	Cluster		
	0 (0.55)	1 (0.16)	2 (0.29)
Fatigue Threshold			
mean	0.0707	0.3077	0.5406
std. dev.	0.1846	0.1652	0.3694
Heart Rate Change			
mean	0.0145	0.1519	0.2742
std. dev.	0.2898	0.1471	0.2867
Ergonomic Risk Score			
mean	0.0361	0.141	0.2412
std. dev.	0.0425	0.0412	0.1064

Time taken to build model (full training data) : 0.07 seconds

=== Model and evaluation on training set ===

Clustered Instances

0 101 (56%)

1 33 (18%)

2 45 (25%)

Log likelihood: 0.77623

Class attribute: Device Code

Classes to Clusters:

	0	1	2	<-- assigned to cluster
34	0	0		\$1.00
26	1	4		\$2.00
29	7	5		\$3.00
12	18	11		\$4.00
0	7	25		\$5.00

Cluster 0 <-- \$1.00

Cluster 1 <-- \$4.00

Cluster 2 <-- \$5.00

Figure 5.7: WEKA clustering output for back under laboratory conditions

Preprocess Classify **Cluster** Associate Select attributes Visualize

Clusterer

Choose **EM** -I 100 -N 3 -X 10 -max 3 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Cluster mode

☐ Use training set

☐ Supplied test set Set...

☐ Percentage split % 66

☒ Classes to clusters evaluation

(Nom) Device Code v

☒ Store clusters for visualization

Ignore attributes

Start Stop

Result list (right-click for options)

14:49:51 - EM

10:18:33 - EM

Clusterer output

=== Run information ===

Scheme: weka.clusterers.EM -I 100 -N 3 -X 10 -max 3 -ll-cv 1.0E-6

Relation: Leg -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Instances: 157

Attributes: 4

 Fatigue Threshold

 Heart Rate Change

 Egonomic Risk Score

Ignored: Device Code

Test mode: Classes to clusters evaluation on training data

=== Clustering model (full training set) ===

EM

==

Number of clusters: 3

Number of iterations performed: 49

Attribute	Cluster		
	0 (0.47)	1 (0.23)	2 (0.3)
Fatigue Threshold			
mean	0.193	0.4965	2.0106
std. dev.	0.228	0.6023	1.6242
Heart Rate Change			
mean	0.0627	0.2475	0.3829
std. dev.	0.235	0.4865	0.1738
Egonomic Risk Score			
mean	0.0284	0.1002	0.1251
std. dev.	0.0653	0.1322	0.0512

Time taken to build model (full training data) : 0.04 seconds

=== Model and evaluation on training set ===

Clustered Instances

0 83 (53%)

1 26 (17%)

2 48 (31%)

Log likelihood: -0.214

Class attribute: Device Code

Classes to Clusters:

 0 1 2 <-- assigned to cluster

28 6 0 | \$6.00

32 3 6 | \$7.00

22 9 10 | \$8.00

 1 8 32 | \$9.00

Cluster 0 <-- \$7.00

Cluster 1 <-- \$8.00

Cluster 2 <-- \$9.00

Figure 5.8: WEKA clustering output for legs under laboratory conditions

Preprocess Classify **Cluster** Associate Select attributes Visualize

Clusterer
Choose **EM** -I 100 -N 2 -X 10 -max 2 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Cluster mode

☐ Use training set

☐ Supplied test set Set...

☐ Percentage split % 66

☒ Classes to clusters evaluation
(Nom) Device Code ▾

☒ Store clusters for visualization

Ignore attributes

Start Stop

Result list (right-click for options)

14:49:51 - EM

10:18:33 - EM

10:24:26 - EM

Clusterer output

=== Run information ===

Scheme: weka.clusterers.EM -I 100 -N 2 -X 10 -max 2 -ll-cv 1.0E-6
Relation: Shoulder -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100
Instances: 124
Attributes: 4
 Fatigue Threshold
 Heart Rate Change
 Ergonomic Risk Score

Ignored: Device Code

Test mode: Classes to clusters evaluation on training data

=== Clustering model (full training set) ===

EM
==

Number of clusters: 2
Number of iterations performed: 3

Attribute	Cluster	
	0 (0.37)	1 (0.63)
Fatigue Threshold		
mean	0.6624	0.0466
std. dev.	0.4836	0.2286
Heart Rate Change		
mean	0.35	0.0117
std. dev.	0.5433	0.3755
Ergonomic Risk Score		
mean	0.3565	0.0285
std. dev.	0.0787	0.0799

Time taken to build model (full training data) : 0.01 seconds

=== Model and evaluation on training set ===

Clustered Instances

0 46 (37%)
1 78 (63%)

Log likelihood: -0.31854

Class attribute: Device Code
Classes to Clusters:

 0 1 <-- assigned to cluster
 0 39 | \$10.00
 2 39 | \$11.00
 44 0 | \$12.00

Cluster 0 <-- \$12.00
Cluster 1 <-- \$10.00

Dataset and performance metrics

Clustering output

Figure 5.9: WEKA clustering output for shoulders under laboratory conditions

Field Clustering Results: An identical clustering process was subsequently conducted to derive corresponding results for the field testing, summarized in Table 5.15. Figure 5.10, Figure 5.11, and Figure 5.12 present the WEKA clustering outputs under field conditions for the back, legs, and shoulders, respectively.

Table 5.15: Field data clustering results

Body Region	Device Code	Cluster Percentage (%)		
		Low	Med	High
Back	1	92	8	0
	2	85	15	0
	3	62	38	0
	4	31	62	8
	5	0	15	85
Leg	6	92	8	0
	7	77	23	0
	8	38	54	8
	9	0	23	77
Shoulder	10	100	0	0
	11	92	0	8
	12	0	0	100

Preprocess

Classify

Cluster

Associate

Select attributes

Visualize

Clusterer

Choose **EM** -I 100 -N 3 -X 10 -max 3 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100

Cluster mode

☐ Use training set

☐ Supplied test set

Set...

☐ Percentage split %

66

☒ Classes to clusters evaluation

(Nom) Device Code

☒ Store clusters for visualization

Ignore attributes

Start

Stop

Result list (right-click for options)

14:49:51 - EM

10:18:33 - EM

10:24:26 - EM

10:56:07 - EM

Clusterer output

=== Run information ===

Scheme: weka.clusterers.EM -I 100 -N 3 -X 10 -max 3 -ll-cv 1.0E-6

Relation: Back

Instances: 65

Attributes: 4

Fatigue Threshold

Heart Rate Change

Ergonomic Risk Score

Ignored: Device Code

Test mode: Classes to clusters evaluation on training data

=== Clustering model (full training set) ===

EM

==

Number of clusters: 3

Number of iterations performed: 16

Attribute	Cluster		
	0 (0.2)	1 (0.28)	2 (0.52)
Fatigue Threshold			
mean	0.698	0.3619	0.0033
std. dev.	0.2827	0.1699	0.1107
Heart Rate Change			
mean	0.382	0.2131	0.0299
std. dev.	0.083	0.132	0.0847
Ergonomic Risk Score			
mean	0.2563	0.0754	0.008
std. dev.	0.0954	0.0653	0.0221

Time taken to build model (full training data) : 0 seconds

=== Model and evaluation on training set ===

Clustered Instances

0 12 (18%)

1 18 (28%)

2 35 (54%)

Log likelihood: 2.30821

Class attribute: Device Code

Classes to Clusters:

0 1 2 <-- assigned to cluster

0 1 12 | \$1.00

0 2 11 | \$2.00

0 5 8 | \$3.00

1 8 4 | \$4.00

11 2 0 | \$5.00

Cluster 0 <-- \$5.00

Cluster 1 <-- \$4.00

Cluster 2 <-- \$1.00

Figure 5.10: WEKA clustering output for back under field conditions

5.4.3 Wearables LOS Classification

The clustering percentages were combined into a single Level of Support Index (LSI_i) per wearable, i , weighting the Low, Medium, and High support categories as $w_L = 1$, $w_M = 2$, and $w_H = 3$, respectively. Each wearable's LSI_i was computed as the sum of these weighted cluster percentages (Equation 5).

$$LSI_i = w_L * p_i^L + w_M * p_i^M + w_H * p_i^H \quad (5)$$

Where:

$$p_i^L + p_i^M + p_i^H = 100 \%$$

The weights $w_L = 1$, $w_M = 2$, and $w_H = 3$, were assigned to ensure that the resulting LSI_i reflects the dominant support category emerging from the clustering analysis. Specifically, a higher proportion of observations classified into the High support cluster will pull LSI_i toward 3, while a higher proportion in the Low support cluster will pull it toward 1. This weighting scheme allows LSI_i to gravitate toward the support level that best characterizes the wearable's overall performance.

Each wearable's continuous Level of Support index value, LSI_i , was then mapped onto three ordinal support levels (S_i) as shown in Equation 6. Since LSI_i is bounded between 1 and 3, where a value of 1 indicates that all observations were assigned to the Low support cluster and a value of 3 indicates that all observations were assigned to the High support cluster, the range was partitioned into three equal-width intervals using equidistant thresholds of 1.67 and 2.33.

$$S_i = \begin{cases} Low & 1.00 \leq LSI_i \leq 1.67 \\ Medium & 1.67 < LSI_i \leq 2.33 \\ High & 2.33 < LSI_i \leq 3.00 \end{cases} \quad (6)$$

An equal-width partition was preferred over data-driven alternatives such as natural-breaks classification because it imposes a fixed, independent partition rather than estimating boundaries from the data. This avoids data-dependent boundaries, which at the present sample size would be sensitive to sampling noise. Thresholds at 1.67 and 2.33 are instead sample-independent and directly comparable across studies.

The support indices (S_i) were discretized into Low, Medium, and High categories because minor LSI_i differences within a category (e.g., 1.03 vs. 1.13) fall within the natural variability of the measurements and may not be reliably distinguished. In contrast, differences across categories (e.g., 1.32 vs. 2.07) are treated as a meaningful basis for comparison. The resulting categories therefore reflect only the differences that are meaningful for comparing devices in this research. Investigating finer distinctions would necessitate larger samples, which remains a possible direction for future work (see Section 8.4).

Laboratory Classification Results: Table 5.16 summarizes the laboratory-based wearable classification results, including the level-of-support index assigned to each device, along with pricing to facilitate cost-benefit analysis.

Table 5.16: Laboratory-based classification of wearable devices by level of support

Body Region	Device Code	Cluster Percentage (%)	LOS Index (LSI_i)	Classification	Price (\$ CAD)
		Low / Med / High			
Back	1	100 / 0 / 0	1.00	LOW	31
	2	84 / 3 / 13	1.29	LOW	50
	3	71 / 17 / 12	1.41	LOW	146
	4	29 / 44 / 27	1.98	MED	465
	5	0 / 22 / 78	2.78	HIGH	2500
Leg	6	82 / 18 / 0	1.18	LOW	32
	7	78 / 7 / 15	1.37	LOW	100
	8	54 / 22 / 24	1.71	MED	216
	9	2 / 20 / 78	2.76	HIGH	145
Shoulder	10	100 / 0 / 0	1.00	LOW	29
	11	95 / 0 / 5	1.10	LOW	48
	12	0 / 0 / 100	3.00	HIGH	1999

Field Classification Results: Table 5.17 summarizes the field-based wearable classification results.

Table 5.17: Field-based classification of wearable devices by level of support

Body Region	Device Code	Cluster Percentage (%)	LOS Index (LSI_i)	Classification	Price (\$ CAD)
		Low / Med / High			
Back	1	92 / 8 / 0	1.08	LOW	31
	2	85 / 15 / 0	1.15	LOW	50
	3	62 / 38 / 0	1.38	LOW	146
	4	31 / 62 / 8	1.77	MED	465
	5	0 / 15 / 85	2.85	HIGH	2500
Leg	6	92 / 8 / 0	1.08	LOW	32
	7	77 / 23 / 0	1.23	LOW	100
	8	38 / 54 / 8	1.69	MED	216
	9	0 / 23 / 77	2.77	HIGH	145
Shoulder	10	100 / 0 / 0	1.00	LOW	29
	11	92 / 0 / 8	1.15	LOW	48
	12	0 / 0 / 100	3.00	HIGH	1999

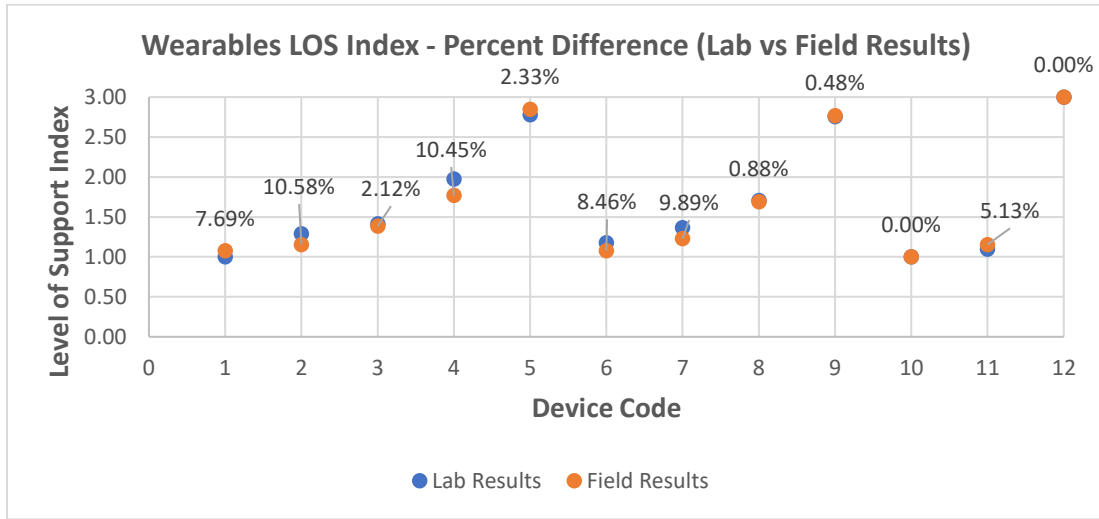
5.4.4 Comparison of Laboratory and Field Wearable Classification Results

This section presents a comparative analysis of the wearable support-level classifications derived from laboratory and field experiments, examining the degree of agreement between the two conditions in terms of classification consistency and statistical relationships.

Classification Agreement: The support level classifications assigned to each wearable device were consistent across both experimental settings for all 12 devices assessed. This agreement suggests that the laboratory experimental protocol adequately replicates the physical demands encountered in the field, supporting the validity of the evaluation framework. Table 5.18 presents the LOS index values and corresponding classifications for each wearable device under both conditions, along with the absolute percent difference (APD) in LOS index between settings. Figure 5.13 further illustrates the distribution of LOS percentage difference values across all devices.

Table 5.18: Comparison of laboratory and field classification results

Body Region	Device Code	Lab Results (n=44)		Field Results (n=13)		LOS Abs Percentage Difference (%)
		LOS Index (LSI_i)	Classification	LOS Index (LSI_i)	Classification	
Back	1	1.00	LOW	1.08	LOW	7.69
	2	1.29	LOW	1.15	LOW	10.58
	3	1.41	LOW	1.38	LOW	2.12
	4	1.98	MED	1.77	MED	10.45
	5	2.78	HIGH	2.85	HIGH	2.33
Leg	6	1.18	LOW	1.08	LOW	8.46
	7	1.37	LOW	1.23	LOW	9.89
	8	1.71	MED	1.69	MED	0.88
	9	2.76	HIGH	2.77	HIGH	0.48
Shoulder	10	1.00	LOW	1.00	LOW	0.00
	11	1.10	LOW	1.15	LOW	5.13
	12	3.00	HIGH	3.00	HIGH	0.00

**Figure 5.13:** Comparison of laboratory and field LOS results

The mean absolute percent difference (MAPD) for the LOS indices across conditions was computed via Equation 7:

$$MAPD = \frac{\sum_i^n APD_i}{n} \quad (7)$$

Where:

i is a given wearable

n is the total number of wearables

The MAPD was 4.83%, indicating a high degree of consistency across experimental settings.

Statistical Relationship: To evaluate the statistical relationship between the laboratory- and field-based LOS indices, three statistical approaches were applied: Spearman's rank correlation, Pearson's correlation, and the Wilcoxon signed-rank test.

1 – Spearman's Rank Correlation

Spearman's rank correlation was selected for comparison as it does not assume a normal distribution of the data and is appropriate for small samples. The Spearman's Rank Correlation coefficient, r_s , is computed via Equation 8:

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (8)$$

Where:

i is a given wearable

n is the total number of pairs/observations

d_i is the difference between the ranks of corresponding variables (x_i and y_i) for a given data pair

Table 5.19 presents the ranked values and squared rank differences used in the computation of r_s .

Because tied values were present, average ranks were assigned within tied groups. The sum of squared rank differences was $\sum d_i^2 = 6.00$. With $n = 12$, the resulting Spearman's rank correlation coefficient was $r_s = 0.979$.

Table 5.19: Spearman's rank correlation computation parameters

i : Device Code	x : LOS Index (Lab)	y : LOS Index (Field)	Rank x_i	Rank y_i	d_i	d_i^2
1	1.00	1.08	1.5	2.5	-1.0	1.00
2	1.29	1.15	5.0	4.5	0.5	0.25
3	1.41	1.38	7.0	7.0	0.0	0.00
4	1.98	1.77	9.0	9.0	0.0	0.00
5	2.78	2.85	11.0	11.0	0.0	0.00
6	1.18	1.08	4.0	2.5	1.5	2.25
7	1.37	1.23	6.0	6.0	0.0	0.00
8	1.71	1.69	8.0	8.0	0.0	0.00
9	2.76	2.77	10.0	10.0	0.0	0.00
10	1.00	1.00	1.5	1.0	0.5	0.25
11	1.10	1.15	3.0	4.5	-1.5	2.25
12	3.00	3.00	12.0	12.0	0.0	0.00
						6.00

2 – Pearson's Correlation

To supplement the rank-based analysis, Pearson's correlation coefficient, r , was computed as a secondary measure of association between the laboratory- and field- based LOS indices. This approach was included because the LOS index is a continuous measurement scale and provides a direct measure of linear agreement between the paired numerical values. However, it was treated as supplementary rather than primary because it is more sensitive to influential values (such as the 3.00/3.00 pair) than Spearman's rank-based coefficient. Pearson's correlation coefficient is computed via Equation 9:

$$r = \frac{\sum_i^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i^n (x_i - \bar{x})^2 \sum_i^n (y_i - \bar{y})^2}} \quad (9)$$

Where:

i is a given wearable

n is the total number of pairs/observations

x is the LOS index for the laboratory-based dataset

y is the LOS index for the field-based dataset

Table 5.20 presents the variables utilized in the computation of r . The resulting Pearson's correlation coefficient was $r = 0.993$.

Table 5.20: Pearson's correlation computation parameters

i : Device Code	x : LOS Index (Lab)	y : LOS Index (Field)	$\bar{x}$	$\bar{y}$
1	1.00	1.08	1.71	1.68
2	1.29	1.15		
3	1.41	1.38		
4	1.98	1.77		
5	2.78	2.85		
6	1.18	1.08		
7	1.37	1.23		
8	1.71	1.69		
9	2.76	2.77		
10	1.00	1.00		
11	1.10	1.15		
12	3.00	3.00		

3 – Wilcoxon Signed-Rank Test

To further assess the statistical comparability of the laboratory and field-based LOS indices, a Wilcoxon signed-rank test was performed to evaluate whether a systematic difference exists between the two conditions. From the initial sample of 12 wearable devices, two zero-difference pairs were excluded as required by the test procedure, yielding an effective sample size of $n = 10$. Within-pair differences were computed, their absolute values were ranked, and each rank was assigned the sign of its corresponding difference. The sums of the positive and negative signed ranks were computed as $W+ = 39$ and $W- = 16$, respectively, and the Wilcoxon test statistic was taken as the smaller of the two, yielding $W = 16$. This value exceeds the two-tailed critical value of 8 at $n = 10$ and $\alpha = 0.05$; therefore, the null hypothesis, that no systematic difference exists between laboratory and field LOS index values, could not be rejected. This result indicates no consistent tendency for one setting to yield higher or lower support indices than the other, supporting the conclusion that laboratory and field LOS measurements are statistically comparable. Table 5.21 presents the parameters used to compute the Wilcoxon test statistic.

Table 5.21: Wilcoxon test statistic computation parameters

Device Code	LOS Index (Lab)	LOS Index (Field)	Difference	Absolute Difference	Sign	Rank	Signed Rank
1	1.00	1.08	-0.077	0.077	-1	6	-6
2	1.29	1.15	0.136	0.136	1	9	9
3	1.41	1.38	0.030	0.030	1	3	3
4	1.98	1.77	0.206	0.206	1	10	10
5	2.78	2.85	-0.065	0.065	-1	5	-5
6	1.18	1.08	0.100	0.100	1	7	7
7	1.37	1.23	0.135	0.135	1	8	8
8	1.71	1.69	0.015	0.015	1	2	2
9	2.76	2.77	-0.013	0.013	-1	1	-1
10	1.00	1.00	0.000				
11	1.10	1.15	-0.056	0.056	-1	4	-4
12	3.00	3.00	0.000				

Practical Implications: The classification agreement analysis, MAPD computation, and the three statistical tests collectively indicate that laboratory-based wearable support classifications are statistically comparable to those obtained in the field. The strong positive correlations, both rank-based (Spearman's $r_s = 0.979$) and linear (Pearson's $r = 0.993$), demonstrate that wearable devices providing higher levels of support in laboratory settings also consistently provided higher levels of support in the field, and vice versa. Complementing this, the Wilcoxon signed-rank test ($W = 16$) revealed no statistically significant systematic difference between the two conditions, confirming that although individual wearables exhibited some variability between laboratory and field LOS values, no consistent directional bias was present.

These findings support the replicability and practical applicability of the proposed evaluation framework. The strong rank-order agreement, corroborating linear association, and absence of systematic bias establish that laboratory-derived classifications provide a meaningful and reliable indication of the level of support a wearable device is expected to deliver during field use.

5.4.5 Cost-Benefit Analysis

Following the classification of wearables into the three levels of support, the assigned LOS index values were examined in relation to retail cost to assess the potential correlation between price and support performance. Figure 5.14 illustrates this relationship, with the coefficient of determination (R^2) yielding values of 0.60 for the laboratory results and 0.63 for the field results. These values indicate a positive relationship between wearable cost and level of support, with higher-priced devices tending to deliver greater support performance.

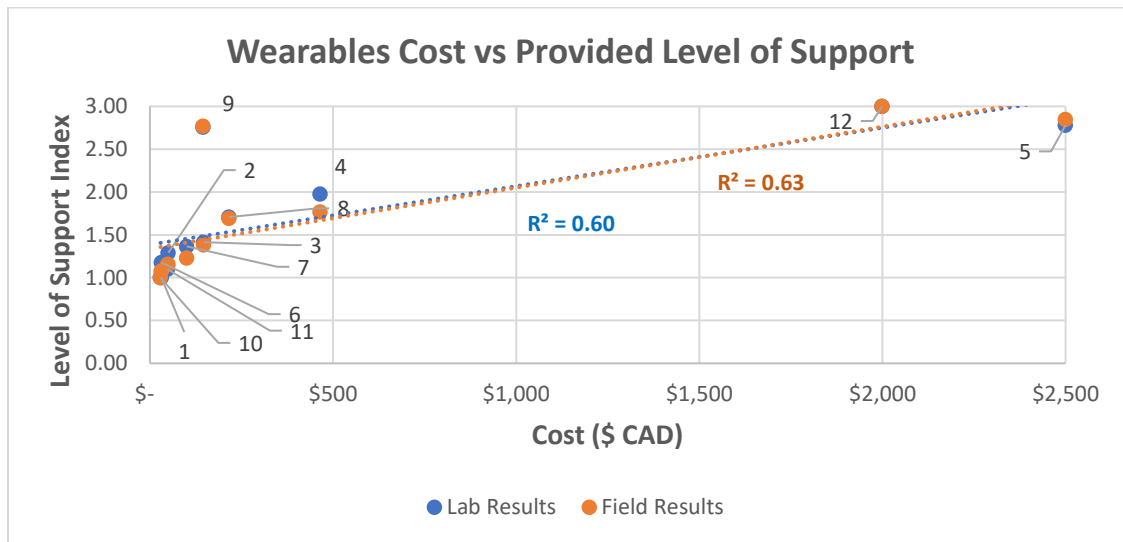


Figure 5.14: Correlation between wearable cost and provided LOS

Table 5.22 presents the observed R^2 values by body region. The back (five devices) and shoulder (three devices) wearables demonstrate strong correlations between cost and LOS. This indicates that within these body regions, retail price is a reliable predictor of support performance.

Table 5.22: Coefficient of determination between wearable device LOS and cost

Body Region	Lab Results	Field Results
Back	0.87	0.95
Leg	0.24	0.26
Shoulder	0.99	0.99
All	0.60	0.63

Figure 5.15, Figure 5.16, Figure 5.17, and Figure 5.18 illustrate the correlations for the back and shoulder wearables for both settings.

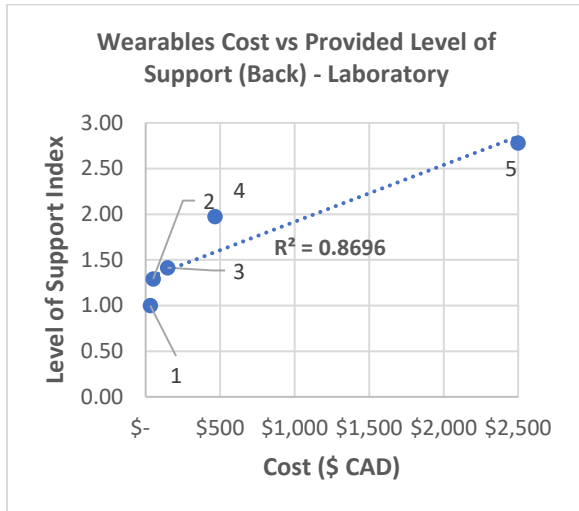


Figure 5.15: Cost-LOS correlation for back wearables (laboratory)

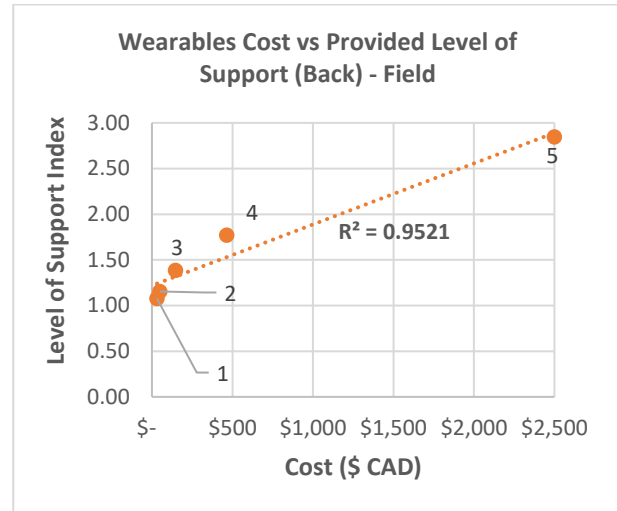


Figure 5.16: Cost-LOS correlation for back wearables (field)

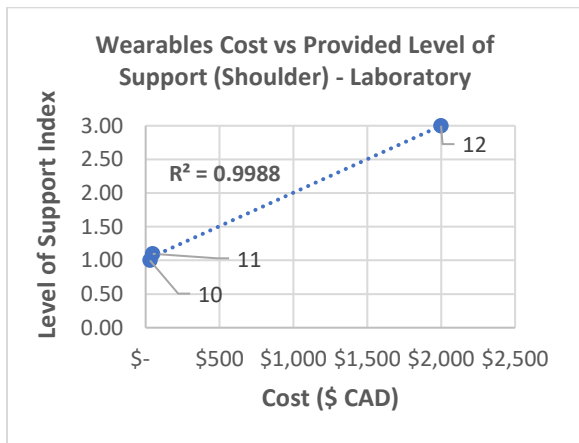


Figure 5.17: Cost-LOS correlation for shoulder wearables (laboratory)

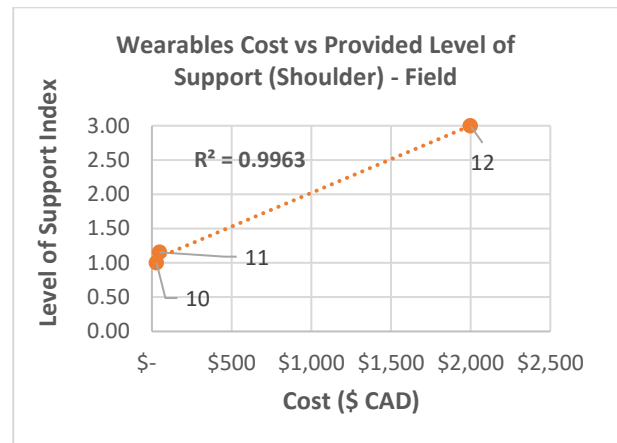


Figure 5.18: Cost-LOS correlation for shoulder wearables (field)

The leg wearables, however, yield a considerably lower R^2 value (0.24 and 0.26 for laboratory and field results, respectively), driven by Wearable 9, which provides a level of support disproportionate to its retail cost. This is illustrated in Figure 5.19 and Figure 5.20.

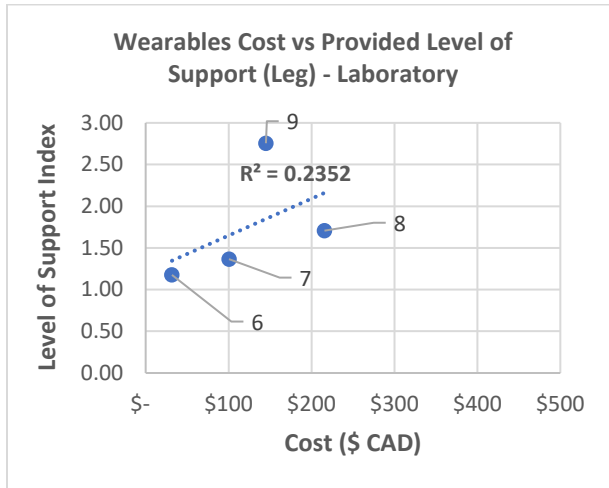


Figure 5.19: Cost-LOS correlation for leg wearables (laboratory)

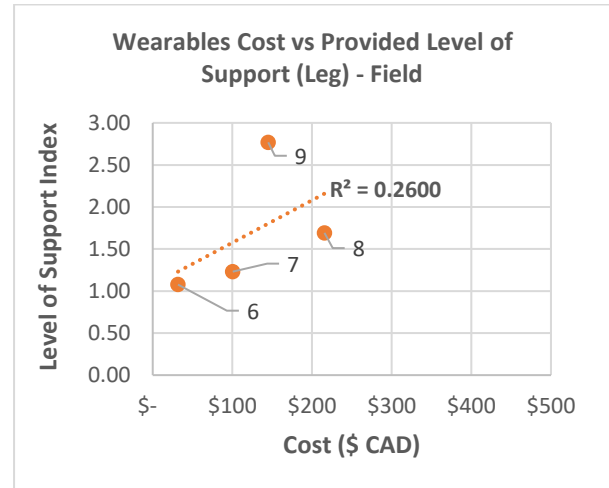


Figure 5.20: Cost-LOS correlation for leg wearables (field)

Wearable 9 delivers a High classification ($LSI_9 = 2.76 - 2.77$) at \$145 CAD, while the more expensive Wearable 8 delivers Medium ($LSI_8 = 1.69 - 1.71$) at \$216 CAD. This result is central to the premise of this research, which is that independent experimental evaluation of wearable support devices is essential to informed device selection, and that retail cost is not always a reliable indicator of support performance. The correlations in Table 5.22 quantify where cost predicts support and where it does not: retail price is a reliable predictor of provided support for the back ($R^2=0.87-0.95$) and shoulder ($R^2=0.99$) wearables, but not for the leg wearables ($R^2=0.24-0.26$). Device selection therefore cannot be made on cost alone. The decision support system of Chapter 6 operates on experimentally derived device support levels rather than cost for this reason. Devices such as Wearable 9 demonstrate the potential benefit of the framework proposed in this research, which provides optimal selection of wearable devices to satisfy a worker's support requirements at a lower cost than a price-based selection would achieve.

5.4.6 Questionnaire Analysis

The user perception-based questionnaire results are analyzed in this section in relation to the measured physical performance testing outcomes. Results are presented in Table 5.23 (laboratory-based data) and Table 5.24 (field-based data) for the three primary questionnaire dimensions from Section 5.3.3: Q1 – comfort level, Q2 – fatigue reduction, and Q3 – range of motion (ROM). Overall, higher-support wearables (as classified by physical performance testing) were associated with higher user-reported fatigue-reduction scores. In contrast, comfort level and ROM varied by body region and showed no consistent relationship with the LOS index.

Table 5.23: Wearable performance testing vs user questionnaire feedback (laboratory results)

Body Region	Physical Performance Testing			User Perception		
	Device Code	LOS Index	Support Classification	Comfort Level	ROM	Fatigue Reduction
Back	1	1.00	LOW	4.44	3.94	1.53
	2	1.29	LOW	4.32	4.35	1.58
	3	1.41	LOW	4.12	4.44	2.20
	4	1.98	MED	4.15	4.17	3.15
	5	2.78	HIGH	4.47	4.28	4.59
Leg	6	1.18	LOW	4.59	4.26	1.47
	7	1.37	LOW	4.02	4.46	1.98
	8	1.71	MED	3.46	4.32	2.44
	9	2.76	HIGH	3.44	3.37	4.44
Shoulder	10	1.00	LOW	4.05	3.15	1.36
	11	1.10	LOW	3.49	3.66	1.46
	12	3.00	HIGH	4.57	3.82	4.32

Table 5.24: Wearable performance testing vs user questionnaire feedback (field results)

Body Region	Physical Performance Testing			User Perception		
	Device Code	LOS Index	Support Classification	Comfort Level	ROM	Fatigue Reduction
Back	1	1.08	LOW	4.38	3.08	1.31
	2	1.15	LOW	3.62	4.15	1.54
	3	1.38	LOW	4.23	4.38	2.38
	4	1.77	MED	4.31	4.15	3.15
	5	2.85	HIGH	4.08	4.15	4.92
Leg	6	1.08	LOW	4.23	4.08	1.15
	7	1.23	LOW	4.31	4.15	1.77
	8	1.69	MED	3.23	4.08	2.46
	9	2.77	HIGH	3.15	3.08	4.38
Shoulder	10	1.00	LOW	4.08	3.38	1.31
	11	1.15	LOW	3.23	3.77	1.62
	12	3.00	HIGH	4.92	3.69	4.54

Figure 5.21 to Figure 5.26 illustrate the relationship between each device's LOS index and participant-reported ratings across the three primary questionnaire dimensions.

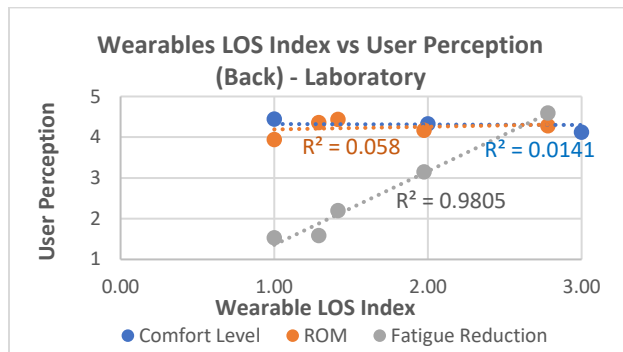


Figure 5.21: Correlation between LOS provided and user perception - Back (lab results)

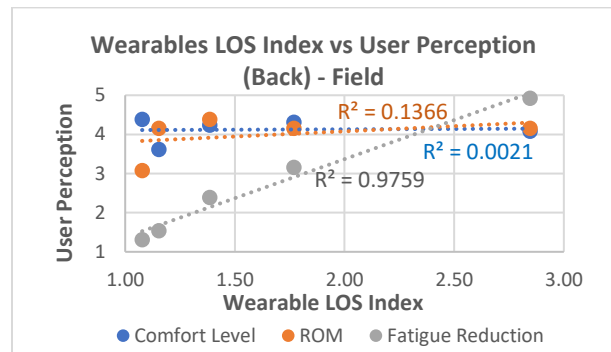


Figure 5.22: Correlation between LOS provided and user perception - Back (field results)

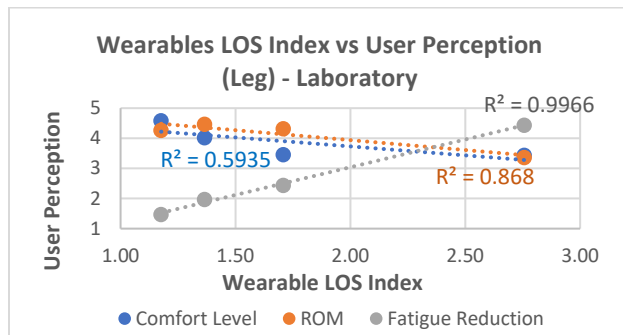


Figure 5.23: Correlation between LOS provided and user perception - Leg (lab results)

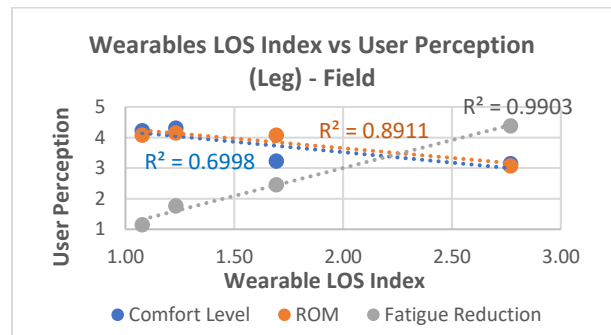


Figure 5.24: Correlation LOS provided and user perception – Leg (field results)

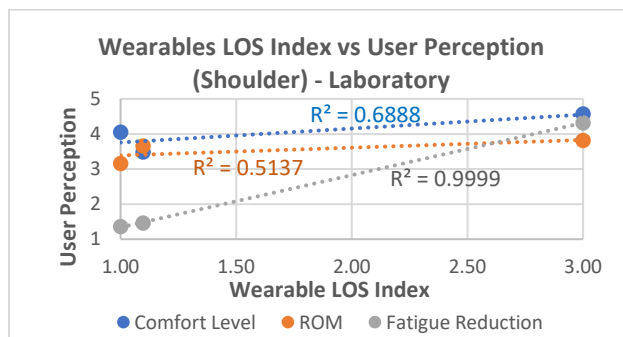


Figure 5.25: Correlation between LOS provided and user perception - Shoulder (lab results)

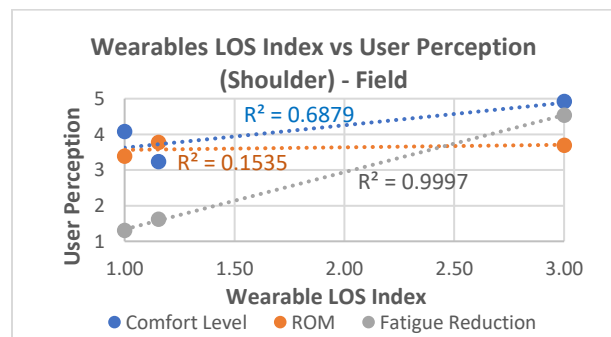


Figure 5.26: Correlation between LOS provided and user perception - Shoulder (field results)

Table 5.25 summarizes the coefficients of determination (R^2) between the LOS provided by each wearable and the questionnaire-based measures under laboratory and field conditions.

Table 5.25: R^2 values for wearables LOS provided and questionnaire outcomes

Body Region	Lab Results			Field Results		
	Comfort Level	ROM	Fatigue Reduction	Comfort Level	ROM	Fatigue Reduction
Back	0.01	0.06	0.98	0.00	0.14	0.98
Leg	0.59	0.87	0.99	0.70	0.89	0.99
Shoulder	0.69	0.51	0.99	0.69	0.15	0.99

Across both environments, LOS shows a strong positive association with perceived fatigue reduction ($R^2 = 0.98$ - 0.99 for all body regions), confirming that participants' perceived fatigue reduction tracks the LOS index assigned to each device. However, its observed relationship with comfort and ROM differs by body region: for the Back, LOS shows no meaningful relationship with either dimension ($R^2 = 0.00$ - 0.14); for the Shoulder, higher LOS is associated with greater comfort ($R^2 = 0.69$) and greater ROM ($R^2 = 0.15$ - 0.51); for the Leg, the association is negative and relatively strong ($R^2 = 0.59$ - 0.89), though the practical difference remains small, with mean ratings spanning roughly one point on the five-point scale across the full range of devices tested. Collectively, these results suggest that higher-LOS wearables generally do not come at a meaningful comfort or mobility cost: the relationship is either absent, favourable, or too low in magnitude to yield a meaningful difference.

Chapter 6: Decision Support System for Worker-Specific Optimal Wearable Selection

6.1 Introduction

The third and final component of the proposed framework is the decision support system (DSS), which consists of two phases: (1) prediction of the worker's required level of support (LOS) based on their specific characteristics; and (2) optimized selection of a wearable device set that satisfies the worker's required LOS, subject to budgetary constraints. Phase 2 resolves all at-risk body regions within a single optimization, so that the recommended device set is determined for the worker as a whole rather than region-by-region. This third component is illustrated in Figure 6.1.

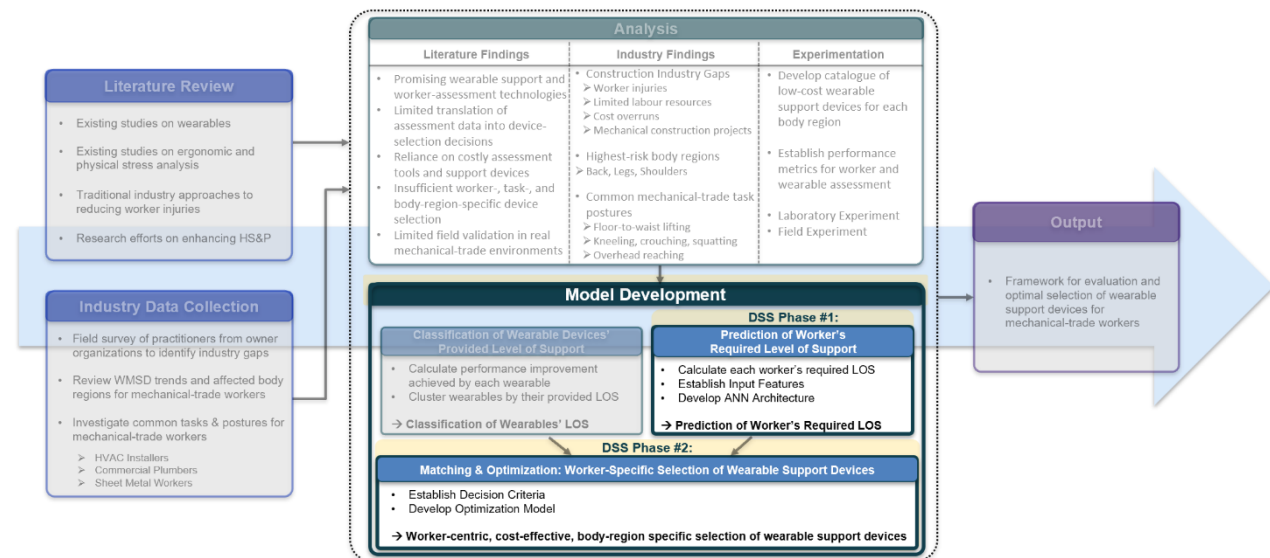


Figure 6.1: Third component of decision support framework

6.2 Prediction of Worker Required Level of Support (DSS Phase #1)

The first phase of the DSS involves the prediction of a worker's required LOS, by body region, based on their individual worker profile. This prediction is a necessary precursor to worker-specific wearable selection, as an appropriate set of support devices cannot be identified for a worker without first establishing their specific support needs. To generate this prediction, a machine learning model was developed, described in the subsequent sections.

A worker's required LOS for a given body region is determined by the simultaneous interaction of multiple anthropometric, demographic, and health-related factors. While LOS requirements can be manually predicted for straightforward cases, such as a young, healthy worker in excellent physical condition requiring minimal support, this heuristic is inadequate for the majority of real-world cases, where workers present with conflicting characteristics that do not fit a clear-cut profile. For instance, a worker's age alone may suggest low support needs, while their anthropometric characteristics may suggest otherwise. Therefore, manually weighing these competing factors consistently and objectively across a diverse workforce is impractical, error-prone, and difficult to standardize.

Machine learning offers a systematic and objective means of accounting for these multivariate interactions. By implementing the prediction of a worker's required LOS as a machine learning classification task, the resulting model can iteratively refine its internal parameters to minimize prediction error. This enables the model to learn the relative importance and combined influence of each input feature directly from empirical data, rather than relying on subjective, rule-of-thumb judgments that may fail to generalize across the diverse worker population encountered in practice.

6.2.1 Dataset Augmentation

To train the model to predict a worker's required LOS, the laboratory experiment participant sample was used, comprising 44 data points from both practitioners and non-practitioners (see Section 5.2.1). In comparison, the field experiment sample contained only 13 data points (practitioners only) and was deemed insufficient to meaningfully train the model. However, even the laboratory sample of $n = 44$ remained relatively small for training a robust predictive model, posing a risk of overfitting. To mitigate this risk, the original dataset was expanded using Gaussian noise augmentation.

Consistent with the study design rationale described in Section 5.2.1, the limited number of unique participants means that the present results should be interpreted as evidence of the

framework's feasibility rather than as definitive, population-level conclusions. The need for larger, more diverse datasets to refine the model is acknowledged as a key direction for future work (Section 8.4).

Augmentation Methodology: Small stochastic perturbations were applied to each observation by sampling from a normal distribution centered at zero with a standard deviation equal to 10% of the respective feature's standard deviation, a perturbation scale consistent with established practice for small datasets. Equations 10 and 11 were utilized to compute the Gaussian noise for each feature:

$$x_{synth} = x_{orig} + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma_{noise}) \quad (10)$$

$$\sigma_{noise} = 0.1 * \sigma_{feature} \quad (11)$$

Where:

x_{orig} is the original datapoint

x_{synth} is the synthetic datapoint

ε is the Gaussian noise value

$\sigma_{feature}$ is the standard deviation of the feature's original sample

Augmentation was performed independently within each body region, with $\sigma_{feature}$ being computed from the 44 original observations belonging to that body region alone. This ensured that the noise magnitude reflected the within-region variability of each feature, particularly relevant to the performance metrics (fatigue threshold, HR Change, ergonomic risk score), which vary in magnitude across body regions. Noise was applied directly to the participant profile variables (height, weight, age) and the performance variables (heart rate before task commencement, heart rate at task completion, fatigue threshold, and ergonomic risk score), after which BMI and body fat percentage for each synthetic data point were derived from the corresponding synthetic age, height, and weight values. This process generated three synthetic observations per original participant, increasing the total sample size from 44 to 176.

Statistical Comparison – Original vs Augmented Data: As shown in Table 6.1, the distributional similarity between the original and augmented samples was evaluated using the mean percentage difference, standard deviation ratio, and the two-sample Kolmogorov-Smirnov (KS) statistic, computed separately for each feature and body region. The KS statistic, reported in the “KS Statistic” column, is defined as the maximum absolute vertical distance between the empirical cumulative distribution functions (ECDFs) of the two samples when plotted on the same set of axes. Smaller KS values indicate closer agreement between distributions. Across nearly all feature-body region combinations, mean percentage difference values were below 1%, SD Ratio values were tightly clustered around 1.005, and KS statistic values were below 0.10, indicating that augmentation did not materially shift the distribution of these variables.

Table 6.1: Distributional similarity between original and augmented samples

Body Region	Participant Feature	Original Sample (n=44)		Augmented Sample (Original + Synthetic) (n=176)		Comparison		
		Mean	St Dev	Mean	St Dev	Mean % Diff	SD Ratio (Aug/Orig)	KS Statistic
Back	Age	37.14	12.95	37.04	13.01	0.27%	1.0043	0.0303
	Height (cm)	174.26	11.43	174.21	11.53	0.03%	1.0087	0.0808
	Weight (kg)	81.60	15.15	81.83	15.15	0.29%	1.0002	0.048
	BMI	26.77	3.64	26.87	3.69	0.38%	1.0126	0.0783
	Body Fat %	25.24	6.12	25.36	6.19	0.49%	1.0115	0.0581
	Fatigue Threshold	18	9.06	18.08	9.03	0.43%	0.996	0.0682
	HR Change	19.67	8.93	19.19	9.34	2.45%	1.0459	0.1061
	Ergonomic Risk Score	2.21	0.24	2.21	0.24	0.03%	0.9997	0.0455
Leg	Age	37.14	12.95	37.04	13.01	0.27%	1.0043	0.0303
	Height (cm)	174.26	11.43	174.21	11.53	0.03%	1.0087	0.0808
	Weight (kg)	81.60	15.15	81.83	15.15	0.29%	1.0002	0.048
	BMI	26.77	3.64	26.87	3.69	0.38%	1.0126	0.0783
	Body Fat %	25.24	6.12	25.36	6.19	0.49%	1.0115	0.0581
	Fatigue Threshold	47.34	28.82	47.32	28.32	0.04%	0.9828	0.053
	HR Change	12.16	4.91	12.09	5.28	0.56%	1.0748	0.0985
	Ergonomic Risk Score	8.57	0.85	8.57	0.84	0%	0.9923	0
Shoulder	Age	37.14	12.95	37.04	13.01	0.27%	1.0043	0.0303
	Height (cm)	174.26	11.43	174.21	11.53	0.03%	1.0087	0.0808
	Weight (kg)	81.60	15.15	81.83	15.15	0.29%	1.0002	0.048
	BMI	26.77	3.64	26.87	3.69	0.38%	1.0126	0.0783
	Body Fat %	25.24	6.12	25.36	6.19	0.49%	1.0115	0.0581
	Fatigue Threshold	60.27	26.87	60.37	26.98	0.16%	1.0041	0.0606
	HR Change	11.35	4.72	10.4	5.29	8.43%	1.1212	0.1742
	Ergonomic Risk Score	0.2	0.03	0.2	0.03	0.01%	0.9892	0.1136

These results are illustrated in Figure 6.2 to Figure 6.13 via ECDF and Q-Q plots for each feature. HR Change exhibited slightly larger deviation than other features, which is expected because it represents the difference between two independently augmented heart-rate measurements (before and after task completion). Across features, these visualizations generally show closely aligned ECDF curves and Q-Q points that largely follow the reference line, further supporting the conclusion that the underlying statistical properties of the original dataset (participant characteristics and task performance) were preserved through the Gaussian augmentation. This supports the validity of the augmented dataset for training the predictive model.

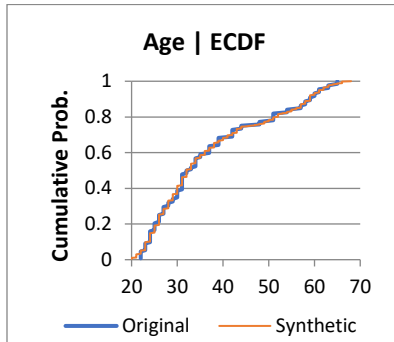


Figure 6.2: Age ECDF plot - original vs augmented sample

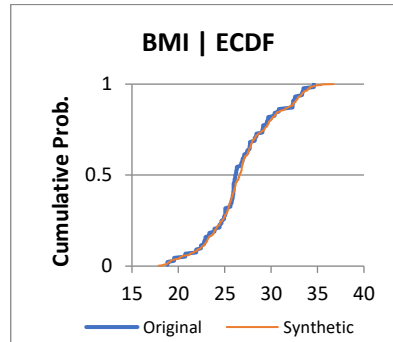


Figure 6.3: BMI ECDF plot - original vs augmented sample

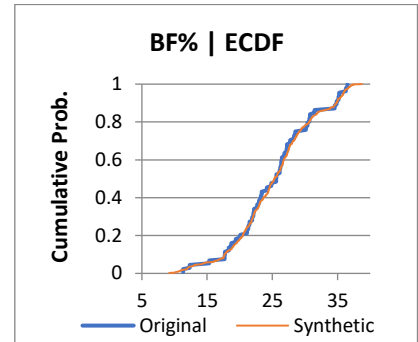


Figure 6.4: BF% ECDF plot - original vs augmented sample

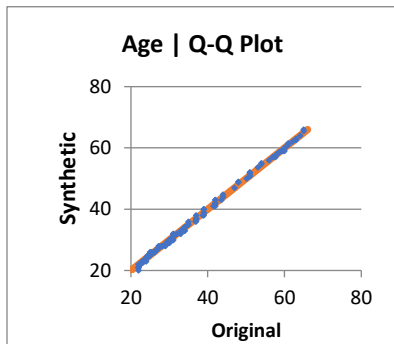


Figure 6.5: Age Q-Q plot - original vs augmented sample

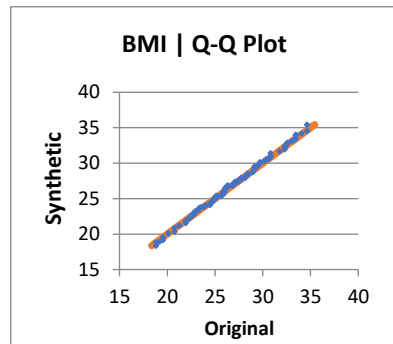


Figure 6.6: BMI Q-Q Plot - original vs augmented sample

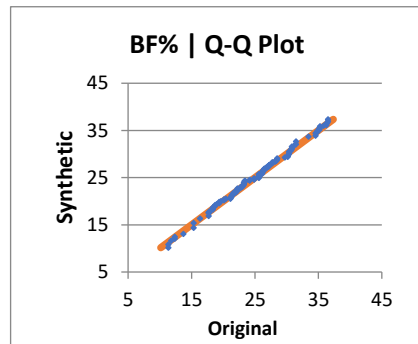


Figure 6.7: BF% Q-Q Plot - original vs augmented sample

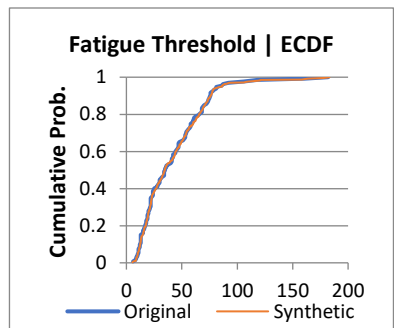


Figure 6.8: Fatigue threshold ECDF plot - original vs augmented sample

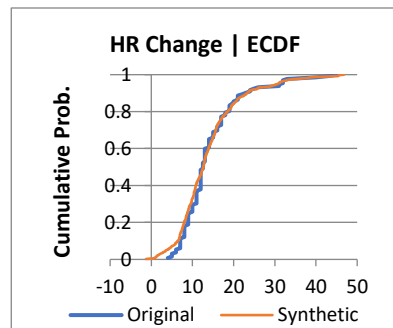


Figure 6.9: HR Change ECDF plot - original vs augmented sample

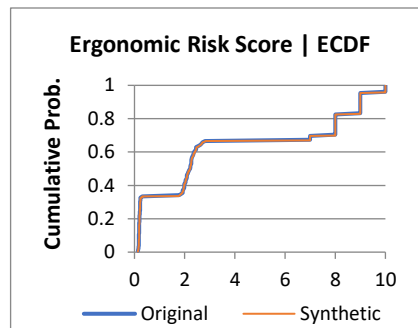


Figure 6.10: Ergonomic risk score ECDF plot - original vs augmented sample

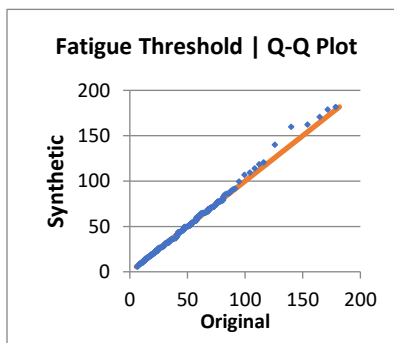


Figure 6.11: Fatigue Threshold Q-Q plot - original vs augmented sample



Figure 6.12: HR Change Q-Q plot - original vs augmented sample

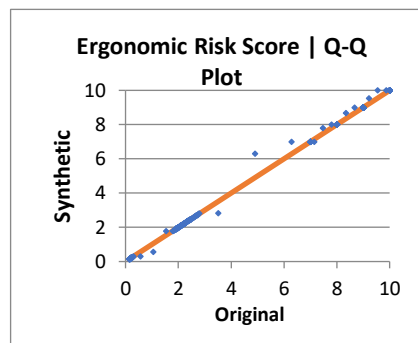


Figure 6.13: Ergonomic risk score Q-Q plot - original vs augmented sample

6.2.2 Calculation of Worker Required Level of Support

To train the predictive model, the required LOS for each participant was calculated based on their baseline performance (without wearables). Two approaches (clustering and analytical methods) were implemented, and their results were compared.

Clustering Method: For the clustering method, WEKA's clustering feature was used to partition the dataset into three clusters based on the three performance assessment metrics (Fatigue Threshold, Heart Rate Change, Ergonomic Risk Score). Each cluster was then associated with a required support level: 1 (Low), 2 (Medium), or 3 (High) by examining average Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score values within the clusters. For example, the cluster with the lowest average values corresponded to participants who required the highest LOS. This process was performed separately for each of the three body regions (shoulder, back, legs).

Analytical Method: For the analytical method, the participants' performance across the three performance metrics (Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score) without wearable devices was plotted against a normal distribution. The participants' relative performances with respect to the three performance metrics were evaluated, and each participant was subsequently grouped into three distinct 'Required Level of Support' categories: High, Medium, and Low.

Prior to evaluating the participants' baseline performance relative to a normal distribution, the performance dataset's distribution was assessed. Normality was examined using Q-Q plots for each body region and performance metric, as shown in Figure 6.14 to Figure 6.22. These plots indicated that the data were approximately normally distributed across all body regions and performance metrics.

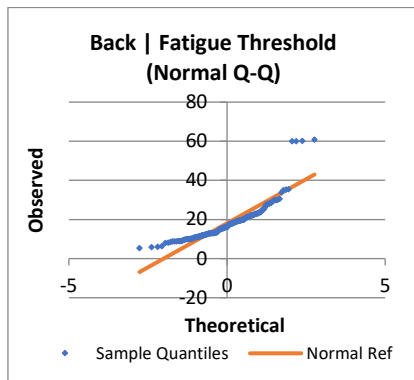


Figure 6.14: Back - fatigue threshold Q-Q normality plot

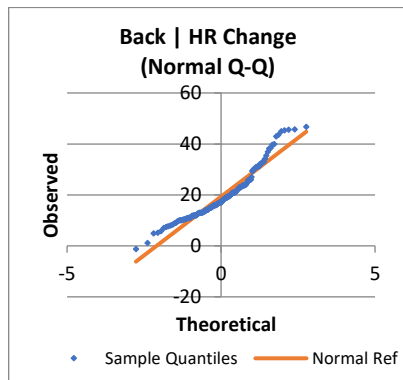


Figure 6.15: Back - HR change Q-Q normality plot

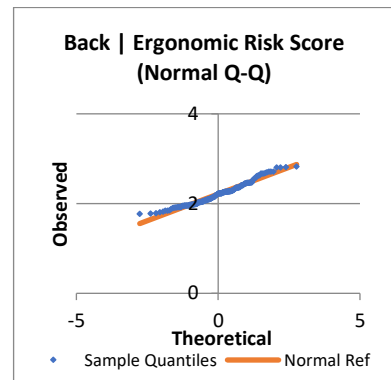


Figure 6.16: Back - ergonomic risk score Q-Q normality plot

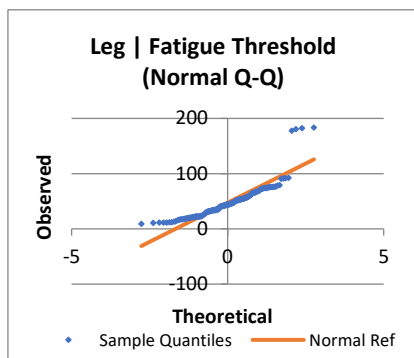


Figure 6.17: Leg - fatigue threshold Q-Q normality plot

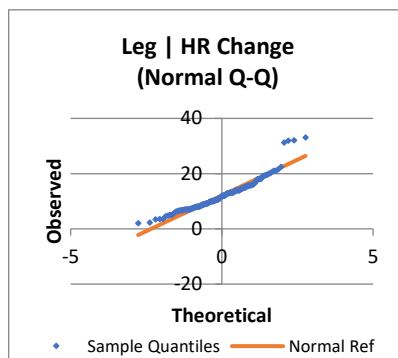


Figure 6.18: Leg - HR change Q-Q normality plot

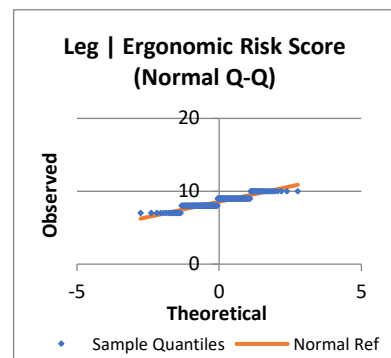


Figure 6.19: Leg - ergonomic risk score Q-Q normality plot

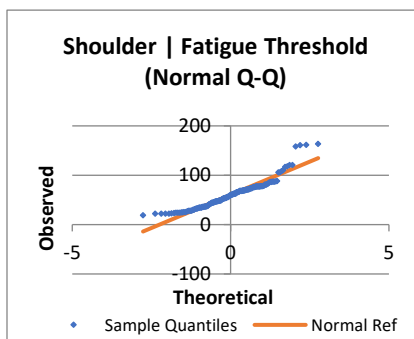


Figure 6.20: Shoulder - fatigue threshold Q-Q normality plot

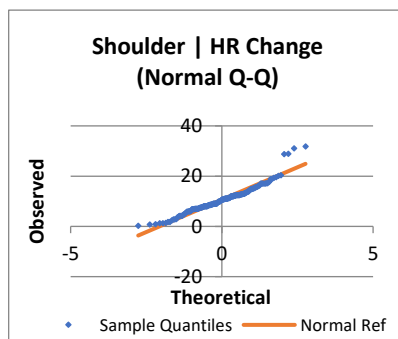


Figure 6.21: Shoulder - HR change Q-Q normality plot

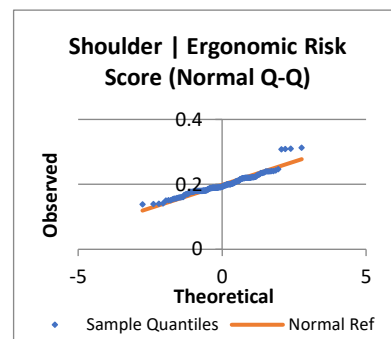


Figure 6.22: Shoulder - ergonomic risk score Q-Q normality plot

Table 6.2 presents the mean, standard deviation, and KS statistic for each performance metric by body region. These results were used to evaluate the extent to which the baseline performance data conformed to a normal distribution. Across all regions and metrics, the observed KS statistics indicate close agreement with a normal distribution, consistent with the trends observed in the Q-Q plots presented in Figure 6.14 to Figure 6.22.

Table 6.2: Normality assessment of participant performance dataset

Body Region	Performance Metric	Mean	St Dev	KS Statistic (vs Normal)
Back	Fatigue Threshold	18.058	9.01	0.1269
	HR Change	19.309	9.217	0.1034
	Ergonomic Risk Score	2.213	0.238	0.0665
Leg	Fatigue Threshold	47.328	28.362	0.1052
	HR Change	12.108	5.177	0.08
	Ergonomic Risk Score	8.568	0.839	0.2281
Shoulder	Fatigue Threshold	60.345	26.879	0.1006
	HR Change	10.635	5.158	0.096
	Ergonomic Risk Score	0.198	0.029	0.0924

Calculation of LOS Required:

The normal distribution population parameters for each body region are summarized in Table 6.3. Because the Ergonomic Risk Score is computed using NIOSH for the back and shoulders and REBA for the legs, the substantial differences in mean ergonomic risk score magnitudes across body regions shown in Table 6.3 (e.g., mean of 2.21 for back and 8.57 for leg) reflect the different scales of the respective algorithms.

Table 6.3: Participant group baseline performance (without wearable devices)

Body Region	Fatigue Threshold		Heart Rate Change		Ergonomic Risk Score	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Back	18.06	9.01	19.31	9.22	2.21	0.24
Leg	47.33	28.36	12.11	5.18	8.57	0.84
Shoulder	60.35	26.88	10.64	5.16	0.20	0.03

Subsequently, percentile values and Z-scores were calculated for each participant to represent their performance with respect to each of the three metrics. Because higher Heart Rate

Change and Ergonomic Risk Score values indicate poorer performance, whereas higher Fatigue Threshold values indicate better performance, the Heart Rate Change and Ergonomic Risk Score percentiles were reverse-scored (computed as $1 - p$) prior to aggregation. This ensured that, for all three metrics, a higher percentile consistently indicated better performance and therefore a lower required level of support.

For each participant, the three sets of Z-scores were averaged to obtain a single composite Z-score. The resulting composite Z-score values were then scaled to obtain a population mean of 0 and standard deviation of 1. These composite Z-score values were then converted into percentile values, ultimately representing each participant's average performance across the three performance metrics. These percentages were then grouped into three distinct 'Required Level of Support' categories: High, Medium, and Low. Participants below the 33rd percentile were assigned to level 3 (require High support), those between the 33rd and 66th percentiles to level 2 (require Medium support), and those above the 66th percentile to level 1 (require Low support). This process was performed separately for each of the three body regions (shoulder, back, legs). Table 6.4 demonstrates this process for a sample participant.

Table 6.4: Calculation of required level of support for sample participant

Participant	Body Region	Fatigue Threshold		Heart Rate Change		Ergonomic Risk Score		Composite			Output
		Percentile	Z-Score	Percentile	Z-Score	Percentile	Z-Score	Composite Z-Score	Scaled Composite Z-Score	Scaled Composite Percentile	
Sample	Back	29.06%	-0.55	80.48%	0.86	42.27%	-0.19	0.04	0.06	53%	2
	Leg	55.05%	0.13	73.99%	0.64	30.49%	-0.51	0.09	0.15	56%	2
	Shoulder	8.85%	-1.35	82.18%	0.92	22.77%	-0.75	-0.39	-0.67	25%	3

Note. The Heart Rate Change and Ergonomic Risk Score percentiles shown in this table are already reverse-scored (computed as $1 - p$), as higher raw values for these two metrics indicate poorer performance. After this reversal, a higher percentile denotes better performance for all three metrics, so that higher composite percentiles correspond to a lower required level of support.

The analytical method was considered more appropriate than clustering for estimating participant-required levels of support because it classified participants by their relative positions within the sample distribution, providing a consistent, predefined classification criterion. A standardized percentile-based approach provides a direct and interpretable basis for assigning participants to ordered support categories according to their relative baseline performance. The use of this approach was further supported by the diversity of the participant group, with substantial variation observed not only across the evaluated performance metrics, but also across participant characteristics, including age, height, weight, sex, and health score. Combined with the approximately normal distribution of participant performance data (as shown in Figure 6.14 to Figure 6.22), this indicates that the sample captures a meaningful range of participant abilities, such that the derived Low, Medium, and High support categories reflect genuine differences in participants' required levels of support. Therefore, the participants' required LOS values derived from the analytical method were carried forward for use in the subsequent stages of this research.

6.2.3 Predictive Model Architecture and Design

Input Features and Target Variable: The input features selected for the predictive model are worker age, sex, body mass index (BMI), body fat percentage (BFP), and health score. BMI, calculated using height and weight, is a widely used screening index that is strongly correlated with body fat in population-level assessments. However, because it is derived solely from mass and stature, it cannot differentiate between fat mass and lean muscle mass. BFP (estimated using age, sex, and BMI via the CUN-BAE equation) addresses this limitation by providing a more precise indication of an individual's physical composition (Gómez-Ambrosi et al., 2012).

Both BMI and BFP were retained as separate inputs, which carries no added measurement burden since both are derived from the same anthropometric and demographic data already being collected (height, weight, age, sex), an approach consistent with broader body-composition research, where a formula-based adiposity estimate is commonly reported alongside BMI, because

it more directly reflects physiological outcomes than BMI alone (Gómez-Ambrosi et al., 2012). Providing both BMI and BFP as separate inputs also reflects a common practice in predictive modeling known as domain knowledge injection: when a relationship between raw variables is already known, it can be provided to the model directly as an input rather than left for the model to establish on its own. Because the CUN-BAE formula linking age, sex, and BMI to body fat is already validated, including BFP removes the need for the model to independently learn that same relationship with a limited dataset, thereby enriching the model's feature space and potentially improving accuracy through this injection of domain knowledge (Borghesi et al., 2020). This pattern is reflected in physiological prediction research, where a BMI-only model was found to overestimate outcomes for individuals with low BMI and low physical activity, a limitation that was partially corrected by adding BFP as an additional input alongside BMI (Gregory, 2024).

Together, these five input variables provide a comprehensive profile of the user and are expected to be key determinants of a worker's ability to perform demanding mechanical construction tasks. These input variables are also logistically straightforward to collect, as they can be obtained through self-reporting and without specialized physical measurement equipment, thereby improving the practical applicability of the DSS in real-world field settings. The target variable for the predictive model is the worker's required LOS.

Data Splitting: To train the predictive model for each body region, the dataset ($n = 176$) was partitioned into 66% for training (116 data points) and 34% for testing (60 data points) per region. This ratio was selected to balance two competing requirements: retaining enough data to train each model effectively, while reserving a test set large enough to yield a reliable estimate of predictive accuracy. With small datasets, the conventional 80/20 split can leave the evaluation set too small to be meaningful. D'souza et al. (2020), for example, trained models on subsets of 1,000, 500, and 100 images. The authors retained an 80/20 training-validation split for the two larger subsets but, for the 100-image subset, expanded the validation set to 40% and reduced the training set to 60%,

because an 80/20 split left too few validation points for statistical significance. Similarly, the 66/34 allocation adopted in this research reserves approximately one-third of the data for testing, which aligns with the optimal splitting guidance derived by Joseph (2022), who recommends a testing fraction of approximately one-quarter to one-third as a reasonable default for machine learning models when the number of model parameters is not predetermined. This is further supported by empirical findings identifying a 70/30 split as the most effective train/test ratio for machine learning models. Nguyen et al. (2021) evaluated ratios from 10/90 to 90/10 across multiple model types over 1,000 simulations and found 70/30 optimal.

Selection of the Predictive Model: To identify the most suitable model for predicting a worker's required LOS, four machine learning algorithms were evaluated: the Multilayer Perceptron (MLP) artificial neural network (ANN), Random Forest, the Support Vector Machine (SVM), and the J48 Decision Tree. Each algorithm was evaluated using its default hyperparameter configuration, allowing its inherent suitability to be assessed before any model-specific optimization. Their performance was compared using three metrics: the Kappa statistic and the weighted-average (across classes) F-Measure and ROC area, as summarized in Table 6.5.

Table 6.5: Comparison of machine learning algorithms for prediction of required LOS

Body Region	Predictive Model	Kappa Statistic	F-Measure (weighted avg.)	ROC Area (weighted avg.)
Back	MLP	0.6679	0.787	0.889
	Random Forest	0.5408	0.707	0.827
	SVM	0.6671	0.786	0.849
	J48 Decision Tree	0.4898	0.672	0.784
Leg	MLP	0.602	0.738	0.805
	Random Forest	0.5778	0.722	0.831
	SVM	0.5746	0.719	0.791
	J48 Decision Tree	0.5775	0.722	0.804
Shoulder	MLP	0.6003	0.729	0.855
	Random Forest	0.5980	0.730	0.892
	SVM	0.6002	0.731	0.809
	J48 Decision Tree	0.496	0.667	0.844

As shown in Table 6.5, the MLP produced the best overall results across the three body regions. It achieved the highest Kappa statistic in all three regions and the highest weighted-average F-Measure for the back and leg regions, while performing comparably to the best alternative for the shoulder region. Although the margins were narrow for individual regions, the MLP was the only model that ranked first or near-first across all three regions simultaneously. The Kappa statistic and F-Measure were prioritized as the primary selection criteria because they provide a more rigorous assessment of classification performance than accuracy alone. The Kappa statistic measures the agreement between the predicted and actual support levels after accounting for agreement achieved by chance, ensuring that the reported performance reflects genuine predictive ability rather than correct predictions arising from class frequency. The F-Measure combines precision and recall into a single, balanced score that captures two complementary measures of accuracy. Precision captures how often the support levels predicted by the model were correct, while recall captures how many of the cases that truly belonged to each support level were successfully identified. Because the F-Measure accounts for both, it captures a model's ability to simultaneously avoid misclassifying cases into incorrect levels and avoid missing cases that belong to a given level. By consistently achieving the strongest results on these chance-adjusted and balanced measures, the MLP demonstrated the most reliable predictive performance across body regions. While the SVM yielded closely competitive results and the Random Forest occasionally attained a marginally higher ROC area, neither matched the MLP's overall consistency.

Beyond its empirical performance on the evaluated metrics, the MLP was selected because neural networks are well-suited to capturing nonlinear relationships between input parameters and the required level of support (Ali et al., 2023). Tabular data of this kind have no spatial structure for a convolutional neural network (CNN) to exploit and no sequential structure for a recurrent neural network (RNN) to model (Borisov et al., 2024; Waqas & Humphries, 2024). A feedforward multilayer perceptron is therefore a suitable neural architecture for such data. Network depth was also constrained by the size of the dataset. Deep networks are prone to overfitting when training samples

are limited (D'souza et al., 2020), and the models were trained on data from 44 participants. The MLP ANN was therefore adopted as the final predictive model and subsequently optimized through hyperparameter tuning. As larger worker datasets become available, more complex models can be benchmarked against the MLP (Section 8.4.1).

Hyperparameter Optimization: WEKA's multilayer perceptron classifier includes a set of tunable hyperparameters that were optimized through an iterative manual tuning process. Initial values were set to WEKA's default settings, after which key hyperparameters (number of hidden neurons, learning rate, momentum, training time, and random seed) were systematically adjusted, with the model being retrained at each iteration. Performance at each iteration was estimated using WEKA's 10-fold cross-validation on the training set, a commonly recommended strategy for hyperparameter optimization (Bischi et al., 2023). Configurations were compared and selected based on the cross-validated (CV) Kappa statistic, which measures chance-adjusted agreement between predicted and actual classes, with cross-validated accuracy reported alongside for validation. For each body region, the configuration achieving the highest cross-validated Kappa was selected, and the test set was reserved for final evaluation.

Selecting hyperparameters through manual configuration (starting with software defaults and refining based on observed results) is a recognized and well-documented approach (Probst et al., 2019; Yang & Shami, 2020; Bischi et al., 2023). Table 6.6 presents the top three configurations obtained for each body region, with the selected configuration shown in bold (Configuration B for Back, A for Leg, and B for Shoulder). The resulting ANN architectures and test-set performance metrics, based on the selected hyperparameter configurations, are reported in the subsequent sections.

Table 6.6: Top ANN hyperparameter configurations and cross-validation performance

ANN	Config.	Hidden Neurons	Learning Rate	Momentum	Training Time	Seed	CV Accuracy	CV Kappa
Back	A	4 neurons	0.4	0.2	500 epochs	2	76.7%	0.6420
	B	12 neurons	0.7	0.2	1000 epochs	1	77.8%	0.6591
	C	10 neurons	0.6	0.2	800 epochs	1	77.8%	0.6586
Leg	A	6 neurons	0.3	0.8	200 epochs	2	78.4%	0.6764
	B	6 neurons	0.4	0.7	400 epochs	2	76.1%	0.6421
	C	10 neurons	0.8	0.2	800 epochs	1	77.8%	0.6664
Shoulder	A	8 neurons	0.5	0.3	800 epochs	1	79.0%	0.6819
	B	5 neurons	0.3	0.8	500 epochs	2	79.0%	0.6834
	C	10 neurons	0.3	0.2	500 epochs	2	77.8%	0.6661

Note. Selected hyperparameter configurations for each body region are shown in bold.

ANN Architecture: To predict the required LOS for each body region, three separate ANNs were developed, one each for the back, legs, and shoulders, with each model trained exclusively on data collected for its respective body region. Each ANN produces a single output: the predicted LOS required by a given worker for that body region. For example, a worker may receive predicted support levels of 3 for the shoulders, 2 for the back, and 1 for the legs, reflecting variation in physical support requirements across body regions.

Formulating worker LOS prediction as a three-class, ordered classification problem is aligned with the support-level categorization applied to wearable devices in this framework. In Chapter 5, each device's continuous Level of Support index is discretized into Low, Medium, and High categories; predicting a worker's required LOS on the same ordinal scale therefore ensures that the predictive model's outputs can be mapped directly onto these discrete device support levels when the DSS selects an appropriate set of devices for a given worker. The architectures of the developed ANNs for the back, leg, and shoulder body regions are illustrated in Figure 6.23, Figure 6.24, and Figure 6.25, respectively.

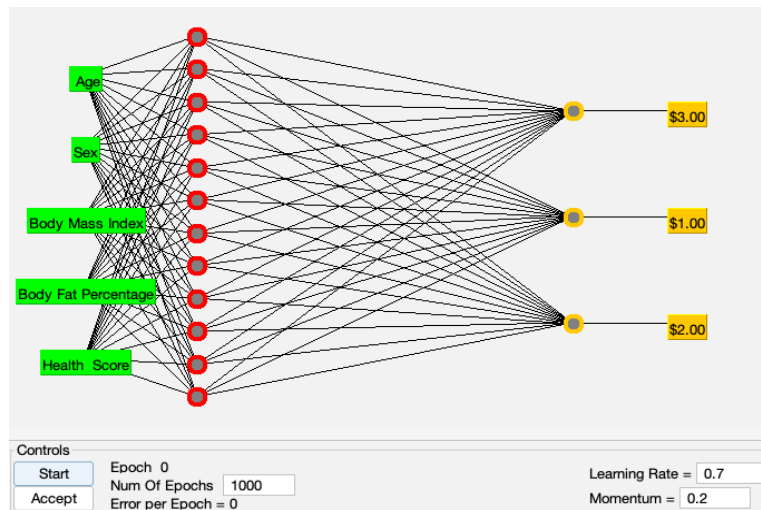


Figure 6.23: ANN for estimating required level of support (back)

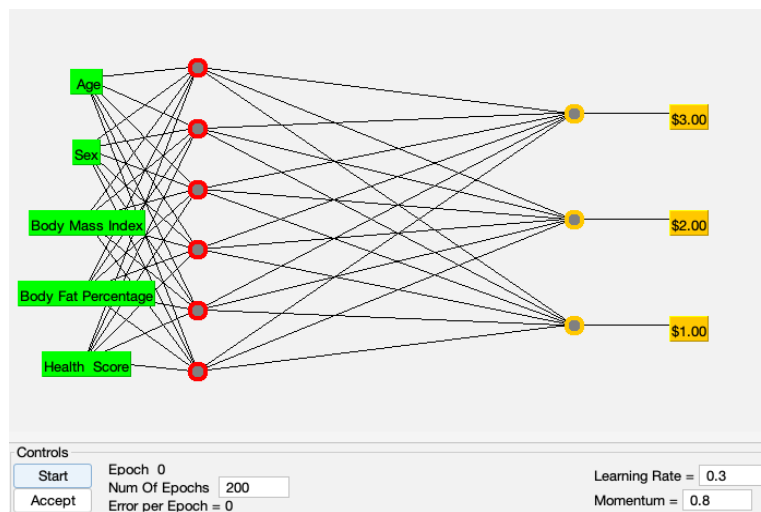


Figure 6.24: ANN for estimating required level of support (leg)

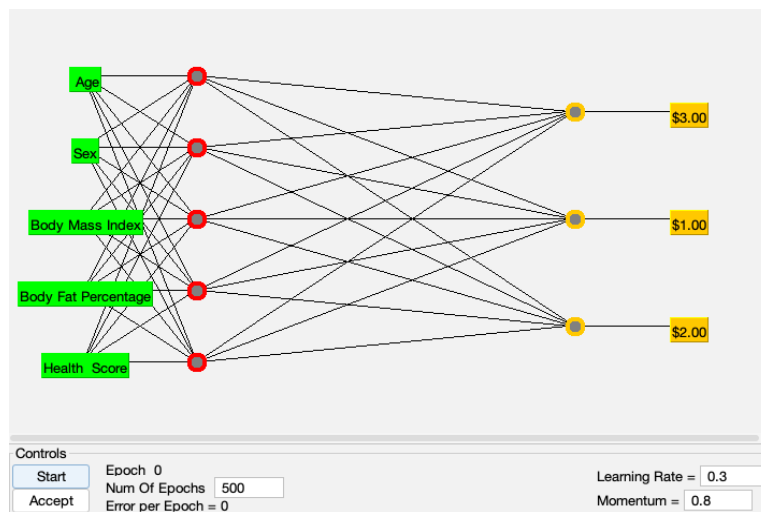


Figure 6.25: ANN for estimating required level of support (shoulder)

6.2.4 Predictive Model Results

Each ANN produces a number in the range of 1 to 3 (representing the LOS required by the user), which aligns with the LOS range provided by the wearables (Low, Medium, and High). The ANN accuracies for estimating the required LOS for the back, legs, and shoulder were 83%, 80%, and 87%, respectively. The evaluation metrics for each ANN are summarized in Table 6.7 and the confusion matrices are shown in Table 6.8.

Table 6.7: Performance of the MLP ANNs for each body region

Body Region	LOS Class	Test Set Accuracy	F-Measure	Recall	Precision	Kappa Statistic	ROC Area
Back	1	83.33%	0.811	0.750	0.882	0.7452	0.879
	2		0.808	0.913	0.724		0.830
	3		0.903	0.824	1.000		0.929
Leg	1	80.00%	0.865	0.889	0.842	0.701	0.942
	2		0.739	0.850	0.654		0.788
	3		0.811	0.682	1.000		0.821
Shoulder	1	86.67%	0.829	0.895	0.773	0.799	0.938
	2		0.844	0.826	0.864		0.893
	3		0.941	0.889	1.000		0.960

Table 6.8: Confusion matrices of the MLP ANNs for each body region

Body Region	True LOS Class	Predicted LOS Class			Total	Accuracy
		1	2	3		
Back	1	15	5	0	20	83.33%
	2	2	21	0	23	
	3	0	3	14	17	
		17	29	14	60	
Leg	1	16	2	0	18	80.00%
	2	3	17	0	20	
	3	0	7	15	22	
		19	26	15	60	
Shoulder	1	17	2	0	19	86.67%
	2	4	19	0	23	
	3	1	1	16	18	
		22	22	16	60	

The confusion matrices presented in Table 6.8 illustrate the classification behaviour of the MLP models across the back, leg, and shoulder regions, each evaluated on 60 cases. The models correctly classified 50, 48, and 52 cases, respectively, corresponding to classification accuracies of 83% for the back, 80% for the leg, and 87% for the shoulder region. The diagonal elements (representing correctly predicted cases) dominate each matrix, indicating that the models can reliably predict across the three levels of support (LOS).

Furthermore, the misclassifications were almost entirely confined to adjacent support levels. In the back and leg regions, no cases were misclassified between the lowest and highest levels (LOS 1 and LOS 3); errors only occurred between adjacent categories. The only exception occurred in the shoulder region, where a single LOS 3 case was predicted as LOS 1. This pattern is favourable for an ordinal problem such as LOS prediction: the models captured the ordered structure of the support levels and, when incorrect, typically deviated by only one adjacent level rather than producing severe misclassifications. Practically, an incorrect prediction would still recommend a support level close to the true requirement.

These results are consistent with the metrics reported in Table 6.7. Across all three regions, the highest support level (LOS 3) achieved a precision of 1.000, indicating that every case predicted as requiring an LOS of 3 was correct. Recall remained generally strong across all classes. The corresponding F-Measure and ROC area values further confirm the balanced and reliable predictive performance of the developed MLP models. The WEKA summary results for the back, leg, and shoulder regions are shown in Figure 6.26, Figure 6.27, and Figure 6.28, respectively.

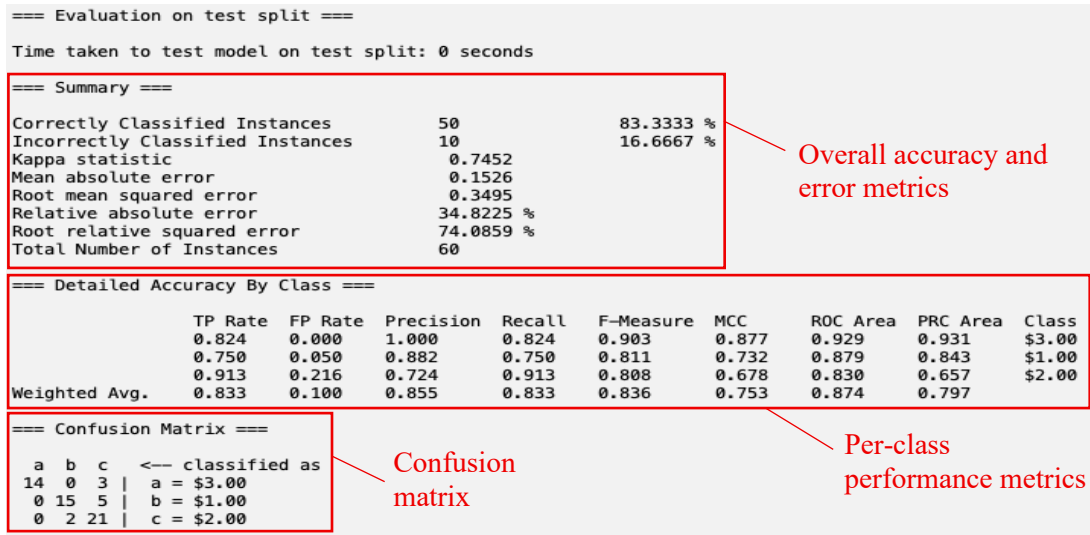


Figure 6.26: Back ANN summary (WEKA)

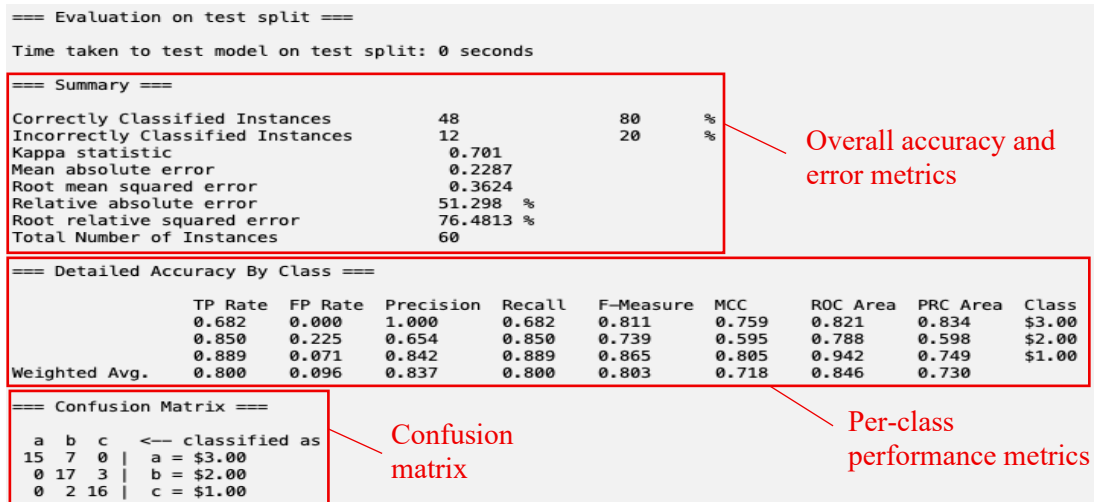


Figure 6.27: Leg ANN summary (WEKA)

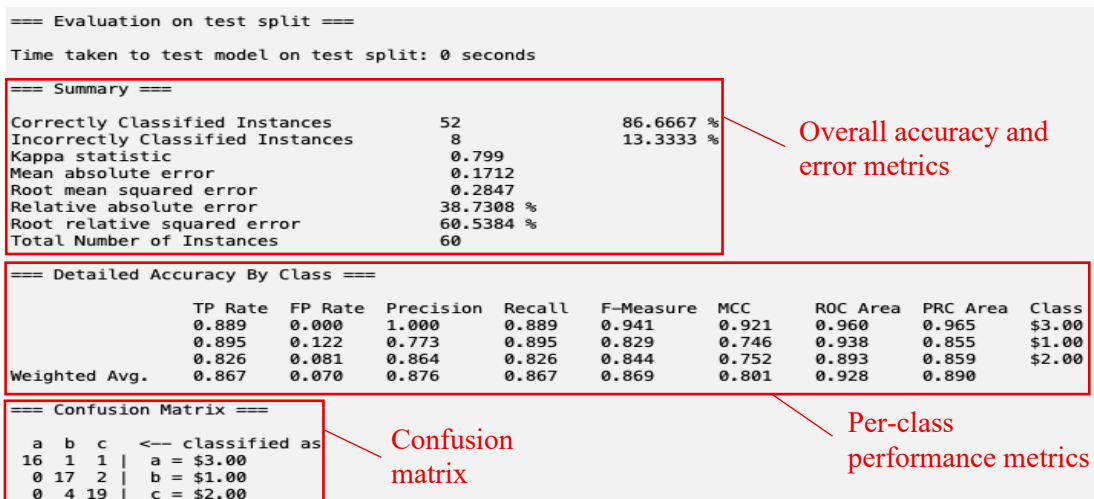


Figure 6.28: Shoulder ANN summary (WEKA)

6.3 Worker-Specific Selection of Wearable Device Set (DSS Phase #2)

Once the required LOS is predicted for a specific worker by body region, the second phase of the DSS leverages an optimization model to select the most cost-effective combination of commercially available wearable support devices that simultaneously meets the worker's support requirements across all at-risk body regions, yielding a single worker-specific device set. The optimization model is implemented in Microsoft Excel using the Solver add-in (Figure 6.29) and is designed to be operated without programming expertise.

Solver Parameters

Set Objective:

To: ☐ Max ☒ Min ☐ Value Of:

By Changing Variable Cells:

Subject to the Constraints:

-
-
-
-
-
-
-
-
-

☒ Make Unconstrained Variables Non-Negative

Select a Solving Method:

Solving Method

Select the GRG Nonlinear engine for Solver Problems that are smooth nonlinear. Select the LP Simplex engine for linear Solver Problems, and select the Evolutionary engine for Solver problems that are non-smooth.

Buttons: Add, Change, Delete, Reset All, Load/Save, Help, Solve, Close

Figure 6.29: Optimization model for worker-specific selection of wearable support devices

6.3.1 Inputs

The optimization model receives four inputs:

- (i) A catalogue of wearable devices (Figure 6.29-a), grouped by body region (Back, Shoulder, Leg), in which each device is assigned a unique device code, LOS provided (an integer on a 1-3 ordinal scale), and unit cost in CAD;
- (ii) Worker-specific predicted LOS requirements produced by the ANN stage (Figure 6.29-b, cells G8 to I8);
- (iii) Any optional body-region opt-outs selected by the worker (Figure 6.29-b, cells G9 to I9);
- (iv) A user-defined budgetary limit (Figure 6.29-c, cell I15), which may vary with trade, employer insurance coverage, and union contribution.

Body Region Opt-Out:

The opt-out row (Figure 6.30-b) enables the worker to exclude a specific body region from the DSS, overriding its ANN-derived LOS requirement. When a checkbox is selected, as shown for Shoulder in the sample image, the model sets that region's Effective LOS Required to zero and constrains the Solver to select no device from the catalogue for that region. The reported total cost then updates to reflect only the selected body regions, allowing the worker to view an accurate procurement cost without needing to manually subtract the price of an unwanted device.

</

Figure 6.30: Optimization model output with shoulder region opted out

6.3.2 Model Formulation

Let $d_r \in \mathcal{D}_r$ denote the device code selected (Figure 6.29-e, cells L9 to N9) for body region $r \in \{\text{Back, Shoulder, Leg}\}$, where $\mathcal{D}_r$ is the discrete set of device codes available in the catalogue for that body region (Figure 6.29-a, column B). For each region, two lookup operations map d_r to its corresponding LOS provided, $S_r(d_r)$ (Figure 6.29-e, cells L8 to N8), and unit cost, $C_r(d_r)$ (Figure 6.29-e, cells L10 to N10), by referencing the wearable device catalogue. The model varies the three device codes d_{back} , $d_{shoulder}$, and d_{leg} (Eq. 12) to minimize total device procurement cost across the three body regions (Eq. 13), subject to per-region LOS sufficiency (Eq. 14), a total-budget constraint (Eq. 15), and catalogue membership (Eq. 16). The formulation is therefore centered around the worker rather than each specific body region, as a single objective and single budget constraint span all three body regions. The model returns one device set evaluated against the worker's requirements as a whole, rather than three independent region-level recommendations.

Decision variables:

$$d_{back} \in D_{Back}, d_{shoulder} \in D_{Shoulder}, d_{leg} \in D_{Leg} \quad (12)$$

Objective:

$$\min_{d_{Back}, d_{Shoulder}, d_{Leg}} (C_{total} - \varepsilon), \quad C_{total} = \sum_r C_r(d_r) \quad (13)$$

Constraints:

$$S_r(d_r) \geq L_r, \quad \forall r \in \{\text{Back, Shoulder, Leg}\} \quad (14)$$

$$\sum_r C_r(d_r) \leq B \quad (15)$$

$$d_r \in D_r, \quad \forall r \in \{\text{Back, Shoulder, Leg}\} \quad (16)$$

Where L_r is the ANN-estimated required LOS for body region r , B is the user-supplied total budget, and ε is the tie-breaking coefficient defined in the subsequent subsection.

6.3.3 Solving Engine

The Evolutionary engine was selected because the model combines (a) discrete, integer-valued decision variables drawn from a finite, predefined catalogue with (b) lookup-based mappings from device code to LOS and cost that are non-smooth and potentially discontinuous. This setup is not suitable for the Simplex LP engine, which requires linear objective and constraint functions, nor for the GRG Nonlinear engine, which is designed for smooth differentiable models. In contrast, the Evolutionary engine is designed for non-smooth and discontinuous problems (e.g., LOOKUP-type mappings) by maintaining a population of candidate solutions and iteratively improving them over the discrete search space defined by Eq. 16. It draws on genetic algorithms and local search methods (Frontline Systems, n.d.), an approach that allows the lookup-based model to be solved in its implemented form, without reformulation. As a heuristic search, however, it cannot prove that the solution it returns is optimal; its solutions are therefore compared with exact solutions in Section 6.6. The Evolutionary engine was configured with Random Seed = 1, Convergence = 1×10^{-4} , Mutation Rate = 0.075, Population Size = 100, and Maximum Time without Improvement = 30 s. The solver parameters are presented in Figure 6.31.

Figure 6.31: Solver parameters for optimization model

The labelled items (1) through (11) in Figure 6.31 perform the following functions within the optimization model:

Objective:

- (1): Minimizes the total cost of the recommended wearable set (Figure 6.29-d, cell I27).

Decision Variables:

- (2): Selects the device code for each body region (cells L9 to N9), which Solver adjusts to identify the optimal solution.

Constraints:

- (3): Restricts the total cost (cell L11) of the selected wearable set to remain within the specified budgetary limit (cell I15).

- (4): Requires the LOS provided by each selected wearable (cells L8 to N8) to meet or exceed the LOS required for its body region (cells G10 to I10).
- (7): Forces all selected device codes (cells L9 to N9) to be integers, ensuring each corresponds to a discrete catalogue entry rather than a fractional value.
- (5), (6): Bound the Back device code (cell L9) to the range of available catalogue codes.
- (8), (9): Bound the Shoulder (cell M9) device code to the range of available catalogue codes.
- (10), (11): Bound the Leg device code (cell N9) to the range of available catalogue codes.

6.3.4 Cost-Equivalence and Tie-Breaking

The term ε in the objective (Eq. 13), shown in Figure 6.29-d, formalizes the definition of “cost-equivalence” between candidate solutions and resolves ties among cost-equivalent sets by favouring the configuration that delivers greater aggregate support. It does not represent procurement cost; the true total device cost reported to the end user is computed independently of this term as the simple sum of the three selected unit costs. The model treats two candidate sets as cost-equivalent if their true total procurement costs are within a fraction τ of one another, where τ is a cost-equivalence threshold (set to 1% in the implemented model).

To implement this within the Solver objective, the tie-breaking coefficient ε is constructed from two underlying quantities: the aggregate LOS surplus of a candidate solution, Δ , and the maximum possible LOS surplus attainable from the catalogue, $\Delta_{\max}$, defined respectively as:

$$\Delta = \sum_r (S_r(d_r) - L_r) \quad (17)$$

$$\Delta_{\max} = \sum_r (S_r^{\max} - L_r) \quad (18)$$

where $S_r^{\max}$ denotes the maximum LOS attainable for body region r from the device catalogue.

The tie-breaking coefficient is then defined as:

$$\varepsilon = \begin{cases} \tau \cdot \frac{\Delta}{\Delta_{\max}} \cdot \sum_r C_r(d_r), & \text{if } \Delta_{\max} > 0 \\ 0, & \text{if } \Delta_{\max} = 0 \end{cases} \quad (19)$$

The Solver objective is then to minimize the true total device cost minus ϵ (Eq. 13). The second case arises only when High support is required in every region, where no LOS surplus is attainable.

Because the maximum possible value of ϵ (attained when $\Delta = \Delta_{max}$) is exactly $\tau \cdot \sum_r C_r(d_r)$, the tie-breaking mechanism can only alter the ranking of solutions whose costs fall within this 1% cost-equivalence range. For candidate sets with a cost difference greater than 1%, strict cost minimization remains the primary driver. This approach ensures that the model recommends the configuration that delivers the highest overall level of support for essentially the same procurement cost. This choice improves the recommendation's cost-effectiveness; for a fixed procurement expenditure, the selected bundle maximizes the support benefit delivered to the worker, thereby yielding the greatest support return per dollar spent. The selected cost-equivalence threshold value of $\tau = 1\%$ was established based on two independent standards. First, the Government of Canada's Directive on Accounting Standards (GC 1010) defines quantitative materiality as 0.5% to 2% of total expenses for the purposes of financial decision-making (Treasury Board of Canada Secretariat, 2023); a 1% threshold falls within this range. Second, AACE International Recommended Practice 18R-97 specifies an expected accuracy range of -3% to +15% even for the most rigorous (Class 1) cost estimates (AACE International, 2020). Since any single estimate is itself subject to at least this degree of uncertainty, a 1% difference between two candidate costs is finer than the estimation method can reliably distinguish, and the two costs can reasonably be regarded as equivalent (AACE International, 2020). Two candidate solutions whose total costs differ by less than 1% are therefore treated as not materially different on cost grounds, making the LOS surplus-based tie-breaker the appropriate basis for selection. The preference for higher support among cost-equivalent options is supported by the questionnaire analysis presented in Section 5.4.6, which found that higher-LOS wearables carry no meaningful perceived Comfort or Range of Motion (ROM) cost; accordingly, recommending a higher-support configuration is unlikely to compromise worker comfort or mobility.

6.3.5 Outputs

Executing the Solver (available via ‘Run Optimization’ macro button shown in Figure 6.29-e) returns the optimized set of wearable devices (d_{back} , $d_{shoulder}$, d_{leg}), their associated LOS provided and costs, the total procurement cost of the prescribed set, and a feasibility indicator (Figure 6.29-e). A solution is reported as feasible only when all body region LOS requirements (Eq. 14) and the budget constraint (Eq. 15) are simultaneously satisfied. Figure 6.32 displays the output scenario of a feasible solution being identified within the available budget:

(a) Wearable Device Catalogue by Body Region					Worker Requirements and Constraints (yellow-shaded cells require user input)					Recommended Wearable Device Set (orange-shaded cells are varied by the Solver)				

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1		(a) Wearable Device Catalogue by Body Region				Worker Requirements and Constraints (yellow-shaded cells require user input)					Recommended Wearable Device Set (orange-shaded cells are varied by the Solver)								
2						(b)					(e)								
3											Run Optimization								
4											Optimized Wearable Selection								
5																			
6		Back				Worker Physical Support Requirements					Back								
7		Device Code	LOS Provided	Device Cost		Predicted LOS Required (ANN-Derived)					2	1	2		LOS of selected wearable (lookup from catalogue)				
8		1	1	\$31.08		Opt out?					☐	☐	☐		Selected device code (variable cells)				
9		2	1	\$50.00		Effective LOS Required (Post-Exclusion)					2	1	2		Cost of selected wearable (lookup from catalogue)				
10		3	1	\$146.46		Min Device Code					1	10	6						
11		4	2	\$465.00		Max Device Code					5	12	9						
12		5	3	\$2,500.00															
13																			
14		Leg																	
15		Device Code	LOS Provided	Device Cost															
16		6	1	\$31.69															
17		7	1	\$100.45															
18		8	2	\$215.58															
19		9	3	\$145.00															
20																			
21		Shoulder																	
22		Device Code	LOS Provided	Device Cost															
23		10	1	\$28.80															
24		11	1	\$47.79															
25		12	3	\$1,998.97															
26																			
27																			
28																			

Figure 6.33: Optimization model output scenario #2 (infeasible solution)

6.4 DSS Visualization

The workflow shown in Figure 6.34 illustrates the developed decision support system for personalized wearable support selection for mechanical-trades workers. The system integrates two parallel classification pathways: a wearable classification pathway, which uses changes in Fatigue Threshold, Heart Rate Change, and Ergonomic Risk Score to determine the LOS provided by each wearable across body regions, and a worker classification pathway, which uses the worker profile to predict their LOS required across body regions. The outputs from both pathways are then input into a multi-criteria optimization model that generates a single worker-specific set of wearable support devices covering all at-risk body regions simultaneously.

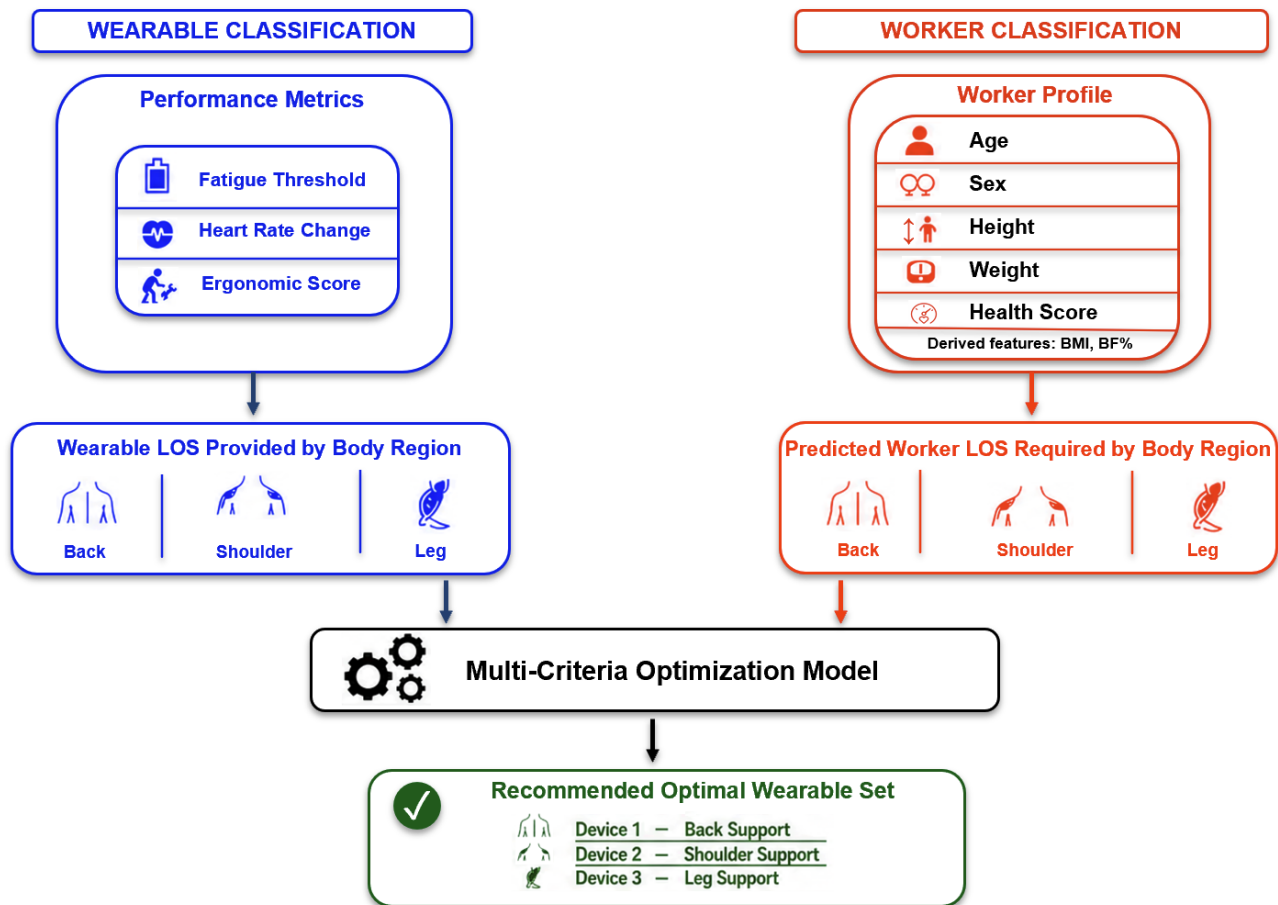


Figure 6.34: Decision support system for optimal wearable device selection

6.5 DSS Mechanical Trades Field Validation

The developed DSS was applied in an authentic mechanical-trades work setting to assess its practical applicability through real-world practitioner cases. To provide an independent test, three practitioners from outside the model-development cohort were recruited to serve as the field-validation participants. The field validation encompassed worker characterization, ANN-based estimation of required support levels, optimization-based wearable device recommendation, supervised task performance with the recommended wearable support devices, and structured collection of worker feedback. These steps applied the complete DSS workflow, demonstrating its end-to-end implementation and providing preliminary evidence of its practical field feasibility in a live mechanical-trades setting.

6.5.1 Worker Characterization

The workers' demographic and anthropometric characteristics were recorded, including age, sex, height, and weight, as well as body region-specific health scores for the back, leg, and shoulder regions. BMI and body fat percentage were subsequently calculated from the recorded measurements. The workers' recorded characteristics were then used as inputs to the developed ANNs for each body region, from which the required level of support for the back, leg, and shoulder regions was independently estimated. A sample ANN prediction of LOS required by body region is shown for the first validation practitioner (VP01) in Figure 6.35, Figure 6.36, and Figure 6.37.

```
=== Re-evaluation on test set ===  
User supplied test set  
Relation:      Back  
Instances:     unknown (yet). Reading incrementally  
Attributes:    6  
  
=== Predictions on user test set ===  


| inst# | actual | predicted | error | prediction |
|-------|--------|-----------|-------|------------|
| 1     | 1:?    | 3:\$2.00  |       | 0.979      |


```

Figure 6.35: ANN prediction of LOS required for VP01 (back)

```
=== Re-evaluation on test set ===  
User supplied test set  
Relation:      Leg  
Instances:     unknown (yet). Reading incrementally  
Attributes:    6  
  
=== Predictions on user test set ===  


| inst# | actual | predicted | error | prediction |
|-------|--------|-----------|-------|------------|
| 1     | 1:?    | 3:\$1.00  |       | 0.971      |


```

Figure 6.36: ANN prediction of LOS required for VP01 (leg)

```
=== Re-evaluation on test set ===  
User supplied test set  
Relation:      Shoulder  
Instances:     unknown (yet). Reading incrementally  
Attributes:    6  
  
=== Predictions on user test set ===  


| inst# | actual | predicted | error | prediction |
|-------|--------|-----------|-------|------------|
| 1     | 1:?    | 3:\$2.00  |       | 1          |


```

Figure 6.37: ANN prediction of LOS required for VP01 (shoulder)

In each figure, the 'actual' column is reported as '?' because no ground-truth LOS label exists for the validation practitioners; WEKA therefore outputs only the predicted class and its associated probability. Class labels appear with a dollar-sign prefix (e.g., '\$2.00') and denote LOS scores. The ANNs predicted scores of 2, 1, and 2 for the back, leg, and shoulder body regions, with prediction confidence of 97.9%, 97.1%, and 100%, respectively. The worker characteristics and ANN outputs for the full field validation cohort are summarized in Table 6.9.

Table 6.9: Field validation worker characteristics and predicted required LOS

Validation Practitioner	Body Region	Worker Characteristics							ANN Prediction LOS Required
		Age	Sex	Height (cm)	Weight (kg)	BMI	BFP (%)	Health Score	
VP01	Back	41	Male	179	84.4	26.33	25.51	1	2
	Leg	41	Male	179	84.4	26.33	25.51	3	1
	Shoulder	41	Male	179	84.4	26.33	25.51	2	2
VP02	Back	48	Male	187	105.7	30.22	31.47	2	3
	Leg	48	Male	187	105.7	30.22	31.47	3	1
	Shoulder	48	Male	187	105.7	30.22	31.47	1	3
VP03	Back	26	Male	173	74.4	24.86	21.32	3	1
	Leg	26	Male	173	74.4	24.86	21.32	3	1
	Shoulder	26	Male	173	74.4	24.86	21.32	2	2

Note. Age, sex, height, weight, BMI, and BF% are worker-level characteristics that are consistent across body regions.

6.5.2 DSS Output and Device Recommendation

The resulting required levels of support by body region, alongside the total available company budget, were passed as inputs to the optimization model. The model subsequently recommended a set of wearable devices (one per body region) best suited to the worker's estimated support requirements and budget constraints. The budget available to the field validation practitioners for the purpose of the validation was \$2,500 per worker. A sample optimization model output for VP01 is presented in Figure 6.38.

<

Figure 6.38: Optimization model recommended wearable devices

The workers' ANN-estimated required support levels and corresponding recommended wearable devices are summarized in Table 6.10. For each body region, the DSS identifies devices whose provided LOS meets or exceeds the ANN-estimated required LOS while adhering to the specified budget constraint. For VP02, the optimization model did not converge on a feasible solution, as the established budget of \$2,500 was insufficient to obtain the required set of devices to meet their support requirements. Accordingly, as per the model's standard functionality, it reported the "Minimum-Cost Support Solution" as discussed in Section 6.3.5, with a total cost of \$4,531. This demonstrates the model's proactive feature to inform the worker of the minimum budget they need to obtain the required set of devices. For the purpose of the field validation, the set of wearables was still provided to the worker for their subsequent feedback.

Table 6.10: DSS-recommended wearable devices by body region

Validation Practitioner	Body Region	Budget Available	LOS Required	DSS-Recommended Wearable Devices		
				Device Code	LOS Provided	Cost
VP01	Back	2500	2	4	2	465
	Leg		1	6	1	32
	Shoulder		2	12	3	1999
						2496
VP02	Back	2500	3	5	3	2500
	Leg		1	6	1	32
	Shoulder		3	12	3	1999
						4531
VP03	Back	2500	1	1	1	31
	Leg		1	6	1	32
	Shoulder		2	12	3	1999
						2062

Note. Budgets and device costs are in \$ CAD.

6.5.3 Mechanical Field Validation Results

To examine the practical application of the DSS recommendations, the workers donned the recommended wearable devices and performed a series of mechanical-trades tasks. These tasks included lifting and positioning of equipment, sustained kneeling and squatting postures during floor-level installations, and overhead fastening. Following task completion, the workers provided

feedback through the eight questionnaire items (Q1-Q8, Table 5.6) and rating system established in Section 5.2.4, capturing their experience with each device across the evaluated body regions. As practitioners with several years of experience performing these tasks without wearables, the workers were well-positioned to assess the recommended devices against a working baseline, and the feedback reflects that direct comparison. The questionnaire results are shown in Table 6.11.

Table 6.11: Worker questionnaire responses for DSS-recommended wearable devices

Validation Practitioner	Body Region	Device Code	Comfort	Fatigue Reduction	Range of Motion Preservation	Task Performance	Ease of Use	Device Compatibility	Likelihood to Recommend	Likelihood to Use Again
VP01	Back	4	4	3	4	5	4	3	4	4
	Leg	6	5	2	4	5	5	4	4	4
	Shoulder	12	4	5	3	5	3	3	4	5
VP02	Back	5	3	5	4	5	3	3	4	4
	Leg	6	5	3	4	3	5	5	3	2
	Shoulder	12	4	5	4	5	3	4	4	4
VP03	Back	1	5	2	4	3	5	4	3	4
	Leg	6	4	2	4	2	5	4	3	3
	Shoulder	12	3	5	3	4	3	3	4	3

The nine worker-device cases in Table 6.11 received a mean rating of 3.8 on the five-point scale across the eight questionnaire items, and 46 of the 72 ratings were 4 or 5. Item means ranged from 3.6 for fatigue reduction to 4.1 for comfort and task performance. Fatigue-reduction ratings increased with the LOS of the device, averaging 2.3 for the two Low-support devices (codes 1 and 6), 3.0 for the Medium-support back device (code 4), and 5.0 for the two High-support devices (codes 5 and 12), consistent with the relationship between LOS and perceived fatigue reduction identified in Section 5.4.6. With respect to support, the recommended devices met the required LOS exactly in seven of the nine cases and exceeded it by one level in two cases (the shoulders of VP01 and VP03), because the catalogue contains no Medium-support shoulder device and the High-support device (code 12) was therefore selected. With respect to budget, the recommended sets cost \$2,496 for VP01 and \$2,062 for VP03, within the \$2,500 available. VP02's requirement of High

support for the back and shoulders could not be met within the available budget, and the model reported the minimum budget of \$4,531 (Table 6.10). Section 6.6 verifies these three results against an exact solver (Table 6.12).

The questionnaire responses in Table 6.11 indicate that the DSS-recommended wearables were generally well accepted by the workers across all evaluated body regions. The workers reported moderate-to-high perceived comfort and preserved range of motion, while perceived fatigue reduction increased with the level of support provided, from low ratings for the Low-support devices to the maximum rating for the High-support devices. Ratings for perceived task performance, ease of use, device compatibility, and willingness to recommend or use the devices again were also generally positive. Collectively, these case-specific findings demonstrate the practical end-to-end implementation of the developed DSS in an authentic mechanical-trades setting and provide preliminary evidence of its field feasibility.

6.6 Verification of the Optimization Model Against an Exact Solver

To verify that the device sets returned by the Evolutionary engine are optimal, which a heuristic search cannot establish on its own, the selection problem of Section 6.3.2 was solved exactly for every requirement profile a worker can present: Low, Medium, or High support in each of the three body regions (27 total requirement combinations), at the \$2,500 budget used in the field validation (Section 6.5.2), and with all three body regions included (no opt-outs). The exact solutions were obtained with a mixed-integer linear programming (MILP) solver, which proves either that a solution is optimal or that no feasible solution exists, and were also checked by exhaustive enumeration of the device catalogue. The field validation recommendations of the Evolutionary engine reported in Section 6.5.2 were then compared with these exact solutions.

A MILP solver requires the objective and constraints to be linear in the decision variables, whereas the model of Section 6.3.2 obtains the LOS provided and the cost of a device by lookup on its device code. The lookup functions were therefore replaced by binary selection variables, one

per catalogue device. Let $x_{r,j}$ equal 1 when device $j \in D_r$ is selected for body region $r \in \{\text{Back, Shoulder, Leg}\}$ and 0 otherwise, and let $s_{r,j}$ and $c_{r,j}$ denote the LOS provided and the unit cost of device j , that is, the catalogue values $S_r(d_r)$ and $C_r(d_r)$ of Section 6.3.2 for $d_r = j$. In these variables, the equations of Sections 6.3.2 and 6.3.4 are restated as follows:

Decision variables:

$$\sum_{j \in D_r} x_{r,j} = 1, \quad x_{r,j} \in \{0,1\} \quad \forall j \in D_r, \quad \forall r \in \{\text{Back, Shoulder, Leg}\} \quad (20)$$

Objective:

$$\min (\sum_r \sum_{j \in D_r} c_{r,j} x_{r,j} - \varepsilon) \quad (21)$$

Constraints:

$$\sum_{j \in D_r} s_{r,j} x_{r,j} \geq L_r, \quad \forall r \in \{\text{Back, Shoulder, Leg}\} \quad (22)$$

$$\sum_r \sum_{j \in D_r} c_{r,j} x_{r,j} \leq B \quad (23)$$

Tie-breaking coefficient:

$$\varepsilon = \begin{cases} \tau \cdot \frac{\sum_r \sum_{j \in D_r} (s_{r,j} - L_r) x_{r,j}}{\Delta_{\max}} \cdot (\sum_r \sum_{j \in D_r} c_{r,j} x_{r,j}), & \text{if } \Delta_{\max} > 0 \\ 0, & \text{if } \Delta_{\max} = 0 \end{cases} \quad (24)$$

where D_r , L_r , B , τ , and $\Delta_{\max}$ retain their definitions from Sections 6.3.2 and 6.3.4. Eq. 20 restates the decision variables and catalogue membership of Eqs. 12 and 16 and selects exactly one device per region. Eqs. 21 to 23 restate the objective (Eq. 13) and the LOS-sufficiency and budget constraints (Eqs. 14 and 15) in these variables, and Eq. 24 restates the tie-breaking coefficient of Eq. 19, with the aggregate LOS surplus (Eq. 17) and the total cost written in the selection variables. For the combination in which High support is required in every region, $\Delta_{\max}$ is zero and ε is zero by the second case of Eq. 24.

The verification was implemented as a Python script, listed in Appendix E. The script reads the device catalogue, the budget, and the cost-equivalence threshold from the DSS workbook, builds Eqs. 20 to 24 for each requirement combination, and solves them, through the Python interface highspy, with HiGHS 1.15.1 (Huangfu & Hall, 2018), an open-source MILP solver that proves optimality using a branch-and-cut algorithm. For requirement combinations proven infeasible, it solves the model again without the budget constraint and without the tie-breaking term to obtain the minimum required budget. Each of the 27 instances was solved to proven optimality or proven infeasibility. The results of the 27 solves are shown in Figure 6.39.

Workbook: Optimization Model.xlsm (sheet New)
EXACT-SOLVER VERIFICATION OF THE DEVICE-SELECTION MODEL (binary form, Eqs. 20-24)
Solver: HiGHS 1.15.1 (highspy); branch and cut; proven optimality or proven infeasibility
Catalogue: back 1-5, leg 6-9, shoulder 10-12 (60 device sets); budget \$2,500.00; tau = 1%
Variables per instance: 12 binary + 47 continuous (linearized products); instances: 27

#	Required LOS (B, L, S)	HiGHS status	Selected set (B, L, S)	LOS provided (B, L, S)	Total cost (\$)	Minimum budget (\$)	Time (ms)
1	(1, 1, 1)	Optimal	1, 6, 10	1, 1, 1	91.56	-	12.1
2	(1, 1, 2)	Optimal	1, 6, 12	1, 1, 3	2,061.73	-	5.7
3	(1, 1, 3)	Optimal	1, 6, 12	1, 1, 3	2,061.73	-	4.5
4	(1, 2, 1)	Optimal	1, 9, 10	1, 3, 1	204.88	-	6.6
5	(1, 2, 2)	Optimal	1, 9, 12	1, 3, 3	2,175.05	-	5.1
6	(1, 2, 3)	Optimal	1, 9, 12	1, 3, 3	2,175.05	-	4.7
7	(1, 3, 1)	Optimal	1, 9, 10	1, 3, 1	204.88	-	4.6
8	(1, 3, 2)	Optimal	1, 9, 12	1, 3, 3	2,175.05	-	0.3
9	(1, 3, 3)	Optimal	1, 9, 12	1, 3, 3	2,175.05	-	0.4
10	(2, 1, 1)	Optimal	4, 6, 10	2, 1, 1	525.49	-	4.4
11	(2, 1, 2)	Optimal	4, 6, 12	2, 1, 3	2,495.66	-	0.3
12	(2, 1, 3)	Optimal	4, 6, 12	2, 1, 3	2,495.66	-	0.3
13	(2, 2, 1)	Optimal	4, 9, 10	2, 3, 1	638.80	-	4.9
14	(2, 2, 2)	Infeasible	4, 9, 12	2, 3, 3	-	2,608.97	0.4
15	(2, 2, 3)	Infeasible	4, 9, 12	2, 3, 3	-	2,608.97	0.4
16	(2, 3, 1)	Optimal	4, 9, 10	2, 3, 1	638.80	-	0.3
17	(2, 3, 2)	Infeasible	4, 9, 12	2, 3, 3	-	2,608.97	0.3
18	(2, 3, 3)	Infeasible	4, 9, 12	2, 3, 3	-	2,608.97	0.4
19	(3, 1, 1)	Infeasible	5, 6, 10	3, 1, 1	-	2,560.49	0.3
20	(3, 1, 2)	Infeasible	5, 6, 12	3, 1, 3	-	4,530.66	0.3
21	(3, 1, 3)	Infeasible	5, 6, 12	3, 1, 3	-	4,530.66	0.4
22	(3, 2, 1)	Infeasible	5, 9, 10	3, 3, 1	-	2,673.80	0.3
23	(3, 2, 2)	Infeasible	5, 9, 12	3, 3, 3	-	4,643.97	0.3
24	(3, 2, 3)	Infeasible	5, 9, 12	3, 3, 3	-	4,643.97	0.3
25	(3, 3, 1)	Infeasible	5, 9, 10	3, 3, 1	-	2,673.80	0.3
26	(3, 3, 2)	Infeasible	5, 9, 12	3, 3, 3	-	4,643.97	0.3
27	(3, 3, 3)	Infeasible	5, 9, 12	3, 3, 3	-	4,643.97	0.2

Result: 14 instances optimal within budget, 13 proven infeasible (minimum budget from a second solve without the budget constraint).
Cross-check: exhaustive enumeration of all 60 device sets with the workbook formulas agreed in 27/27 instances.

Figure 6.39: Output of the exact-solver verification script (HiGHS 1.15.1 through highspy)

As an independent check, the same 27 requirement combinations were also solved by exhaustive enumeration across the 60 possible device sets offered by the catalogue (5 back × 4 leg × 3 shoulder devices; listed in Appendix D). For each set, the script computed the total cost, the LOS provided in each region, and the objective value with the workbook's formulas (Eqs. 13 to 15 and the tie-breaking term of Eq. 19), and the feasible set with the lowest objective value was

selected. The enumeration returned the same set, or the same minimum budget, as HiGHS in every requirement combination, which confirms the HiGHS solver's results. Table 6.12 provides the exact solution for each of the 27 requirement combinations: the lowest-cost device set that meets the required LOS in all three regions, its total cost, and whether that cost is within the \$2,500 budget.

Table 6.12: Lowest-cost qualifying device set for each of the 27 combinations of required LOS

Required Back LOS	Required Leg LOS	Required Shoulder LOS	Lowest-Cost Qualifying Set, Device Codes (B, L, S)	LOS Provided (B, L, S)	Total Cost (\$)	Within Budget
Low	Low	Low	1, 6, 10	1, 1, 1	91.56	Yes
Low	Low	Medium	1, 6, 12 ^a	1, 1, 3	2,061.73	Yes
Low	Low	High	1, 6, 12	1, 1, 3	2,061.73	Yes
Low	Medium	Low	1, 9, 10	1, 3, 1	204.88	Yes
Low	Medium	Medium	1, 9, 12	1, 3, 3	2,175.05	Yes
Low	Medium	High	1, 9, 12	1, 3, 3	2,175.05	Yes
Low	High	Low	1, 9, 10	1, 3, 1	204.88	Yes
Low	High	Medium	1, 9, 12	1, 3, 3	2,175.05	Yes
Low	High	High	1, 9, 12	1, 3, 3	2,175.05	Yes
Medium	Low	Low	4, 6, 10	2, 1, 1	525.49	Yes
Medium	Low	Medium	4, 6, 12 ^b	2, 1, 3	2,495.66	Yes
Medium	Low	High	4, 6, 12	2, 1, 3	2,495.66	Yes
Medium	Medium	Low	4, 9, 10	2, 3, 1	638.80	Yes
Medium	Medium	Medium	4, 9, 12	2, 3, 3	2,608.97	No
Medium	Medium	High	4, 9, 12	2, 3, 3	2,608.97	No
Medium	High	Low	4, 9, 10	2, 3, 1	638.80	Yes
Medium	High	Medium	4, 9, 12	2, 3, 3	2,608.97	No
Medium	High	High	4, 9, 12	2, 3, 3	2,608.97	No
High	Low	Low	5, 6, 10	3, 1, 1	2,560.49	No
High	Low	Medium	5, 6, 12	3, 1, 3	4,530.66	No
High	Low	High	5, 6, 12 ^c	3, 1, 3	4,530.66	No
High	Medium	Low	5, 9, 10	3, 3, 1	2,673.80	No
High	Medium	Medium	5, 9, 12	3, 3, 3	4,643.97	No
High	Medium	High	5, 9, 12	3, 3, 3	4,643.97	No
High	High	Low	5, 9, 10	3, 3, 1	2,673.80	No
High	High	Medium	5, 9, 12	3, 3, 3	4,643.97	No
High	High	High	5, 9, 12	3, 3, 3	4,643.97	No

Note. B, L, S = back, leg, shoulder; LOS 1, 2, 3 = Low, Medium, High; device codes as in the catalogue of Figure 6.29-a; costs in \$ CAD, computed from the unrounded catalogue unit costs. A qualifying set meets the required LOS in every region. ^a Set recommended for validation practitioner VP03; ^b VP01; ^c minimum budget for VP02.

Every run of the Excel-based Evolutionary engine reported in this research matches these exact solutions. For the three validation practitioners of Section 6.5.2 (Table 6.10), the device sets recommended for VP01 and VP03 are the proven optimal sets for their requirement combinations, and the \$4,531 reported for VP02 is the proven minimum required budget for that requirement combination. In all three field validation cases, the Evolutionary engine returned the proven optimum or the exact minimum required budget.

Eqs. 20 to 24 were used only to obtain the exact solutions; the DSS itself runs on the Excel implementation. The device set listed for each requirement combination in Table 6.12 is its lowest-cost qualifying set and does not depend on the budget; the budget determines only whether that set is affordable, so Table 6.12 also applies to budgets other than \$2,500 and can be used to check any run of the model without opt-outs.

6.7 Summary of Validation

Table 6.13 summarizes the validation performed at each level of the framework, as reported in Chapters 5 and 6. The device classification of Chapter 5 was validated by evaluating the same devices, with the same performance metrics, on real mechanical-trade tasks in the field and comparing the field classification with the laboratory classification (Section 5.4.4). The predictive models were validated internally on held-out test records (Section 6.2.4). The complete DSS was validated in the field with practitioners from outside the model-development cohort (Section 6.5), and its optimization phase was additionally verified against exact solutions (Section 6.6).

Table 6.13: Validation performed at each level of the framework

Level	What Was Validated	Method	Result
Device classification (Component 2; Section 5.4.4)	LOS classification of the 12 catalogued devices derived from laboratory data	Field evaluation of the same devices on real mechanical-trade tasks with the 13 practitioners; classification agreement, MAPD, Spearman, Pearson, and Wilcoxon signed-rank tests	Identical classification for all 12 devices; MAPD of 4.83%; Spearman correlation of 0.979 and Pearson correlation of 0.993; no systematic laboratory-field difference (Wilcoxon $W = 16$)
Predictive models (Component 3; Sections 6.2.3-6.2.4)	ANN prediction of the required LOS for the back, legs, and shoulders	Internal validation: 66/34 training-test split (60 test records per region) with 10-fold cross-validation for hyperparameter tuning	Test-set accuracy of 83.3%, 80.0%, and 86.7%; cross-validated accuracy of 77.8%, 78.4%, and 79.0%
Decision support system (Component 3; Sections 6.5 and 6.6)	Optimality of the device selection and the complete workflow from worker characteristics to device use	Exact MILP solutions and enumeration for all 27 requirement combinations; field application with practitioners from outside the development cohort and an eight-item questionnaire	The recommendations for the three practitioners are the proven optimal sets (VP01 and VP03) or the exact minimum budget (\$4,531 for VP02, above the \$2,500 budget); mean worker rating of 3.8 out of 5 across the eight items

Note. ANN = artificial neural network; LOS = level of support; MAPD = mean absolute percent difference; MILP = mixed-integer linear programming; VP = validation practitioner.

Chapter 7: Framework Generalization to Additional Construction Trades

7.1 Introduction

This chapter examines the applicability of the proposed framework to construction trades beyond the mechanical trades for which it was developed. Section 4.3 identified the back, legs, and shoulders as the body regions most frequently affected by WMSDs among mechanical-trades workers, and derived the working postures that load those regions. Together, these findings determined which wearable support devices were procured, how the experimental tasks of Chapter 5 were designed, and which body regions the decision support system addresses.

The framework is therefore tied to a trade in two specific ways: (1) its device catalogue addresses the back, legs, and shoulders because these were the body regions most frequently injured among mechanical-trades workers, and (2) its device classifications were measured while participants performed the postures through which mechanical-trades workers load those regions. A trade therefore falls within the framework's conditions of application where its workers are injured in the same body regions and work in the same postures. Where these conditions are met, the framework's components may be applied without repetition of the underlying experimental work. This chapter assesses whether four further construction trades (electrical work, carpentry, masonry, and drywalling) meet those conditions, using compensation claim records for the body regions (Section 7.2) and published physical demands analyses for the working postures (Section 7.3), and then sets out what applying the framework to a new trade requires of each of its components (Section 7.4).

7.2 WMSD-Affected Body Regions Across Construction Trades

This section examines the WMSD-affected body regions of four construction trades outside the mechanical group and establishes the extent to which they correspond to the regions the framework targets, thereby addressing the first of the two conditions of application set out in Section 7.1.

7.2.1 Injury Data Collection

The body region analysis of Section 4.3.1 was repeated for four additional construction trades. To ensure the comparison represented a range of work types rather than a set of closely related trades, the construction skilled trades were first grouped into five categories of work, namely mechanical services, electrical services, structural and framing, envelope and heavy material, and interior finishing. One trade was then drawn from each category. Table 7.1 identifies the resulting trades together with the WorkSafeBC construction industry classification units from which their injury records were obtained.

Table 7.1: Trades analyzed and their industry classification units (WorkSafeBC, 2026)

Trade Analyzed	WorkSafeBC Industry Classification Unit
Mechanical trades (<i>reference group, Chapters 4–6</i>)	<ul style="list-style-type: none">• Commercial Refrigeration or Commercial Air Conditioning Work• Plumbing, Heating, Vent, or Residential Air Conditioning• Commercial Tank or Boiler Installation or Removal• Mechanical Insulation• Welding Services or Ornamental Metal Installation• Pool, Spa, or Hot Tub Installation
Electrical work	<ul style="list-style-type: none">• Electrical Work
Carpentry	<ul style="list-style-type: none">• Finishing Carpentry• Framing or Residential Forming
Masonry	<ul style="list-style-type: none">• Masonry
Drywalling	<ul style="list-style-type: none">• Drywalling or Acoustic Board Installation

WMSD-related injury records for each trade were obtained from WorkSafeBC for the period 2021 to 2025 (WorkSafeBC, 2026). Consistent with the scope of Section 4.3.1, records were filtered to the accident types constituting musculoskeletal exposure, namely overexertion, other bodily motion, and repetitive motion, and were then categorized by affected body region. The back and shoulder correspond directly to single WorkSafeBC body-part categories and required no aggregation. The leg region was aggregated, in accordance with Section 4.3.1, from the knee, the ankle, toes and feet, and other parts of the lower extremity.

Section 4.3.1 drew on three sources across two provinces because its purpose was to identify mechanical-trades worker injury trends as reliably as possible, and agreement between independent sources strengthens such a finding. In comparison, this analysis compares multiple trades against each other, and a difference between two trades is more meaningful if both figures were produced from the same source. Sourcing injury data from WorkSafeBC alone ensures that all five trade groups are derived from the same jurisdiction and reporting period, under a common accident-type filter and body-region classification. Any difference observed between trades is therefore attributable to the trades themselves, rather than to variation in how reporting bodies define occupational categories or classify injuries. For this reason, the mechanical-trades figures reported in this chapter were extracted specifically for the present comparison, and differ marginally from those reported in Section 4.3.1.

It should be noted that this analysis concerns which body regions are affected by WMSDs, and not how frequently WMSDs occur within each trade. The disproportionate WMSD burden borne by the mechanical trades, established in Chapter 1, is a separate measure and is not revisited in this chapter. The proposed framework is intended for application wherever WMSDs are an identified concern, and the analysis that follows establishes which body regions require support once that concern is present.

7.2.2 Distribution of WMSD Claims by Body Region

Table 7.2 presents the distribution of WMSD claims across the four most frequently affected body regions for each trade group, with Figure 7.1 and Figure 7.2 illustrating the same data.

Table 7.2: WMSD claims by affected body region, 2021-2025 (WorkSafeBC, 2026)

Trade group	Claims (n)	Back	Legs	Shoulder	Wrist, fingers, hand	Back, legs and shoulders combined
Mechanical trades (reference group)	2,083	46.6%	12.5%	12.8%	9.1%	71.9%
Electrical work	889	41.1%	12.6%	13.5%	14.2%	67.2%
Carpentry	505	44.4%	8.9%	15.0%	11.9%	68.3%
Masonry	201	40.8%	9.5%	19.4%	10.4%	69.7%
Drywalling	354	36.4%	9.9%	18.1%	10.5%	64.4%
	1,949	41.0%	10.8%	15.3%	12.5%	67.2%

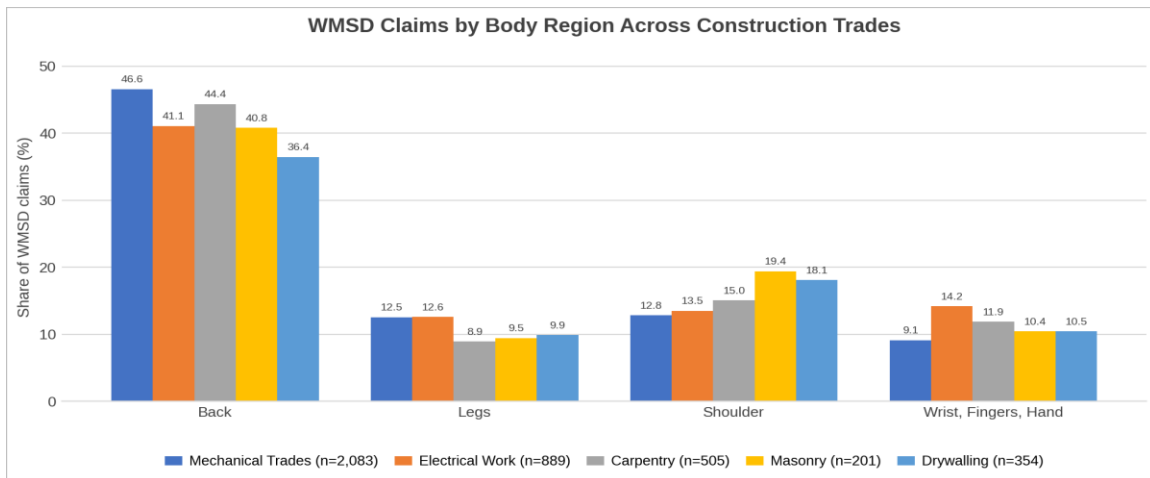


Figure 7.1: WMSDs by body region across construction trades, 2021-2025 (WorkSafeBC, 2026)

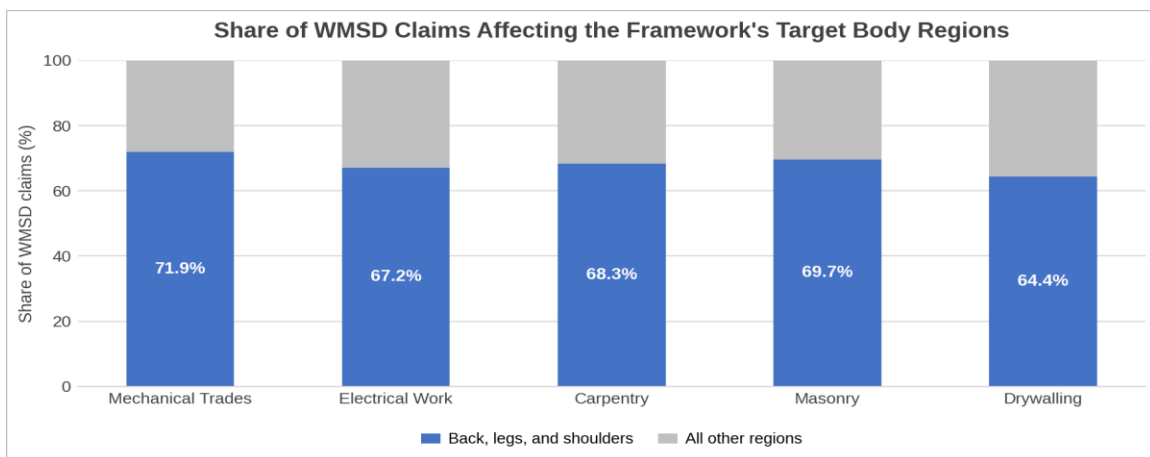


Figure 7.2: Share of WMSDs affecting target body regions, by trade (WorkSafeBC, 2026)

7.2.3 Identification of Shared At-Risk Regions

1 – Predominance of the back region: The back is the most frequently affected body region in every trade analyzed. Back claims account for 46.6% of WMSD claims in the mechanical trades, and range from 36.4% in drywalling to 44.4% in carpentry among the remaining trades, with the four trades analyzed combined at 41.0%. In each case, the back exceeds the next most affected region by a factor of more than two. This corresponds directly to the finding of Section 4.3.2, in which the back was identified as the leading affected region among mechanical-trades workers.

2 – Coverage of the target body regions: The back, legs, and shoulders together account for approximately two-thirds of WMSD claims in every trade analyzed. Their combined share is 71.9% in the mechanical trades and ranges from 64.4% in drywalling to 69.7% in masonry among the remaining trades, a spread of 7.5 percentage points across five trade groups performing substantially different work. It is expected that the mechanical trades return the highest value, given that the target regions were selected from mechanical-trades injury data, but the difference is one of magnitude rather than kind: even drywalling, the trade returning the lowest value, remains within eight percentage points of the mechanical trades. The 71.9% obtained here also corresponds closely to the approximately 72% reported in Section 4.3.2, which was drawn from a different reporting period and a broader set of sources. That two independent extractions agree to within a fraction of a percentage point supports the stability of the Chapter 4 finding.

3 – Variation in ranking between trades: While the three target regions predominate throughout, their relative ranking varies between trades. Leg claims account for 12.5% of WMSD claims in the mechanical trades and 12.6% in electrical work, but between 8.9% and 9.9% in carpentry, masonry, and drywalling. The inclusion of leg support within the framework is therefore well founded for the mechanical trades, while carrying proportionally less weight in the remaining three. Section 7.3 examines the working postures of these trades and identifies the source of this variation.

4 – A Region Beyond Current Coverage: A fourth region appears consistently across the profiles; the wrist, fingers, and hand account for 9.1% of WMSD claims in the mechanical trades and between 10.4% and 14.2% in the trades analyzed. Component 1 of the framework identifies this region wherever it ranks among a trade's most affected, and the framework would therefore correctly flag this requirement. Meeting the requirement is a matter of catalogue coverage: devices addressing the wrist and hand would be procured and evaluated under the existing Section 5.2 protocol and added to the catalogue, after which framework components 2 and 3 would recommend them exactly as they recommend the devices already classified. Doing so would raise coverage in every trade analyzed, the mechanical trades included, and this represents the clearest opportunity for extension of the framework.

Analyzed together, these findings establish that the body regions identified in Section 4.3.2 from mechanical-trades injury data are the predominant WMSD-affected regions across every construction trade examined. The framework was developed and validated for the mechanical trades, where its coverage is highest at 71.9% of WMSD claims, and the analysis above demonstrates that the regions it targets are not particular to that trade group. They account for approximately two-thirds of the WMSD burden in electrical work, carpentry, masonry, and drywalling as well. The back and shoulders are heavily affected in all five trade groups. The legs are affected to differing degrees, ranging from 8.9% to 12.6% across the five groups. Section 7.3 investigates working postures across the various trades and establishes that this leg region variation corresponds to the frequency with which each trade works at floor level.

7.3 Working Postures Across Construction Trades

This section examines the working postures adopted by the same four trades and establishes the extent to which they correspond to the postures under which the wearable devices were evaluated in Chapter 5, thereby addressing the second condition of application set out in Section 7.1.

7.3.1 Posture Data Collection

Section 4.3.3 derived the working postures adopted by mechanical-trade workers through three methods: an image-based review, field observations with practitioner input, and published Physical Demands Analyses (PDAs). The resulting posture set, comprising floor-to-waist and knee-to-waist lifting, overhead reaching, and kneeling, crouching, or squatting, determined the experimental tasks under which the wearable support devices were evaluated in Chapter 5. The classifications produced by that evaluation are consequently valid for trades working in these postures.

This section examines whether the four trades analyzed adopt the same postures. As the posture set is already derived, the analysis is one of confirmation rather than derivation, and the published PDAs alone are therefore sufficient. PDAs for the relevant occupations were obtained from the Alberta Construction Association (ACA) and reviewed against the mechanical-trade figures reported in Section 4.3.3, the two sets being directly comparable as both report posture frequency as a percentage of the workday on the same five-band scale. The PDA documents reviewed were those for the Electrician (Alberta Construction Association, 2021b), the Framing Carpenter (2021c) and Journeyman Finishing Carpenter (2021e), corresponding to the two classification units analyzed in Section 7.2, the Journeyman Bricklayer (2021d), and the Drywaller (2021a).

7.3.2 Posture Frequencies by Trade

Table 7.3 presents the posture frequencies recorded for each trade analyzed, alongside those reported for the mechanical trades in Section 4.3.3. Frequencies are expressed as the percentage of the workday over which each posture is performed, and the lifting entries additionally record the load range associated with each frequency band.

Table 7.3: Working posture frequencies by trade, as percentage of workday (Alberta Construction Association, 2020a, 2020b, 2021a-f)

Trade	Occupation (PDA)	Floor- and knee-to-waist lifting	Overhead reaching	Kneeling	Crouching	Squatting
Mechanical trades <i>reference group</i> <i>(posture data from Section 4.3.3)</i>	HVAC installer	6–33% (40+ lbs); 34–66% (11–22 lbs)	34–66%	6–33%	6–33%	Not reported
	Commercial plumber	6–33% (44+ lbs); 34–66% (22–44 lbs); 67–100% (11–22 lbs)	34–66%	34–66%	34–66%	34–66%
	Sheet metal worker	6–33% (12–40 lbs)	6–33%	67–100%	Not reported	6–33%
Electrical work	Electrician	34–66% (up to 50 lbs); 6–33% (50+ lbs)	34–100%	34–66%	34–66%	34–66%
Carpentry	Framing carpenter	6–33% (up to 110 lbs); 34–66% (11–22 lbs)	6–33%	6–33%	1–5%	Not required
	Journeyman finishing carpenter	6–33% (44+ lbs); 34–66% (11–22 lbs)	6–33%	6–33%	6–33%	6–33%
Masonry	Journeyman bricklayer	6–33% (44+ lbs); 34–66% (limited to heavy)	1–5%	6–33%	6–33%	Not required
Drywalling	Drywaller	6–33% (up to 90 lbs)	34–66%	6–33%	6–33%	34–66%

Note. Where a PDA states that a posture is not performed, the entry reads "not required"; where a posture is not addressed by the source, it reads "not reported".

7.3.3 Correspondence with the Evaluated Posture Set

The Chapter 5 wearable device classifications were established under the most common mechanical-trade task postures and therefore remain valid for any trade that works in those same postures. This comparison examines whether the four additional analyzed trades do so. Each trade performs floor-to-waist and knee-to-waist lifting, overhead reaching, and at least two of the three floor-level postures, at frequencies falling within the ranges recorded for the mechanical trades. No trade is dominated by a posture outside the evaluated set, and the wearable classifications therefore apply to these trades.

Heavy lifting falls within the same 6 to 33% frequency band in every trade analyzed. Maximum loads are not directly comparable, as the mechanical-trade PDAs report open-ended

bands (40+ lbs, 44+ lbs) rather than upper limits. Additionally, framing carpenters and bricklayers record squatting as not required, and framing carpenters crouch only rarely, but both perform kneeling and floor-to-waist lifting and neither therefore falls outside the evaluated posture set.

The posture frequencies additionally corroborate the injury profiles established in Section 7.2.2. Electrical work is the only trade analyzed to record kneeling, crouching, and squatting each at 34 to 66% of the workday, matching commercial plumbers, and it is likewise the only trade analyzed whose leg claim share matches that of the mechanical trades, at 12.6% against 12.5%. The three trades adopting these postures less frequently return leg shares of 8.9 to 9.9%. Compensation claim records and published physical demands analyses are independent of one another, and both identify the same relationship between floor-level exposure and leg injury. Section 7.2.3 established that the additional trades share the framework's target body regions; the present section establishes that they also work in the postures under which the devices were evaluated. Both conditions of application set out in Section 7.1 are therefore met.

7.4 Applying the Framework to Additional Trades

Sections 7.2 and 7.3 establish that the trades analyzed share both the at-risk body regions and the working postures upon which the framework depends. On this basis, this section sets out what the application of the framework to such a trade requires of each of its three components, as summarized in Table 7.4.

Table 7.4: Requirements for applying each framework component to a new trade

Framework component		Requires repetition	What is required	Experimental work needed
1	Industry data collection	Yes	<ul style="list-style-type: none"> • Trade injury records • Review of trade activities and postures 	None
2	Wearable evaluation and LOS classification	No, provided the trade's at-risk regions and postures correspond	<ul style="list-style-type: none"> • Confirmation of correspondence 	None, unless body regions or postures fall outside those tested
3	Decision support system	No	<ul style="list-style-type: none"> • Worker profile (age, sex, BMI, BFP, and health score) • Budget • Device catalogue 	None

7.4.1 Component 1 – Industry Data Collection

Component 1 must be repeated in full for each new trade, following the two-stage process described in Section 4.3.

Injury Data Analysis: WMSD-related injury records for the trade are obtained and categorized by affected body region, and the most frequently affected regions are identified. Section 7.2 completes this step for the four trades analyzed in this chapter.

Activity and Posture Review: The trade's common working postures are confirmed to fall within those under which the wearable devices were evaluated in Chapter 5. Section 7.3 completes this step for the four trades analyzed.

Neither step requires experimentation, as injury records and published PDAs are both publicly available. This is what renders the application of the framework to a further trade practicable within the resources available to an employer or safety practitioner.

7.4.2 Component 2 – Wearable Evaluation and LOS Classification

Component 2 depends upon the body regions targeted and the postures evaluated, and not upon the trade to which the wearer belongs. It therefore requires no repetition where a trade's at-risk regions and working postures correspond to those established for the mechanical trades. Sections

7.2 and 7.3 establish this correspondence for all four trades analyzed, and the classified device catalogue of Chapter 5 is therefore applicable to them. The basis for this is set out below, together with the limitation that applies to it.

The classified device catalogue of Table 5.16 assigns each of the 12 devices a level of support, derived through cluster analysis of measured performance and expressed by the Level of Support Index (LSI_i) of Equation 5. Each classification describes the support a device delivers to a wearer performing a given task. It is a property of the device, measured under defined loading conditions, and does not vary with the trade of the wearer.

The laboratory and field classifications reported in Table 5.16 and Table 5.17 substantiate this, agreeing for all 12 devices. Each device received the same Low, Medium, or High classification whether evaluated on the simulated laboratory tasks of Table 5.3 or on the real mechanical-trade tasks of Table 5.4. Changing the back task from a 4 kg box lift at 30 cm to the lifting of pipe and ductwork sections on a jobsite did not alter the assigned support level of any device. The classification is therefore stable where the specific task changes while the underlying posture is held constant, which is largely the nature of the difference between trades: a carpenter lifting framing lumber and a plumber lifting a pipe section perform the same posture with different materials.

This evidence carries an important limitation. Both the laboratory and field evaluations used mechanical-trade tasks performed by mechanical-trade practitioners, so the agreement between them shows only that a device's classification is stable when the same posture is performed in two different ways within one trade. Another trade performing that posture may lift heavier materials, hold the position longer, or repeat it more often, any of which could plausibly affect the support a device delivers. The correspondence established in Sections 7.2 and 7.3 therefore places a trade within the conditions the framework was built for, but does not substitute for evaluating the devices in that trade directly. Doing so would require the Chapter 5 field protocol to be repeated with practitioners of that trade, and this is identified as a direction for future work in Chapter 8.

As shown in Table 7.4, framework component 2 requires extension only where a trade's at-risk regions fall outside the back, legs, and shoulders, or where its predominant postures fall outside those evaluated. In either case, further devices are procured and evaluated under the existing Section 5.2 protocol, thereby extending the catalogue without any change to the framework itself.

7.4.3 Component 3 – Decision Support System

Component 3 requires no repetition for a new trade, as both of its phases operate upon inputs describing the individual worker rather than the trade.

Prediction of Required LOS (DSS Phase #1): The three ANNs developed in Section 6.2.3 take five inputs: worker age, sex, BMI, body fat percentage, and health score. All five describe the worker, and none identifies their trade, employer, or work environment. A worker of any trade supplies the same five values, each obtainable by self-report.

The target variable, required LOS, was derived in Section 6.2.2 from each participant's baseline performance without wearables, measured through fatigue threshold, heart rate change, and ergonomic risk score while the participant performed the experimental tasks. The models therefore estimate the support a worker requires when performing the postures those tasks reproduce, and Section 7.3 establishes that the trades analyzed adopt those postures.

One condition applies to the use of these predictive models: the models produce reliable estimates only for inputs falling within the range of the training data. Three of the five model inputs raise no concern: sex and health score are bounded by definition, and age spanned 22 to 65 years across the 44 participants, covering the working age range of the construction workforce. BMI and body fat percentage are continuous, so a worker whose values fall outside the range recorded in Section 5.2.1 would receive a prediction extrapolated beyond the training data. This limitation applies equally within the mechanical trades and is therefore a property of the models rather than of their application to a further trade.

Optimization of Device Selection (Phase #2): The optimization model of Section 6.3 receives four inputs: the device catalogue, comprising each device's code, provided LOS, and unit cost; the worker's predicted LOS requirements; any body-region opt-outs; and a budgetary limit. It minimizes total procurement cost subject to per-region LOS sufficiency, the budget constraint, and catalogue membership.

None of these inputs is trade-specific, and the model therefore operates the same way for a worker of any trade. Section 6.3.1 anticipates variation in the budget across trades, noting that the budgetary limit may vary with trade, employer insurance coverage, and union contribution.

7.5 Summary

The framework developed in Chapters 4 through 6 depends upon two characteristics of the trade it serves: the body regions most frequently affected by WMSDs, and the working postures through which those regions are loaded. This chapter has established that both recur across the broader construction sector.

Repeating the body region analysis of Section 4.3 for electrical work, carpentry, masonry, and drywalling identified the back as the leading affected region in every trade, at 36.4% to 44.4% of WMSD claims, with the three target regions together accounting for 64.4% to 69.7%. The published physical demands analyses established that all four work in the postures under which the device catalogue was evaluated, at frequencies within the ranges recorded for the mechanical trades. The trades differ on one point: the proportion of leg claims, ranging from 8.9% to 12.6%. This variation is accounted for by the posture data: leg injury claims are highest in the mechanical trades and electrical work, at 12.5% and 12.6%, and these are the two trades whose workers spend the most time kneeling, crouching, and squatting; the remaining three adopt those postures less often. The body regions a trade injures therefore follow closely from the postures its workers adopt.

Applying the framework to a further trade requires repetition of component 1 alone, which involves no experimental work. Components 2 and 3 apply without repetition where the trade's at-risk body regions and working postures correspond to those established for the mechanical trades. The Chapter 5 wearable device LOS classifications were shown to be identical across laboratory and field tasks for all 12 devices, while the Chapter 6 decision support system takes only individual worker characteristics and a budgetary limit as input. That laboratory-field agreement was established within the mechanical trades, and confirming that the classifications hold under the tasks of another trade remains a matter for experimental evaluation in that trade.

The framework was developed and validated for the mechanical trades, where its coverage is highest at 71.9% of WMSD claims. The analysis presented in this chapter establishes that the body regions and working postures upon which it depends are not particular to that trade group. All four trades analyzed meet the conditions under which the framework was developed, its target regions accounting for approximately two-thirds of the WMSD burden in each. The framework may therefore be applied to these trades without repetition of the experimental work of Chapters 5 and 6, subject to confirmation of device performance under their own tasks. The chapter thereby provides the procedure for extending the framework to a further trade: the two conditions it must meet, the records by which they are tested, and the component-by-component requirements of Table 7.4. The wrist, fingers, and hand constitute the principal region not presently served, and evaluating devices for that region under the existing Chapter 5 protocol, as recommended in Chapter 8, would raise coverage in every trade, including the mechanical trades.

Chapter 8: Conclusions and Future Research

8.1 Introduction

The mechanical trades are under sustained pressure from a shrinking skilled workforce, rising injury-related labour costs, and declining productivity. Persistent challenges, particularly the high prevalence of work-related musculoskeletal disorders (WMSDs) among HVAC technicians, plumbers, pipefitters, sheet metal workers, and welders, and the resulting premature workforce attrition, have remained largely unresolved for decades. This thesis develops a structured framework that directly addresses these challenges. By assessing risk at the level of individual body regions and selecting a combination of low-cost devices that supports all of a given worker's at-risk regions simultaneously under an explicit budget constraint, this work establishes a foundation for decision-support tools that are both technically rigorous and economically accessible. It demonstrates that data-driven, worker-specific wearable selection is feasible and capable of supporting WMSD risk reduction in resource-constrained environments. Accordingly, this work responds directly to the industry's need for evidence-based, field-validated tools aimed at reducing injury-driven attrition and strengthening the resilience of the skilled mechanical-trades workforce.

8.2 Research Summary and Conclusions

8.2.1 Research Summary

WMSDs account for one of the largest shares of lost time and compensation cost in the mechanical trades. HVAC technicians, plumbers, pipefitters, sheet metal workers, and welders routinely adopt physically demanding postures including trunk flexion, trunk rotation, kneeling, squatting, crouching, and overhead reaching, which place sustained demands on the back, legs, and shoulders. Industry data examined in this research show that WMSD-related claims among mechanical-trades workers have remained largely stable over the past decade, consistently accounting for roughly one-third of all lost-time injuries (WorkSafeBC, 2026). Overexertion and repetitive motion stand out as the dominant injury mechanisms, together accounting for a disproportionate share of claim costs

(approximately 28%) and lost workdays (approximately 39%) in the mechanical trades (WorkSafeBC, 2026).

A field survey conducted as part of this work further confirmed that limited labour resources, cost overruns, and compressed schedules are among the most pressing challenges facing owner organizations, with mechanical projects identified as the most challenging project type due to their scale, complexity, and direct impact on critical building systems such as HVAC, boilers, chillers, and plumbing. Reducing WMSDs is therefore not only a worker health priority but also a project delivery concern, with direct implications for labour availability, claim costs, and schedule performance. In an industry facing a shortage of skilled mechanical-trades workers, preventing injuries that remove experienced workers from the job or contribute to their premature departure from the trade represents a practical strategy for preserving skilled workforce capacity.

Although wearable support devices have received growing attention for ergonomic support, prior research has been constrained by several interrelated limitations: a predominant focus on high-cost wearable support devices; a narrow analytical scope that typically examines a single task or body region in isolation; reliance on costly assessment tools such as EMG and IMU systems; and an absence of structured selection mechanisms that account for the individual worker's anthropometric, demographic, and health profile. Most prior evaluations have also been conducted primarily under controlled laboratory conditions, leaving field-level applicability largely untested. As a result, mechanical-trades practitioners currently lack an evidence-based, accessible mechanism for matching workers with appropriate support devices. To address these limitations, this research developed a worker-oriented decision-support framework that integrates low-cost wearable technologies, accessible performance assessment metrics, machine-learning-based prediction across multiple body regions, and cost-constrained optimization modelling, informed by both laboratory and field experimentation with practicing trades workers. Rather than matching a single device to a single body region, the framework treats the worker as the unit of analysis, providing a

combination of devices selected to support all of that worker's at-risk regions at once. The framework comprises three sequential components.

Regarding the identification of industry needs and at-risk body regions, a field survey of experienced practitioners across 13 owner organizations confirmed that labour and cost pressures are among the most prevalent practitioner concerns and identified wearable sensing as one of the most promising technologies for advancing worker health and safety. In parallel, WMSD-related injury records for mechanical-trades workers were compiled from the IHSA, WSIB, and WorkSafeBC over a ten-year period, encompassing specialties such as HVAC, plumbing, pipefitting, and welding. Recent data from the WSIB, IHSA, and WorkSafeBC consistently identified the back, legs, and shoulders as the body regions most frequently involved in WMSD claims. The back emerged as the most frequently affected region, followed by the legs and shoulders, providing a basis for targeting these three regions in subsequent experimentation. Standard mechanical-trade activities were also reviewed to identify the postures and motions most commonly imposed on workers. Three sources were used: field images, on-site observations, and published Physical Demands Analyses (PDAs) from the Alberta Construction Association (ACA) covering HVAC installers, commercial plumbers, and sheet metal workers. These sources confirmed that mechanical-trades work is dominated by overhead reaching, trunk flexion and rotation, kneeling, squatting, and crouching, along with frequent floor-to-waist and knee-to-waist material handling. The ACA PDAs further quantified the intensity of these demands: for example, HVAC installers spend 34-66% of the workday in overhead reaching, and sheet metal workers spend 67-100% of the workday kneeling.

The experimental component was undertaken with the aim of quantifying the support that low-cost wearable devices provide to each of the identified body regions. A study was conducted with 44 laboratory participants (31 non-practitioners and 13 practitioners) who performed simulated tasks; the 13 practitioners also performed field tasks. Practitioners were recruited from the University of Waterloo Plant Operations team and other private organizations and primarily consisted of

plumbers, steamfitters, and millwrights. Participants spanned a wide range of heights and weights and were intentionally selected to capture variability in body type and physical condition for evaluating wearable effectiveness.

Twelve commercially available wearable devices (five back, four leg, three shoulder), ranging in price from \$29 to \$2,500 CAD, were evaluated under each participant's use. Most devices were priced below \$250 CAD, reflecting the framework's emphasis on affordability; a small number of higher-priced devices were included when their support capabilities were notably superior. Three tasks were designed to load each target region. Laboratory tasks consisted of repetitive box lifting (back), sustained squatting (legs), and sustained overhead arm holding (shoulders). Field tasks mirrored these demands using standard mechanical-trade activities: lifting pipe or ductwork sections (back), floor-level plumbing rough-in (legs), and overhead drilling or welding of pipe or duct hangers (shoulders).

Performance was quantified using three accessible assessment metrics: Fatigue Threshold, Heart Rate Change (post-task minus pre-task heart rate), and Ergonomic Risk Score (derived via TuMeke software using the REBA and NIOSH algorithms). Mean percentage change values were computed for laboratory and field tasks. Subjective feedback was also collected via an eight-item, five-point Likert questionnaire covering comfort, fatigue reduction, range of motion, task effectiveness, distraction, equipment compatibility, and willingness to recommend or reuse the device.

A clustering algorithm was then applied to the performance metrics to assign each wearable support device to a Low, Medium, or High level of support (LOS) category. The back and leg wearables produced three clearly distinguishable LOS categories. For the shoulder wearables, no Medium-support device emerged from the tested set; Wearables 10 and 11 were classified as Low support, while Wearable 12 (Hilti EXO-S) was classified as High support. The classification proved stable across laboratory and field settings: all twelve devices received the same support-level

assignment in the laboratory and in the field, with a mean absolute percentage difference of 4.83% in LOS index. Rank and linear agreement were both strong (Spearman's $r_s = 0.979$; Pearson's $r = 0.993$), and a Wilcoxon signed-rank test found no significant systematic difference between conditions. These findings indicate that the laboratory protocol is transferable to field conditions. The classification was then examined against device cost and user perception. Cost correlated positively with assigned LOS, most strongly for the back and shoulder wearables ($R^2 = 0.87$ - 0.99). Questionnaire responses showed strong agreement with the LOS classification on perceived fatigue reduction ($R^2 = 0.98$ - 0.99 across all three body regions), providing independent confirmation of the LOS index. Comfort and range of motion showed no consistent penalty at higher LOS: the relationship was absent for the back, favourable for the shoulder, and negative for the leg, though spanning approximately one point on a five-point scale.

Lastly, this research developed a two-phase decision support system (DSS) to translate these results into worker-specific device recommendations. In the first phase, each worker's required LOS was determined from their unassisted baseline performance on the same three metrics used to classify the devices, and the required LOS (1-3) for each body region was predicted using an artificial neural network (ANN) trained on a comprehensive worker profile, including age, sex, Body Mass Index (BMI), Body Fat Percentage (BFP), and body region-specific health scores. Cross-validation accuracies of 77.8% (back), 78.4% (leg), and 79.0% (shoulder), with Kappa statistics of 0.659, 0.676, and 0.683, respectively, indicate that the ANN models extract meaningful, above-chance patterns from worker profile data.

In the second phase, the predicted required LOS for all three body regions was passed simultaneously to an evolutionary optimization model that selected the most cost-effective combination of wearables satisfying the worker's support requirements within a user-defined budget. Its results for the three field-validation practitioners were verified against an exact mixed-integer linear programming solver (Section 6.6). Because a single objective and a single budget constraint

spanned all three body regions, the model returned one device set evaluated against the worker's requirements as a whole rather than assembled from independent per-region choices. This was implemented in Microsoft Excel with the Solver add-in to accommodate non-programmer users. A tie-breaking coefficient preferred configurations with greater aggregate support among cost-equivalent solutions, supported by questionnaire findings showing negligible correlation between higher LOS provided and reduced perceived comfort or range of motion. When the budget was insufficient, the model returned an explicit infeasibility status and the minimum required budget, providing actionable guidance to procurement decision-makers. The DSS was further trialed in a live field setting with mechanical-trades workers, providing an initial indication that the full workflow, from worker characterization to wearable recommendation, can be applied in the field.

Finally, the applicability of the framework beyond the mechanical trades was examined. The injury data and working-posture analyses were repeated for electrical work, carpentry, masonry, and drywalling, using WorkSafeBC records for 2021 to 2025 and published PDAs for the corresponding occupations. The back was the leading affected region in every trade, at 36.4% to 44.4% of WMSD claims, and the three target regions together accounted for 64.4% to 69.7%, against 71.9% for the mechanical trades. All four trades were found to work in the postures under which the device catalogue was evaluated, at frequencies within the ranges recorded for the mechanical trades. Applying the framework to a trade meeting these conditions therefore requires repetition of the industry data collection component alone, with the classified device catalogue and the DSS applying without further experimental work.

8.2.2 Key Conclusions

The main conclusions of this research, one for each objective in Section 1.3, are as follows:

1. Owner-organization practitioners identify labour and cost pressures as among their most prevalent challenges and wearable sensing as one of the most promising technologies for worker health and safety. The back, legs, and shoulders are the body regions most affected by WMSDs in the mechanical trades, accounting for approximately 72% to 80% of WMSD

claims in WorkSafeBC and WSIB records, and they are loaded by a recurring set of working postures: floor-to-waist and knee-to-waist lifting, overhead reaching, trunk flexion and rotation, kneeling, squatting, and crouching.

2. Low-cost wearable support devices differ measurably in the support they provide, and that support can be classified consistently: all 12 devices received the same LOS classification in the laboratory and the field, and the LOS index agreed with user-perceived fatigue reduction ($R^2 = 0.98-0.99$). Retail price was strongly correlated with the support provided by back and shoulder devices ($R^2 = 0.87-0.99$) but not with that of leg devices ($R^2 = 0.24-0.26$), and device selection therefore cannot be made on cost alone.
3. A worker's required LOS can be predicted from five readily obtained characteristics (age, sex, BMI, body fat percentage, and health score), with cross-validated accuracies of 77.8%, 78.4%, and 79.0% for the back, legs, and shoulders. A single cost-minimizing optimization across all three regions then converts these predictions into one worker-specific device set, or reports the minimum budget required when the available budget is insufficient. In the field validation, the DSS recommended device sets within the \$2,500 budget for two of the three practitioners and, for the remaining practitioner, reported a minimum budget of \$4,531; the recommended devices were generally well accepted.
4. The framework applies beyond the mechanical trades wherever workers sustain injuries to the same body regions and adopt the same working postures. In electrical work, carpentry, masonry, and drywalling, the back, legs, and shoulders account for 64.4% to 69.7% of WMSD claims, compared with 71.9% in the mechanical trades, and workers adopt the postures under which the devices were evaluated. The framework may therefore be applied to these trades without repetition of the experimental work of Chapters 5 and 6, Sections 7.2 and 7.3 having completed the industry data collection component; confirming device performance under the tasks specific to each trade is the next step (Section 8.4.1).

Table 8.1 shows where each research gap identified in Section 2.4 is addressed.

Table 8.1: Research gaps and the means by which this research addresses them

Research Gap	Objective(s)	Addressed In	Approach
Absence of device-level selection in conventional controls	3	Sections 6.3 and 6.5	The DSS selects a specific device for each at-risk body region of an individual worker.
Promising technologies require translation into intervention	2-3	Chapters 5-6	Physiological and ergonomic measurements are translated into device classifications and worker-specific device recommendations.
Task- and worker-dependent device suitability	1, 3, 4	Sections 4.3 and 6.2; Chapter 7	Target body regions and postures are derived from injury data and task analysis, each worker's required LOS is predicted by body region from individual characteristics, and Chapter 7 shows that these regions and postures recur in four further trades.
Insufficient field validation	2-3	Sections 5.4.4 and 6.5	All 12 wearable support devices received the same LOS classification in laboratory and field trials, and the DSS was applied in the field with three practitioners.
Reliance on high-cost support devices and assessment tools	2	Chapter 5	The 12 support devices, priced from \$29 to \$2,500 CAD, with the majority below \$250, were assessed with a wrist-worn wearable sensor (Apple Watch Ultra 2) for heart rate, a digital stopwatch and the Borg CR10 scale for fatigue threshold, and smartphone video analyzed with AI-driven ergonomic software (TuMeke) for ergonomic risk.
Disconnect between strain measurement and device selection	2-3	Sections 5.4 and 6.2-6.3	The same performance metrics determine the LOS each device provides and the LOS each worker requires, linking measured strain directly to device selection.
Incomplete coverage in existing selection frameworks	1-4	Chapters 4-7	The proposed selection method uses directly measured strain, is developed for mechanical-trade construction work, is validated in the field, and extends to other trades under the conditions established in Chapter 7.

8.3 Research Contributions

This research advances construction occupational health by introducing a data-driven decision-support framework for the tailored selection of low-cost wearable devices for mechanical-trades workers. Compared to the existing literature, the main contributions are organized into two categories: contributions to the body of knowledge (Section 8.3.1) and contributions to industry practice (Section 8.3.2).

8.3.1 Contributions to the Body of Knowledge

The following contributions extend the body of knowledge on the evaluation and selection of wearable support devices:

- **Common-Scale LOS Index for Device Capability and Worker Need:** A novel LOS index (Attalla et al., 2026) uses a single set of performance metrics to derive two complementary quantities on a shared scale: the LOS each device provides, obtained by clustering measured performance improvement, and the LOS each worker requires, obtained from unassisted baseline performance. Expressing device capability and worker requirement in common units allows for direct matching of devices to worker body regions. The LOS index is corroborated externally by user-perceived fatigue reduction ($R^2 = 0.98-0.99$ across all three body regions).
- **Simultaneous Multi-Region Device Combination Selection:** Rather than focusing on a single task or body region, the DSS predicts the worker's required LOS for the back, legs, and shoulders, then identifies the combination of devices that best satisfies all three requirements under a single shared budget. Because a single objective and budget constraint span all three regions, the resulting recommendation is tailored to the individual worker as a whole rather than assembled from independent per-region selections. These three regions account for approximately 72% to 80% of WMSD claims among mechanical-trades workers, so a recommendation addressing them jointly targets the substantial majority of the claim burden in these trades.
- **Lab-to-Field Validation of Wearable Performance:** The experimental component pairs controlled laboratory trials with practitioner-based field trials on real mechanical-trade tasks. Agreement between the two settings is established on three distinct bases: identical support-level classification for all twelve devices, strong rank and linear correlation between laboratory and field LOS indices, and the absence of any systematic directional bias. This provides quantitative grounds for treating laboratory-measured support levels as valid for real field tasks.

- **Body Region-Specific Methodological Framing:** A key methodological advantage is the framework's focus on body region-specific stresses rather than the detailed dynamics of individual tasks. The regions targeted are established from both the injury distribution and the working postures that load them. This framing generalizes well across mechanical-trade tasks, where execution varies widely among contractors, workers, and tools, but the underlying body regions placed under load remain consistent: overhead work loading the shoulders, lifting and trunk flexion loading the back, and kneeling, squatting, and crouching loading the legs.
- **Worker-Specific Prediction of Support Requirements:** By incorporating user anthropometric, demographic, and health data into machine learning-based prediction of worker support requirements, the framework tailors device selection to the individual worker rather than relying on generic trade- or task-level guidelines.
- **Integration of Machine Learning and Cost-Constrained Optimization:** The DSS integrates a WEKA-based ANN with an evolutionary optimization engine implemented in Microsoft Excel's Solver add-in. This design ensures that recommendations are both physiologically appropriate and financially feasible, and that the DSS remains operable by occupational health or procurement staff without programming expertise.
- **Established Conditions for Application Beyond the Mechanical Trades:** The framework's dependence on a trade is isolated to two characteristics, namely the body regions most affected by WMSDs and the working postures through which those regions are loaded, both of which are shown to recur across the construction sector. A comparison of injury records and published physical demands analyses across five trade groups establishes that the back, legs, and shoulders account for approximately two-thirds of WMSD claims in electrical work, carpentry, masonry, and drywalling, and that all four adopt the postures under which the device catalogue was evaluated. This defines the conditions of application for the framework across construction, and specifies the procedure by which a further trade may be brought within its scope.

8.3.2 Contributions to Industry Practice

The following contributions address the needs and constraints of construction organizations:

- **Industry-Grounded Problem Definition:** Informed by a field survey of 13 owner organizations and a multi-source WMSD injury analysis spanning approximately a decade, the framework directly addresses a validated industry need: improving mechanical-trade worker safety through reduced WMSDs and mitigating the construction industry's skilled labour shortage through reduced injury-driven attrition.
- **Accessible Assessment Methodology:** The study validates the use of low-cost measurement instruments (a wrist-worn wearable sensor for heart rate, a digital stopwatch and the Borg CR10 scale for fatigue threshold, and smartphone video analyzed with AI-driven ergonomic software for ergonomic risk) for wearable and participant assessments as a practical alternative to high-cost, research-grade sEMG and IMU systems (\$24,000-55,000 CAD for sEMG systems, Motion Lab Systems, 2026; \$2,300-5,400 CAD per IMU module, Mouser Electronics, 2026), thereby lowering the entry barrier for organizations with limited instrumentation budgets.
- **Validation of Low-Cost Wearable Efficacy for Mechanical-Trades Workers:** Whereas prior research has focused primarily on high-cost devices with limited consideration of budgetary realities, this research demonstrates that affordable wearables can provide measurable support to mechanical-trades workers, and that devices targeting the same body region differ substantially in support level, enabling fit-for-purpose selection.

In combination, these contributions extend the existing body of knowledge on mechanical-trades injury risk and wearable device performance by identifying the body regions most prone to WMSDs, the postures that place them under load, and the degree of support different wearables provide. This understanding is translated into practical capability through a methodological framework for wearable device selection that is multi-region, worker-specific, budget-aware, and generalizable, thereby contributing to the reduction of WMSD risk among mechanical-trades workers. By helping organizations deploy feasible preventive supports before worker injuries lead

to lost time or workforce exit, the framework has the potential to support the retention of experienced trades workers, a particularly important objective under persistent skilled-labour constraints.

8.4 Limitations and Future Research

Despite the capabilities and benefits this research presents, several opportunities for future refinement remain:

8.4.1 Future Research Related to Experimentation

- **Expanded Sample Size and Diversity:** As noted in the experiment design (see Sections 5.2.1 and 6.2.1), the sample in this research was scoped to establish the feasibility of the proposed framework rather than to support broadly generalizable conclusions. Although the laboratory sample (44 participants) was broadly aligned with the demographic composition of Ontario's construction workforce, the field sample (13 participants) was drawn from a smaller, all-male practitioner cohort, which limits generalizability across other demographics. The dataset was nonetheless sufficient to establish feasibility, yielding statistically significant performance improvements, distinguishable device LOS classifications, and accurate predictive models across all three body regions. Future work could conduct field studies with a larger and more demographically diverse sample of mechanical-trades workers, expanding beyond the all-male field cohort used in this study, enabling more robust ANN training, greater statistical power, and external validation across age groups, sexes, body types, fitness levels, and trade specialties. A larger dataset would also allow more complex model types, such as deep neural networks, to be benchmarked against the current MLP.
- **Field Evaluation in Additional Trades:** Chapter 7 establishes that electrical work, carpentry, masonry, and drywalling share the body regions and working postures for which the framework was developed, and that its components apply to them without repetition of the experimental work. Device performance in those trades has not, however, been measured directly. Future

work could repeat the Chapter 5 field protocol with practitioners of each trade, confirming that the support levels assigned under mechanical-trade tasks hold under their own tasks.

- **Trade-Specific Evaluation Process:** Future work could build on the body region-based findings to develop a standardized evaluation process for assessing wearable effectiveness across specific mechanical trades and tasks, reflecting distinct physical demands such as sustained overhead work for HVAC installers versus prolonged kneeling for commercial plumbers.
- **Enhanced Precision via EMG/IMU Sensors:** While this research intentionally relies on low-cost, accessible measurement instruments to maintain affordability and field practicality, future iterations could incorporate EMG and IMU sensors alongside the existing metrics to further improve assessment precision of worker and wearable performance.
- **Expanded Wearable Device Catalogue:** Future experimentation could include a wider catalogue of wearable devices, particularly for the shoulder region, where the tested devices produced only Low and High classifications, to provide more granular optimization options as the commercial market evolves. Chapter 7 further identifies the wrist, fingers, and hand as the most frequently affected body region not addressed by the current catalogue, accounting for 9.1% of WMSD claims in the mechanical trades and up to 14.2% in the trades analyzed. Evaluating devices for that region under the Section 5.2 protocol would extend coverage across all trades examined.

8.4.2 Future Research Related to the Decision Support System

- **Additional Predictive Features:** Future iterations of the predictive model could incorporate additional input features, such as human factors (e.g., trade experience, injury history, chronic conditions), to further refine the prediction of required worker LOS.
- **Expanded Optimization Model Decision Criteria:** Future DSS iterations could incorporate a 'device attributes' dimension into the optimization model, based on 1) device specifications (e.g.,

weight, adjustability, durability, heat retention), and 2) subjective user feedback from the questionnaires (e.g., range of motion, comfort). This would allow device selection to be tailored beyond LOS requirements alone, accounting for individual worker needs and preferences. With the present catalogue, the Evolutionary engine returned the proven optimum in every case reported (Section 6.6), and it would be expected to remain suitable for such an expanded model. Because a heuristic search cannot prove that its solution is optimal, its recommendations for an expanded catalogue or set of criteria can be checked by solving the linear formulation of Section 6.6 (extended to the added criteria) with an exact solver.

- **Automated Criteria Weighting and Model Updating via AI:** Beyond the ANN and optimization components developed in this work, future iterations could apply broader AI techniques to weight decision criteria such as cost and provided support automatically rather than by fixed rule, to update the recommendation logic as use of the system accumulates, and to retrain the predictive models as additional worker data are collected. AI could also be used to estimate the LOS classification of newly released devices from their specifications, using the tested devices as an initial training set, providing a screening aid to prioritize which devices warrant full experimental evaluation. Such extensions would allow the DSS to stay current as the wearable market and the user base evolve, without manual reconfiguration.
- **Software Implementation for End-User Deployment:** Although the Excel-based DSS interface prioritizes accessibility, a dedicated software interface could improve usability, reduce input errors, and support device catalogue updates, with potential integration into contractor and owner safety-management platforms.
- **Economic Evaluation and Funding of Adoption:** Future work could quantify the return on device investment, such as avoided injury claims and productivity gains, and examine which parties should fund the devices and the mechanisms through which their purchase could be financed, given that the available budget may vary with trade, employer insurance coverage, and union contribution.

References

- AACE International. (2020). Recommended Practice No. 18R-97: Cost Estimate Classification System – As Applied in Engineering, Procurement, and Construction for the Process Industries (Rev. August 7, 2020). AACE International. https://web.aacei.org/docs/default-source/toc/toc_18r-97.pdf
- Abuwarda, Z., & Hegazy, T. (2019). Multi-Dimensional Optimization Model for Schedule Fast-Tracking without Over-Stressing Construction Workers. Canadian Journal of Civil Engineering. <https://mc06.manuscriptcentral.com/cjce-pubs>
- Abuwarda, Z., Hegazy, T., Oetomo, A., & Morita, P. P. (2023). Using Wearables to Monitor and Mitigate Workers' Fatigue. In S. Walbridge, M. Nik-Bakht, K. T. W. Ng, M. Shome, M. S. Alam, A. el Damatty, & G. Lovegrove (Eds.), Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021: CSCE21 Construction Track Volume 2 (Lecture Notes in Civil Engineering, Vol. 247, pp. 587–597). Springer. https://doi.org/10.1007/978-981-19-0968-9_47
- Abuwarda, Z., Mostafa, K., Oetomo, A., Hegazy, T., & Morita, P. (2022). Wearable devices: Cross benefits from healthcare to construction. Automation in Construction, 142, 104501. <https://doi.org/10.1016/j.autcon.2022.104501>
- ACHR News. (n.d.). Apprentice readiness programs help prepare future sheet metal workers [Photograph]. The ACHR News. <https://www.achrnews.com/articles/163941-apprentice-readiness-programs-help-prepare-future-sheet-metal-workers>
- Alateeq, M. M., Fathimathul, F. R., & Ali, M. A. S. (2023). Construction Site Hazards Identification Using Deep Learning and Computer Vision. Sustainability (Switzerland), 15(3), 2358. <https://doi.org/10.3390/su15032358>
- Alberta Construction Association. (2020a, October 15). *Physical demands analysis: Commercial plumber*. <https://albertaconstruction.org/wp-content/uploads/2020/10/Commercial-Plumbing-PDA-for-ACA-October-15-2020.pdf>
- Alberta Construction Association. (2020b, October 15). *Physical demands analysis: HVAC installer*. <https://albertaconstruction.org/wp-content/uploads/2020/10/HVAC-Installer-PDA-for-ACA-October-15-2020.pdf>
- Alberta Construction Association. (2021a, July 29). *Physical demands analysis: Drywaller*. <https://albertaconstruction.org/wp-content/uploads/2021/07/ACA-PDA-for-Drywaller-July-29-2021.pdf>
- Alberta Construction Association. (2021b, February 8). *Physical demands analysis: Electrician*. <https://albertaconstruction.org/wp-content/uploads/2021/02/Commercial-Electrician.pdf>
- Alberta Construction Association. (2021c, July 29). *Physical demands analysis: Framing carpenter*. <https://albertaconstruction.org/wp-content/uploads/2021/07/ACA-PDA-for-Framing-Carpenter-July-29-2021.pdf>
- Alberta Construction Association. (2021d, January 29). *Physical demands analysis: Journeyman bricklayer*. <https://albertaconstruction.org/wp-content/uploads/2021/01/Bricklayer-PDA-for-ACA-January-29-2021.pdf>

- Alberta Construction Association. (2021e, April 6). *Physical demands analysis: Journeyman finishing carpenter*. <https://albertaconstruction.org/wp-content/uploads/2021/04/Journeyman-Finishing-Carpenter-PDA-for-ACA-April-6-2021.pdf>
- Alberta Construction Association. (2021f, July 29). *Physical demands analysis: Sheet metal worker – field installation*. <https://albertaconstruction.org/wp-content/uploads/2021/07/ACA-PDA-for-Sheet-Metal-Worker-Field-Installation-July-29-2021-1.pdf>
- Alcan, V., & Zinnuroğlu, M. (2023). Current developments in surface electromyography. *Turkish Journal of Medical Sciences*, 53(5), 1019–1031. <https://doi.org/10.55730/1300-0144.5667>
- Ali, R., Hussain, J., & Lee, S. W. (2023). Multilayer perceptron-based self-care early prediction of children with disabilities. *DIGITAL HEALTH*, 9, Article 20552076231184054. <https://doi.org/10.1177/20552076231184054>
- ALIS Alberta. (n.d.). Sheet metal worker [Photograph]. Government of Alberta. <https://alis.alberta.ca/occinfo/occupations-in-alberta/occupation-profiles/sheet-metal-worker/>
- Alwasel, A., Abdel-Rahman, E. M., Haas, C. T., & Lee, S. (2017). Experience, productivity, and musculoskeletal injury among masonry workers. *Journal of Construction Engineering and Management*, 143(6), 05017003. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001308](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001308)
- Ambro Controls. (n.d.). How to prevent back pain as a HVAC technician [Photograph]. <https://ambrocontrols.com/how-to-prevent-backpain-as-a-hvac-technician/>
- Antwi-Afari, M. F., Li, H., Anwer, S., Li, D., Yu, Y., Mi, H.-Y., & Wuni, I. Y. (2021). Assessment of a passive exoskeleton system on spinal biomechanics and subjective responses during manual repetitive handling tasks among construction workers. *Safety Science*, 142, 105382. <https://doi.org/10.1016/j.ssci.2021.105382>
- Antwi-Afari, M. F., Li, H., Chan, A. H. S., Seo, J., Anwer, S., Mi, H.-Y., Wu, Z., & Wong, A. Y. L. (2023). A science mapping-based review of work-related musculoskeletal disorders among construction workers. *Journal of Safety Research*, 85, 114-128. <https://doi.org/10.1016/j.jsr.2023.01.011>
- Antwi-Afari, M. F., Li, H., Yu, Y., & Kong, L. (2018). Wearable insole pressure system for automated detection and classification of awkward working postures in construction workers. *Automation in Construction*, 96, 433–441. <https://doi.org/10.1016/j.autcon.2018.10.004>
- Anwer, S., Li, H., Antwi-Afari, M. F., Umer, W., & Wong, A. Y. L. (2021). Associations between physical or psychosocial risk factors and work-related musculoskeletal disorders in construction workers based on literature in the last 20 years: A systematic review. *Applied Ergonomics*, 93, Article 103373. <https://doi.org/10.1016/j.apergo.2021.103373>
- Aparicio, C. C., Balzan, A., & Trabucco, D. (2020). Robotics in construction: Framework and future directions. *International Journal of High-Rise Buildings*, 9(1), 105–111. <https://doi.org/10.21022/IJHRB.2020.9.1.105>
- Aryal, A., Ghahramani, A., & Becerik-Gerber, B. (2017). Monitoring fatigue in construction workers using physiological measurements. *Automation in Construction*, 82, 154–165. <https://doi.org/10.1016/j.autcon.2017.03.003>

ASME. (2025). ASME A17.1-2025/CSA B44:25, Safety Code for Elevators and Escalators. American Society of Mechanical Engineers / CSA Group.

Associated General Contractors of America, & National Center for Construction Education and Research. (2025a). 2025 workforce survey analysis. https://www.agc.org/sites/default/files/users/user21902/2025%20Workforce%20Survey%20Analysis_V2.pdf

Associated General Contractors of America, & National Center for Construction Education and Research. (2025b). 2025 workforce survey results: National results [Fact sheet]. https://www.agc.org/sites/default/files/users/user21902/2025_Workforce_Survey_National_FINAL_m.pdf

Attalla, A., Attalla, O., Moussa, A., Shafique, D., Raeen, S. B., & Hegazy, T. (2023). Construction Robotics: Review of Intelligent Features. *International Journal of Intelligent Robotics and Applications*, 7(3), 535–555. <https://doi.org/10.1007/s41315-023-00275-1>

Attalla, A., Attalla, O., Saeed, F., Tayeh, B. A., & Hegazy, T. (2025). Reducing workers' back, shoulder, and leg stresses using low-cost wearables. *Proceedings of the CSCE Construction Specialty Conference and ASCE Construction Research Congress (CSCE/CRC 2025)*. <https://doi.org/10.22260/CRC-CSCE-2025/0045>

Attalla, O., Attalla, A., & Hegazy, T. (2024). Robotic Programming for Simplified Construction Applications. *Proceedings of the Canadian Society for Civil Engineering Annual Conference 2023, Volume 5: Construction Track*, 341–347. Springer Nature. https://doi.org/10.1007/978-3-031-61503-0_25

Attalla, O., Attalla, A., Saeed, F., & Hegazy, T. (2026). Optimal Selection of Affordable Wearable Devices that Minimize Construction Stresses on Multiple Body Parts. *Journal of Construction Engineering and Management*, 152(12), 04026223. <https://doi.org/10.1061/JCEMD4.COENG-18305>

Awolusi, I., & Sulbaran, T. (2021). Decision support framework for selecting wearable Internet of Things devices for safety management in construction. *EPiC Series in Built Environment*, 2, 320–329.

Balogh, D., Cui, X., Mayer, M., Koehncke, N., Dueck, R., & Lang, A. E. (2025). Reliability and agreement during the Rapid Entire Body Assessment: Comparing rater expertise and artificial intelligence. *PLOS ONE*, 20(5), e0323262. <https://doi.org/10.1371/journal.pone.0323262>

Bangaru, S. S., Wang, C., & Aghazadeh, F. (2022). Automated and Continuous Fatigue Monitoring in Construction Workers Using Forearm EMG and IMU Wearable Sensors and Recurrent Neural Network. *Sensors*, 22(24), 9729. <https://doi.org/10.3390/s22249729>

Bennett, S. T., Han, W., Mahmud, D., Adamczyk, P. G., Dai, F., Wehner, M., Veeramani, D., & Zhu, Z. (2023). Usability and Biomechanical Testing of Passive Exoskeletons for Construction Workers: A Field-Based Pilot Study. *Buildings*, 13(3), 822. <https://doi.org/10.3390/buildings13030822>

Bischi, B., Binder, M., Lang, M., Pielok, T., Richter, J., Coors, S., Thomas, J., Ullmann, T., Becker, M., Boulesteix, A.-L., Deng, D., & Lindauer, M. (2023). Hyperparameter optimization: Foundations, algorithms, best practices, and open challenges. *WIREs Data Mining and Knowledge Discovery*, 13(2), e1484. <https://doi.org/10.1002/widm.1484>

- Boilermakers Labour-Management Health and Safety Committee. (2015, April). Boilermakers – Health & Safety Manual. Infrastructure Health & Safety Association. <http://www.ihsa.ca/PDFs/Products/Id/M071.pdf>
- Borisov, V., Leemann, T., Seßler, K., Haug, J., Pawelczyk, M., & Kasneci, G. (2024). Deep neural networks and tabular data: A survey. *IEEE Transactions on Neural Networks and Learning Systems*, 35(6), 7499–7519. <https://doi.org/10.1109/TNNLS.2022.3229161>
- Borg, G. A. V. (1982). Psychophysical bases of perceived exertion. *Medicine & Science in Sports & Exercise*, 14(5), 377–381. <https://doi.org/10.1249/00005768-198205000-00012>
- Borghesi, A., Baldo, F., & Milano, M. (2020). Improving deep learning models via constraint-based domain knowledge: A brief survey. arXiv preprint. <https://doi.org/10.48550/arXiv.2005.10691>
- Bosch, T., van Eck, J., Knitel, K., & de Looze, M. (2016). The effects of a passive exoskeleton on muscle activity, discomfort and endurance time in forward bending work. *Applied Ergonomics*, 54, 212-217. <https://doi.org/10.1016/j.apergo.2015.12.003>
- British Columbia Institute of Technology. (n.d.). Sheet metal [Photograph]. BCIT. <https://www.bcit.ca/programs/sheet-metal/>
- Butler, T. (2016). Exoskeleton technology: Making workers safer and more productive. *Professional Safety*, 61(9), 33-36.
- Campanini, I., Disselhorst-Klug, C., Rymer, W. Z., & Merletti, R. (2020). Surface EMG in clinical assessment and neurorehabilitation: Barriers limiting its use. *Frontiers in Neurology*, 11, 934. <https://doi.org/10.3389/fneur.2020.00934>
- CCOHS. (2024a). Work-related musculoskeletal disorders (WMSDs). <https://www.ccohs.ca/oshanswers/diseases/rmirsi.html>
- CCOHS. (2024b). Work-related musculoskeletal disorders (WMSDs) – Risk factors. <https://www.ccohs.ca/oshanswers/diseases/wmsd/risk.html>
- CCOHS. (2025). Construction worker – General (health and safety issues and preventive measures). https://www.ccohs.ca/oshanswers/occup_workplace/construction_worker.html
- CDL Electric. (n.d.). Plumbing construction [Photograph]. <https://cdlelectric.com/plumbing-construction/>
- Chen, X., Yu, Y., Wang, Y., & Hu, Z.-Z. (2025). Multimodal data fusion for ergonomic assessment of construction workers in visually obstructed environments. *Automation in Construction*, 179, 106495. <https://doi.org/10.1016/j.autcon.2025.106495>
- Cheng, B., Fan, C., Fu, H., Huang, J., Chen, H., & Luo, X. (2022b). Measuring and Computing Cognitive Statuses of Construction Workers Based on Electroencephalogram: A Critical Review. *IEEE Transactions on Computational Social Systems*, 9(6), 1644–1659. <https://doi.org/10.1109/TCSS.2022.3158585>
- Cheng, J. C. P., Wong, P. K. Y., Luo, H., Wang, M., & Leung, P. H. (2022a). Vision-based monitoring of site safety compliance based on worker re-identification and personal protective equipment classification. *Automation in Construction*, 139, 104312. <https://doi.org/10.1016/j.autcon.2022.104312>

- Cheng, M.-Y., Huang, K.-Y., & Hutomo, M. (2018). Multiobjective Dynamic-Guiding PSO for Optimizing Work Shift Schedules. *Journal of Construction Engineering and Management*, 144(9), 04018089. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001548](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001548)
- Chung, J., Quirk, D. A., Applegate, M., Rouleau, M., Degenhardt, N., Galiana, I., Dalton, D., Awad, L. N., & Walsh, C. J. (2024). Lightweight active back exosuit reduces muscular effort during an hour-long order picking task. *Communications Engineering*, 3, 35. <https://doi.org/10.1038/s44172-024-00180-w>
- Comper, M. L. C., Dennerlein, J. T., Evangelista, G. D. S., Rodrigues Da Silva, P., & Padula, R. S. (2017). Effectiveness of job rotation for preventing work-related musculoskeletal diseases: A cluster randomised controlled trial. *Occupational and Environmental Medicine*, 74(8), 545–552. <https://doi.org/10.1136/oemed-2016-104077>
- Construction Safety Association of Manitoba. (2020, April). COVID-19 Prevention Best Practices for Construction Sites. Construction Safety. <https://www.constructionsafety.ca/wp-content/uploads/2020/04/COVID-19-Prevention-Best-Practices-March-23.pdf>
- Construction Safety Association of Manitoba. (2021a, February). Site Visits – Best Practices. Construction Safety. <https://www.constructionsafety.ca/wp-content/uploads/2021/02/CSAM-Site-Visits-Best-Practices-2021.02.01.pdf>
- Construction Safety Association of Manitoba. (2021b, June). Principles of Safety Management – Construction Safety. Construction Safety. <https://www.constructionsafety.ca/wp-content/uploads/2021/06/Principles-of-Safety-Management-Manual.pdf>
- Crea, S., Beckerle, P., de Looze, M., De Pauw, K., Grazi, L., Kermavnar, T., Masood, J., O’Sullivan, L. W., Pacifico, I., Rodriguez-Guerrero, C., Vitiello, N., Ristic-Durrant, D., & Veneman, J. (2021). Occupational exoskeletons: A roadmap toward large-scale adoption. *Wearable Technologies*, 2, e11. <https://doi.org/10.1017/wtc.2021.11>
- CSA Group. (2023). CSA B52:23, Mechanical Refrigeration Code. CSA Group.
- CSA Group. (2024). CSA B51:24, Boiler, Pressure Vessel, and Pressure Piping Code. CSA Group.
- Da Costa, B. R., & Vieira, E. R. (2010). Risk factors for work-related musculoskeletal disorders: A systematic review of recent longitudinal studies. *American Journal of Industrial Medicine*, 53(3), 285–323. <https://doi.org/10.1002/ajim.20750>
- Di Natali, C., Buratti, G., Dellera, L., & Caldwell, D. G. (2024). Equivalent weight: Application of the assessment method on real task conducted by railway workers wearing a back-support exoskeleton. *Applied Ergonomics*, 118, 104278. <https://doi.org/10.1016/j.apergo.2024.104278>
- Dodge Data & Analytics. (2018). Safety management in the construction industry 2017 [SmartMarket report]. Dodge Data & Analytics. https://www.cpwr.com/wp-content/uploads/Dodge_Safety_Report_2017.pdf
- Donisi, L., Cesarelli, G., Pisani, N., Ponsiglione, A. M., Ricciardi, C., & Capodaglio, E. M. (2022). Wearable sensors and artificial intelligence for physical ergonomics: A systematic review of literature. *Diagnostics*, 12(12), 3048. <https://doi.org/10.3390/diagnostics12123048>

- Drees, T., Luttmmer, J., & Nagarajah, A. (2023). A framework for the systematic selection of occupational exoskeletons. *Procedia CIRP*, 119, 1134–1139. <https://doi.org/10.1016/j.procir.2023.02.185>
- Drees, T., Ralfs, L., Reimeir, B., Lemmerz, K., Weidner, R., & Kuhlenkötter, B. (2025). Methodology for the knowledge-based selection of occupational exoskeletons. *Production Engineering*, 19, 763–780. <https://doi.org/10.1007/s11740-025-01338-x>
- D'souza, R. N., Huang, P.-Y., & Yeh, F.-C. (2020). Structural analysis and optimization of convolutional neural networks with a small sample size. *Scientific Reports*, 10(1), 834. <https://doi.org/10.1038/s41598-020-57866-2>
- Dunson-Todd, M., Nik-Bakht, M., & Hammad, A. (2024). Experimental evaluation of exoskeletons for rebar workers using a realistic controlled test. In V. A. González, J. Zhang, B. García de Soto, & I. Brilakis (Eds.), *Proceedings of the 41st International Symposium on Automation and Robotics in Construction (ISARC 2024)* (pp. 513–520). International Association for Automation and Robotics in Construction. <https://doi.org/10.22260/ISARC2024/0067>
- Fan, C., Mei, Q., & Li, X. (2024). 3D pose estimation dataset and deep learning-based ergonomic risk assessment in construction. *Automation in Construction*, 164, 105452. <https://doi.org/10.1016/j.autcon.2024.105452>
- Fasoyinu, A. A., Azhar, S., Sattineni, A., & Toyin, J. O. (2025). Wearable sensing devices for construction safety: Research trends, applications, challenges, and future opportunities. *Automation in Construction*, 179, 106424. <https://doi.org/10.1016/j.autcon.2025.106424>
- Fournier, D. E., Yung, M., Somasundram, K. G., Du, B. B., Rezvani, S., & Yazdani, A. (2023). Quality, productivity, and economic implications of exoskeletons for occupational use: A systematic review. *PLOS ONE*, 18(6), e0287742. <https://doi.org/10.1371/journal.pone.0287742>
- Frontline Systems. (n.d.). Excel Solver – Algorithms and methods used. <https://www.solver.com/excel-solver-algorithms-and-methods-used>
- Gallagher, S., & Heberger, J. R. (2013). Examining the interaction of force and repetition on musculoskeletal disorder risk: A systematic literature review. *Human Factors*, 55(1), 108–124. <https://doi.org/10.1177/0018720812449648>
- Golabchi, A., Chao, A., & Tavakoli, M. (2022). A systematic review of industrial exoskeletons for injury prevention: Efficacy evaluation metrics, target tasks, and supported body postures. *Sensors*, 22(7), 2714. <https://doi.org/10.3390/s22072714>
- Gómez-Ambrosi, J., Silva, C., Catalán, V., Rodríguez, A., Galofré, J. C., Escalada, J., Valentí, V., Rotellar, F., Romero, S., Ramírez, B., Salvador, J., & Frühbeck, G. (2012). Clinical usefulness of a new equation for estimating body fat. *Diabetes Care*, 35(2), 383–388. <https://doi.org/10.2337/dc11-1334>
- Gonsalves, N. J., Ogunseiju, O. R., Akanmu, A. A., & Nnaji, C. A. (2021). Assessment of a passive wearable robot for reducing low back disorders during rebar work. *Journal of Information Technology in Construction*, 26, 936–952. <https://doi.org/10.36680/J.ITCON.2021.050>
- Gonsalves, N., Akanmu, A., Gao, X., Agee, P., & Shojaei, A. (2023). Industry perception of the suitability of wearable robot for construction work. *Journal of Construction Engineering and Management*, 149(5), 04023017. <https://doi.org/10.1061/JCEMD4.COENG-12762>

- Gregory, J. M. (2024). Modeling VO₂max with relative fitness and BMI. *Journal of Biosciences and Medicines*, 12(12), 466–492. <https://doi.org/10.4236/jbm.2024.1212037>
- Guo, H., Yu, Y., Xiang, T., Li, H., & Zhang, D. (2017). The availability of wearable-device-based physical data for the measurement of construction workers' psychological status on site: From the perspective of safety management. *Automation in Construction*, 82, 207–217. <https://doi.org/10.1016/j.autcon.2017.06.001>
- Halek, R. B. A., Dev, A., Chew, K. H., & Hannan, M. A. (2025). Evaluation of validity and reliability of Rapid Upper Limb Assessment (RULA) method in research experiment: A systematic review. *Open Journal of Safety Science and Technology*, 15(1), 1–13. <https://doi.org/10.4236/ojsst.2025.151001>
- Harbin, M. (2006, July 1). Refrigerant Safety 101. Facilitiesnet. <https://www.facilitiesnet.com/hvac/article/Refrigerant-Safety-101--4833>
- Harris, W., Dufoe, D., Brooks, R. D., & Trueblood, A. (2025, June). Musculoskeletal disorder (MSD) trends in construction [Data bulletin]. CPWR – The Center for Construction Research and Training. <https://stacks.cdc.gov/view/cdc/260014>
- Herzing College. (n.d.). Typical HVAC careers and salaries [Photograph]. <https://blog.herzing.ca/trades/typical-hvac-careers-and-salaries>
- Hita-Gutiérrez, M., Gómez-Galán, M., Díaz-Palau, A., Callejón-Ferre, Á. J., & Pérez-Alonso, J. (2020). An overview of REBA method applications in the world. *International Journal of Environmental Research and Public Health*, 17(8), 2635. <https://doi.org/10.3390/ijerph17082635>
- Hsie, M., Hsiao, W.-T., Cheng, T.-M., & Chen, H.-C. (2009). A model used in creating a work-rest schedule for laborers. *Automation in Construction*, 18(6), 762–769. <https://doi.org/10.1016/j.autcon.2009.02.010>
- Huangfu, Q., & Hall, J. A. J. (2018). Parallelizing the dual revised simplex method. *Mathematical Programming Computation*, 10(1), 119–142. <https://doi.org/10.1007/s12532-017-0130-5>
- Hughes Plumbing Services. (n.d.). *Emergency plumber – Newbury Park* [Photograph]. <https://hughesplumbingservices.com/emergency-plumber-newbury-park/>
- Hwang, S., Seo, J., Jebelli, H., & Lee, S. (2016). Feasibility analysis of heart rate monitoring of construction workers using a photoplethysmography (PPG) sensor embedded in a wristband-type activity tracker. *Automation in Construction*, 71, 372–381. <https://doi.org/10.1016/j.autcon.2016.08.029>
- Hwang, S., & Lee, S. H. (2017). Wristband-type wearable health devices to measure construction workers' physical demands. *Automation in Construction*, 83, 330–340. <https://doi.org/10.1016/j.autcon.2017.06.003>
- Infrastructure Health & Safety Association. (2017, March 31). Rate Group 707 - Mechanical and Sheet Metal Work – Member Firm Injury Performance. IHSA. <https://www.ihsa.ca/pdfs/statistics-research/2016/injury-performance-data/rate-group-707.pdf>
- Infrastructure Health & Safety Association. (2019, August). Construction Health and Safety Manual. IHSA. https://www.ihsa.ca/resources/health_safety_manual.aspx

- Infrastructure Health & Safety Association. (2020). Rate Group 707 – Mechanical and Sheet Metal Work – Member Firm Injury Performance, 2015–2019. IHSA. <https://www.ihsa.ca/pdfs/statistics-research/2019/injury-performance-data/rate-group-707.pdf>
- Infrastructure Health & Safety Association. (2023a). Personal Protective Equipment (PPE). IHSA. https://www.ihsa.ca/topics_hazards/ppe.aspx
- Infrastructure Health & Safety Association. (2023b). IHSA Training Course List. IHSA. <https://www.ihsa.ca/Training/Course-List>
- Infrastructure Health & Safety Association. (2023c). Eight Best Practices for Independent Operators and Small Businesses. IHSA. <https://www.ihsa.ca/SmallBusiness/8-best-practices-for-io-sb.aspx>
- Jamshidi, E. J., Yusup, Y., Kayode, J. S., & Kamaruddin, M. A. (2022). Detecting outliers in a univariate time series dataset using unsupervised combined statistical methods: A case study on surface water temperature. *Ecological Informatics*, 69, 101672. <https://doi.org/10.1016/j.ecoinf.2022.101672>
- Ji, X., Hettiarachchige, R. O., Littman, A. L. E., & Piovesan, D. (2023). Using digital human modelling to evaluate the risk of musculoskeletal injury for workers in the healthcare industry. *Sensors*, 23(5), Article 2781. <https://doi.org/10.3390/s23052781>
- Johnson, L. (2017, February 22). Thorough training, hazard awareness needed for HVAC workers. *The Safety Mag*. <https://www.thesafetymag.com/ca/topics/safety-and-ppe/thorough-training-hazard-awareness-needed-for-hvac-workers/183846>
- Joseph, V. R. (2022). Optimal ratio for data splitting. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 15(4), 531–538. <https://doi.org/10.1002/sam.11583>
- Kee, D. (2022). Systematic comparison of OWAS, RULA, and REBA based on a literature review. *International Journal of Environmental Research and Public Health*, 19(1), 595. <https://doi.org/10.3390/ijerph19010595>
- Kim, H., Kim, K., & Kim, H. (2016). Vision-Based Object-Centric Safety Assessment Using Fuzzy Inference: Monitoring Struck-By Accidents with Moving Objects. *Journal of Computing in Civil Engineering*, 30(4), 04015075. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000562](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000562)
- Kim, I. J. (2017). The Role of Ergonomics for Construction Industry Safety and Health Improvements. *Journal of Ergonomics*, 7(2), e166. <https://doi.org/10.4172/2165-7556.1000e166>
- Kim, J., Lee, K., & Jeon, J. (2024). Systematic literature review of wearable devices and data analytics for construction safety and health. *Expert Systems With Applications*, 257, 125038. <https://doi.org/10.1016/j.eswa.2024.125038>
- Koc, K., Ekmekcioğlu, Ö., & Gurgun, A. P. (2023). Determining susceptible body parts of construction workers due to occupational injuries using inclusive modelling. *Safety Science*, 164, 106157. <https://doi.org/10.1016/j.ssci.2023.106157>
- Kong, Y.-K., Kim, J. H., Shim, H.-H., Shim, J.-W., Park, S.-S., & Choi, K.-H. (2023). Efficacy of passive upper-limb exoskeletons in reducing musculoskeletal load associated with overhead tasks. *Applied Ergonomics*, 109, 103965. <https://doi.org/10.1016/j.apergo.2023.103965>

- Lee, G., Bae, J., Jacobs, J. V., & Lee, S. (2024). Wearable heart rate sensing and critical power-based whole-body fatigue monitoring in the field. *Applied Ergonomics*, 121, 104358. <https://doi.org/10.1016/j.apergo.2024.104358>
- Lei, T., Seo, J., Liang, K., Xu, J., Li, H., Zhou, Y., Khan, M., & Heung, K. H. (2024). Lightweight active soft back exosuit for construction workers in lifting tasks. *Journal of Construction Engineering and Management*, 150(7), 04024073. <https://doi.org/10.1061/JCEMD4.COENG-14490>
- Li, X., Chow, K. H., Zhu, Y., & Lin, Y. (2016). Evaluating the impacts of high-temperature outdoor working environments on construction labor productivity in China: A case study of rebar workers. *Building and Environment*, 95, 42–52. <https://doi.org/10.1016/j.buildenv.2015.09.005>
- Lo, J. H., Lin, L. K., & Hung, C. C. (2023). Real-Time Personal Protective Equipment Compliance Detection Based on Deep Learning Algorithm. *Sustainability (Switzerland)*, 15(1), 391. <https://doi.org/10.3390/su15010391>
- Lung Cancer Center. (n.d.). *HVAC workers and lung cancer* [Photograph]. <https://www.lungcancercenter.com/who-lung-cancer-affects/hvac-workers/>
- Madinei, S., & Nussbaum, M. A. (2023). Estimating lumbar spine loading when using back-support exoskeletons in lifting tasks. *Journal of Biomechanics*, 147, 111439. <https://doi.org/10.1016/j.jbiomech.2023.111439>
- Mahmud, D., Bennett, S. T., Zhu, Z., Adamczyk, P. G., Wehner, M., Veeramani, D., & Dai, F. (2022). Identifying Facilitators, Barriers, and Potential Solutions of Adopting Exoskeletons and Exosuits in Construction Workplaces. *Sensors*, 22(24), 9987. <https://doi.org/10.3390/s22249987>
- Mänttari, S., Rauttola, A.-P., Halonen, J., Karkulehto, J., Säynäjäkangas, P., & Oksa, J. (2023). Effects of an exoskeleton on muscle activity in tasks requiring arm elevation: Part I – Experiments in a controlled laboratory setting. *Work*, 79(2), 739–751. <https://doi.org/10.3233/WOR-230217>
- Matthews, G., & Desmond, P. A. (2002). Task-induced fatigue states and simulated driving performance. *Quarterly Journal of Experimental Psychology Section A*, 55(2), 659–686. <https://doi.org/10.1080/02724980143000505>
- McMorrow, S. (2020a, March 5). HVAC Technician Tool List: Must-have Tools for Service. HVACR Career Connect NY. <https://hvacrcareerconnectny.com/hvac-technician-tool-list/>
- McMorrow, S. (2020b, August 20). Refrigeration & HVAC Safety Tips for Technicians. HVACR Career Connect NY. <https://hvacrcareerconnectny.com/refrigeration-hvac-safety-for-technicians/>
- Mehdizadeh, A., Vinel, A., Hu, Q., Schall, M. C., Gallagher, S., & Sesek, R. F. (2020). Job rotation and work-related musculoskeletal disorders: a fatigue-failure perspective. *Ergonomics*, 63(4), 461–476. <https://doi.org/10.1080/00140139.2020.1717644>
- Milosevic, B., Benatti, S., & Farella, E. (2017). Design challenges for wearable EMG applications. In *Design, Automation & Test in Europe Conference & Exhibition (DATE)* (pp. 1432–1437). IEEE. <https://doi.org/10.23919/DATE.2017.7927217>

- Milwaukee Tool. (n.d.-a). HVAC career [Photograph]. One Key Resources. <https://onekeyresources.milwaukeeetool.com/en/hvac-career>
- Milwaukee Tool. (n.d.-b). Plumbing career [Photograph]. One Key Resources. <https://onekeyresources.milwaukeeetool.com/en/plumbing-career>
- Mohapatra, S., Verma, A., & Girish, N. (2022). Lifting capacity prediction model using physical performance measures among construction workers. *Scientific Reports*, 12(1), 1096. <https://doi.org/10.1038/s41598-022-05106-0>
- Monica, L., Draicchio, F., Ortiz, J., Chini, G., Toxiri, S., & Anastasi, S. (2021). Occupational Exoskeletons: A New Challenge for Human Factors, Ergonomics and Safety Disciplines in the Workplace of the Future. *Lecture Notes in Networks and Systems*, 222 LNNS, 118–127. https://doi.org/10.1007/978-3-030-74611-7_17
- Motion Lab Systems. (2026). *EMG systems* [Product catalog]. Retrieved June 15, 2026, from <https://motion-labs.myshopify.com/collections/emg-systems>
- Mouser Electronics. (2026). *IMU – inertial measurement unit sensors* [Product catalog]. Retrieved June 15, 2026, from <https://www.mouser.ca/c/?type=IMU+-+Inertial+Measurement+Unit>
- Musso, M., Oliveira, A. S., & Bai, S. (2024). Influence of an upper limb exoskeleton on muscle activity during various construction and manufacturing tasks. *Applied Ergonomics*, 114, 104158. <https://doi.org/10.1016/j.apergo.2023.104158>
- Nath, N. D., Behzadan, A. H., & Paal, S. G. (2020). Deep learning for site safety: Real-time detection of personal protective equipment. *Automation in Construction*, 112, 103085. <https://doi.org/10.1016/j.autcon.2020.103085>
- National Safety Council. (2025). Work injury costs. In *Injury facts*. NSC. <https://injuryfacts.nsc.org/work/costs/work-injury-costs/>
- Neumann, W. P., Wells, R. P., Norman, R. W., Frank, J., Shannon, H., Kerr, M. S., & the OUBPS Working Group. (2001). A posture and load sampling approach to determining low-back pain risk in occupational settings. *International Journal of Industrial Ergonomics*, 27(2), 65–77. [https://doi.org/10.1016/S0169-8141\(00\)00038-X](https://doi.org/10.1016/S0169-8141(00)00038-X)
- Nguyen, Q. H., Ly, H.-B., Ho, L. S., Al-Ansari, N., Le, H. V., Tran, V. Q., Prakash, I., & Pham, B. T. (2021). Influence of data splitting on performance of machine learning models in prediction of shear strength of soil. *Mathematical Problems in Engineering*, 2021, 4832864. <https://doi.org/10.1155/2021/4832864>
- Occupational Health and Safety Act (OHSA), R.S.O. 1990, c. O.1. (2025, November 27). <https://www.ontario.ca/laws/statute/90o01#BK47>
- Occupational Health and Safety Act (OHSA), R.S.O. 1990, c. O.1. O. Reg. 213/91: Construction Projects. (2026, April 20). <https://www.ontario.ca/laws/regulation/910213>
- Occupational Health and Safety Act (OHSA), R.S.O. 1990, c. O.1. O. Reg. 297/13: Occupational Health and Safety Awareness Training. (2021, January 1). <https://www.ontario.ca/laws/regulation/130297>
- Occupational Health and Safety Act (OHSA), R.S.O. 1990, c. O.1. Reg. 851: Industrial Establishments. (2022, July 1). <https://www.ontario.ca/laws/regulation/900851>

- Occupational Safety and Health Administration. (n.d.). Construction Industry. United States Department of Labor. <https://www.osha.gov/construction>
- Ojelade, A., Morris, W., Kim, S., Kelson, D., Srinivasan, D., Smets, M., & Nussbaum, M. A. (2023). Three passive arm-support exoskeletons have inconsistent effects on muscle activity, posture, and perceived exertion during diverse simulated pseudo-static overhead nutrunning tasks. *Applied Ergonomics*, 110, 104015. <https://doi.org/10.1016/j.apergo.2023.104015>
- Ojha, A., Gautam, Y., Jebelli, H., & Akanmu, A. (2024). Physiological impact of powered back-support exoskeletons in construction: Analyzing muscle fatigue, metabolic cost, ergonomic risks, and stability. *Automation in Construction*, 168, 105742. <https://doi.org/10.1016/j.autcon.2024.105742>
- Okunola, A., Afolabi, A., Akanmu, A., & Jebelli, H. (2024). Facilitators and barriers to the adoption of active back-support exoskeletons in the construction industry. *Journal of Safety Research*, 90, 402–415. <https://doi.org/10.1016/j.jsr.2024.05.010>
- Okunola, A., Akanmu, A., Jebelli, H., & Afolabi, A. (2025). Assessment of active back-support exoskeleton on carpentry framing tasks: Muscle activity, range of motion, discomfort, and exertion. *International Journal of Industrial Ergonomics*, 107, 103716. <https://doi.org/10.1016/j.ergon.2025.103716>
- Ortiz, B. L., Gupta, V., Kumar, R., Jalin, A., Cao, X., Ziegenbein, C., Singhal, A., Tewari, M., & Choi, S. W. (2024). Data preprocessing techniques for AI and machine learning readiness: Scoping review of wearable sensor data in cancer care. *JMIR mHealth and uHealth*, 12, e59587. <https://doi.org/10.2196/59587>
- Padula, R. S., Comper, M. L. C., Sparer, E. H., & Dennerlein, J. T. (2017). Job rotation designed to prevent musculoskeletal disorders and control risk in manufacturing industries: A systematic review. *Applied Ergonomics*, 58, 386–397. <https://doi.org/10.1016/j.apergo.2016.07.018>
- Pappas Parts & Service. (n.d.). *Ductless mini-split repair* [Photograph]. <https://pappaspartsandservice.com/>
- Park, S., Seong, S., Ahn, Y., & Kim, H. (2023). Real-Time Fatigue Evaluation Using Ecological Momentary Assessment and Smartwatch Data: An Observational Field Study on Construction Workers. *Journal of Management in Engineering*, 39(3), 04023008. <https://doi.org/10.1061/JMENEAE.2023.4953>
- Peterson, M. (2018, August 18). 5 Important Safety Guidelines for New HVAC Technicians. *Contracting Business*. <https://www.contractingbusiness.com/residential-hvac/article/20870479/5-important-safety-guidelines-for-new-hvac-technicians>
- Pinho, J. P., & Forner-Cordero, A. (2022). Shoulder muscle activity and perceived comfort of industry workers using a commercial upper limb exoskeleton for simulated tasks. *Applied Ergonomics*, 101, 103718. <https://doi.org/10.1016/j.apergo.2022.103718>
- Pomerleau. (2022, May 26). Exoskeletons: The future of construction productivity augmentation. Pomerleau. <https://pomerleau.ca/en/article/innovation/exoskeletons-future-construction-productivity-augmentation>
- Probst, P., Boulesteix, A.-L., & Bischl, B. (2019). Tunability: Importance of hyperparameters of machine learning algorithms. *Journal of Machine Learning Research*, 20(53), 1–32. <https://doi.org/10.48550/arXiv.1802.09596>

- Qu, Y., Wang, X., Tang, X., Liu, X., Hao, Y., Zhang, X., Liu, H., & Cheng, X. (2025). A review of wearable back-support exoskeletons for preventing work-related musculoskeletal disorders. *Biomimetics*, 10(5), 337. <https://doi.org/10.3390/biomimetics10050337>
- Ratke, E. J., McMaster, H., Vellucci, C. L., Larson, D. J., Holmes, M. W. R., & Beaudette, S. M. (2025). Ability of a passive back-support exoskeleton to mitigate fatigue-related adaptations in a complex repetitive lifting task. *Journal of Biomechanics*, 181, 112553. <https://doi.org/10.1016/j.jbiomech.2025.112553>
- Refrigeration and Air Conditioning Labour-Management Health and Safety Committee. (2021, March). Refrigeration and Air-Conditioning Trade – Health and Safety Manual. IHSA. <https://www.ihsa.ca/PDFs/Products/Id/M074.pdf>
- Schwartz, A. H., Albin, T. J., & Gerberich, S. G. (2019). Intra-rater and inter-rater reliability of the Rapid Entire Body Assessment (REBA) tool. *International Journal of Industrial Ergonomics*, 71, 111–116. <https://doi.org/10.1016/j.ergon.2019.02.010>
- Schweizer, T., & Gilgen-Ammann, R. (2025). Wrist-worn and arm-worn wearables for monitoring heart rate during sedentary and light-to-vigorous physical activities: Device validation study. *JMIR Cardio*, 9, e67110. <https://doi.org/10.2196/67110>
- Shakourisalim, M., Wang, X., Beltran Martinez, K., Golabchi, A., Komeili, A., & Tavakoli, M. (2024). A comparative study of biomechanical assessments in laboratory and field settings for manual material handling tasks using exoskeletons. *Frontiers in Bioengineering and Biotechnology*, 12, 1358670. <https://doi.org/10.3389/fbioe.2024.1358670>
- Statistics Canada. (2024). Gross domestic product (GDP) at basic prices, by industry, monthly (Table 36-10-0434-01). Government of Canada. <https://doi.org/10.25318/3610043401-eng>
- Stefana, E., Marciano, F., Rossi, D., Cocca, P., & Tomasoni, G. (2021). Wearable devices for ergonomics: A systematic literature review. *Sensors*, 21(3), 777. <https://doi.org/10.3390/s21030777>
- Suresh, V., & Narwade, R. (2022). Smart construction safety helmet: A construction safety tool embedded with health monitoring and salary deduction function. In *Sustainable Technology and Advanced Computing in Electrical Engineering: Proceedings of ICSTACE 2021* (pp. 1149–1168). Springer.
- The Business Research Company. (2025). Construction wearable technology global market report 2025. The Business Research Company. <https://www.thebusinessresearchcompany.com/report/construction-wearable-technology-global-market-report>
- Treasury Board of Canada Secretariat. (2023). Directive on Accounting Standards: GC 1010 Financial Statement Concepts (Materiality). Government of Canada. <https://www.tbs-sct.canada.ca/pol/doc-eng.aspx?id=32510>
- TuMeke Ergonomics. (2025). TuMeke Risk Suite [Computer software]. <https://www.tumeke.io/product/overview>
- Turner, J. A., Chaaban, C. R., & Padua, D. A. (2024). Validation of OpenCap: A low-cost markerless motion capture system for lower-extremity kinematics during return-to-sport tasks. *Journal of Biomechanics*, 171, 112200. <https://doi.org/10.1016/j.jbiomech.2024.112200>

- U.S. Bureau of Economic Analysis. (2024). Value added by industry: Construction (GDP by industry data). U.S. Department of Commerce. <https://www.bea.gov/data/gdp/gdp-industry>
- U.S. Bureau of Labor Statistics. (2026). Employer-reported workplace injuries and illnesses, 2024 (USD-L-26-0007) [News release]. U.S. Department of Labor. <https://www.bls.gov/iif/>
- Uhlrich, S. D., Falisse, A., Kidziński, Ł., Muccini, J., Ko, M., Chaudhari, A. S., Hicks, J. L., & Delp, S. L. (2023). OpenCap: Human movement dynamics from smartphone videos. *PLOS Computational Biology*, 19(10), e1011462. <https://doi.org/10.1371/journal.pcbi.1011462>
- Umer, W., Antwi-Afari, M. F., Li, H., Szeto, G. P. Y., & Wong, A. Y. L. (2018). The prevalence of musculoskeletal symptoms in the construction industry: A systematic review and meta-analysis. *International Archives of Occupational and Environmental Health*, 91(2), 125–144. <https://doi.org/10.1007/s00420-017-1273-4>
- Umer, W., Li, H., Lu, W., Szeto, G. P. Y., & Wong, A. Y. L. (2018). Development of a tool to monitor static balance of construction workers for proactive fall safety management. *Automation in Construction*, 94, 438–448. <https://doi.org/10.1016/j.autcon.2018.07.024>
- Valero, E., Sivanathan, A., Bosché, F., & Abdel-Wahab, M. (2016). Musculoskeletal disorders in construction: A review and a novel system for activity tracking with body area network. *Applied Ergonomics*, 54, 120–130. <https://doi.org/10.1016/j.apergo.2015.11.020>
- Verdantix. (2025). Global corporate survey 2025: EHS budgets, priorities and tech preferences. Verdantix. <https://www.verdantix.com/venture/report/global-corporate-survey-2025--ehs-budgets--priorities-and-tech-preferences>
- Vinel, A., Mehdizadeh, A., Schall, M. C., Jr., Gallagher, S., & Sesek, R. F. (2018). An Optimization Framework for Job Rotation to Better Assess the Impact on Overall Risk. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 62(1), 843–847. <https://doi.org/10.1177/1541931218621192>
- Walter, T., Stutzig, N., & Siebert, T. (2023). Active exoskeleton reduces erector spinae muscle activity during lifting. *Frontiers in Bioengineering and Biotechnology*, 11, 1143926. <https://doi.org/10.3389/fbioe.2023.1143926>
- Wang, M., Wong, P., Luo, H., Kumar, S., Delhi, V., & Cheng, J. (2019). Predicting safety hazards among construction workers and equipment using computer vision and deep learning techniques. *Proceedings of the 36th ISARC 2019*, 399–406. <https://doi.org/10.22260/isarc2019/0054>
- Wang, X., Dong, X. S., Choi, S. D., & Dement, J. M. (2017). Work-related musculoskeletal disorders among construction workers in the United States from 1992 to 2014. *Occupational and Environmental Medicine*, 74(5), 374–380. <https://doi.org/10.1136/oemed-2016-103943>
- Waqas, M., & Humphries, U. W. (2024). A critical review of RNN and LSTM variants in hydrological time series predictions. *MethodsX*, 13, Article 102946. <https://doi.org/10.1016/j.mex.2024.102946>
- Widyanti, A. (2020). Validity and inter-rater reliability of postural analysis among new raters. *Malaysian Journal of Public Health Medicine*, 20(Special 1), 161–166. <https://doi.org/10.37268/mjphm/vol.20/no.Special1/art.707>

- Workplace Safety and Insurance Board. (2018). Health and safety statistics. <https://safetycheck.onlineservices.wsib.on.ca/safetycheck/explore/search?lang=en>
- Workplace Safety and Insurance Board. (2024). By the numbers: 2023 WSIB statistical report (Schedule 1). WSIB Ontario. <https://www.wsib.ca/en/statisticalreport>
- WorkSafeBC. (2026). Industry health & safety data. WorkSafeBC. <https://www.worksafebc.com/en/about-us/data-insights/industry-health-safety-data>
- Wrenchit Up. (n.d.). 7 precautions for a professional plumber [Photograph]. <https://www.wrenchitup.ca/academy/repository/7-precautions-for-a-professional-plumber/>
- Yan, X., Li, H., Wang, C., Seo, J., Zhang, H., & Wang, H. (2017). Development of ergonomic posture recognition technique based on 2D ordinary camera for construction hazard prevention through view-invariant features in 2D skeleton motion. *Advanced Engineering Informatics*, 34, 152–163. <https://doi.org/10.1016/j.aei.2017.11.001>
- Yan, Z., Han, B., Du, Z., Huang, T., Bai, O., & Peng, A. (2021). Development and testing of a wearable passive lower-limb support exoskeleton to support industrial workers. *Biocybernetics and Biomedical Engineering*, 41(1), 221–238. <https://doi.org/10.1016/j.bbe.2020.12.010>
- Yang, B., Zhang, B., Zhang, Q., Wang, Z., Dong, M., & Fang, T. (2022). Automatic detection of falling hazard from surveillance videos based on computer vision and building information modeling. *Structure and Infrastructure Engineering*, 18(7), 1049–1063. <https://doi.org/10.1080/15732479.2022.2039217>
- Yang, L., & Shami, A. (2020). On hyperparameter optimization of machine learning algorithms: Theory and practice. *Neurocomputing*, 415, 295–316. <https://doi.org/10.1016/j.neucom.2020.07.061>
- Yoon, J., Park, J., Lee, C.-h., & Bang, Y.-b. (2024). Upper limb power-assist wearable robot for handling repetitive medium- to low-weight loads in daily logistics tasks. *Robotics and Autonomous Systems*, 181, 104780. <https://doi.org/10.1016/j.robot.2024.104780>
- Yu, Y., Li, H., Yang, X., Kong, L., Luo, X., & Wong, A. Y. L. (2019a). An automatic and non-invasive physical fatigue assessment method for construction workers. *Automation in Construction*, 103, 1–12. <https://doi.org/10.1016/j.autcon.2019.02.020>
- Yu, Y., Umer, W., Yang, X., & Antwi-Afari, M. F. (2021). Posture-related data collection methods for construction workers: A review. *Automation in Construction*, 124, 103538. <https://doi.org/10.1016/j.autcon.2020.103538>
- Yu, Y., Yang, X., Li, H., Luo, X., Guo, H., & Fang, Q. (2019b). Joint-Level Vision-Based Ergonomic Assessment Tool for Construction Workers. *Journal of Construction Engineering and Management*, 145(5), 04019025. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001647](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001647)
- Zhang, J., Zhang, D., Liu, X., Liu, R., & Zhong, G. (2019a). A framework of on-site construction safety management using computer vision and real-time location system. *ICSIC 2019*, 327–333. <https://doi.org/10.1680/icsic.64669.327>
- Zhang, L., Diraneyya, M. M., Ryu, J., Haas, C. T., & Abdel-Rahman, E. (2019b). Automated monitoring of physical fatigue using jerk. *Proceedings of the 36th ISARC 2019*, 989–997. <https://doi.org/10.22260/isarc2019/0132>

- Zhang, M., Sparer, E. H., Murphy, L. A., Dennerlein, J. T., Fang, D., Katz, J. N., & Caban-Martinez, A. J. (2015). Development and validation of a fatigue assessment scale for U.S. construction workers. *American Journal of Industrial Medicine*, 58(2), 220–228.
<https://doi.org/10.1002/ajim.22411>
- Zheng, L., Pan, C., Wei, L., Bahreinizad, H., Chowdhury, S., Ning, X., & Santos, F. (2024). Shoulder-assist exoskeleton effects on balance and muscle activity during a block-laying task on a simulated mast climber. *International Journal of Industrial Ergonomics*, 104, 103652.
<https://doi.org/10.1016/j.ergon.2024.103652>
- Zhu, Z., Dutta, A., & Dai, F. (2021). Exoskeletons for manual material handling – A review and implication for construction applications. *Automation in Construction*, 122, 103493.
<https://doi.org/10.1016/j.autcon.2020.103493>
- Zingman, A., Earnest, S., Lowe, B. D., & Branche, C. M. (2017, June 15). Exoskeletons in construction: Will they reduce or create hazards? Centers for Disease Control and Prevention.
<https://blogs.cdc.gov/niosh-science-blog/2017/06/15/exoskeletons-in-construction/>

Appendices

Appendix A: Wearable Support Devices Considered

Back			
Product	Support	Description	Image
Apex 2	Passive	Back-support device that provides up to 100 lb of relief during repetitive lifting tasks	
Auxivo LiftSuit	Passive	Provides 240 N (approx. 63 lb) of support during lifting tasks. Weighs 2 lb	
Biolift	Passive	Exoskeleton that uses compressed air spring technology to provide up to 44 lb of lumbar support during repetitive lifting and bending tasks. Total weight: 8.8 lb	
CX Soft Back	Passive	Aids with posture control for standing and lifting. Supports light-duty tasks only.	
Hybrid Assisted Limb (HAL) for Labour Support	Active	Bioelectric exoskeleton supports the back during heavy lifting. Its headgear reads muscle signals and moves the device as per the user's intentions. Weighs 7 pounds, fits users 120-180 cm tall and weighing 40-80 kg, and runs for 4.5 hours on a single charge.	
IX Back air	Passive	Adjustable back-support device that reduces lumbar muscle loading during lifting, bending, and stooping. Captures and redistributes the user's biomechanical energy. Delivers up to 33 lb of back assistance while weighing just 6.8 lb	
IX Back	Passive	A heavy-duty exoskeleton that provides up to 55 lb of back support for demanding lifting tasks. It encourages proper posture by transferring upper-body loads to the thighs, reducing lower back strain.	

Laevo Flex	Passive	Back-supporting exoskeleton that provides relief during repetitive motions	
Muscle Suit	Active	Device that reduces lifting strain by generating up to 56 pounds of force. Weighing 8 pounds, the system utilizes pneumatic artificial muscles powered by a back-mounted high-pressure compressed-air cylinder.	
Paexo Back	Passive	Supports pick-and-carry tasks by transferring the load from the back to the legs. Weighs 9 lb and provides 55 lb of relief. Adjustable support level and accommodates heights of 160-190 cm.	
Personal Lift Assist Device	Passive	Decreases spinal compressive and shear forces as well as reduces lower back muscle activation during lifting, lowering and forward bending tasks.	
SafeLift	Active	Motorized exoskeleton providing up to 240 N of lifting assistance during repetitive tasks, with integrated movement tracking for ergonomic risk assessment.	
Skelex Edge	Passive	Back-support exoskeleton that reduces back muscle activation by up to 40% during lifting and repetitive tasks. Includes integrated knee pads and weighs 0.55 lb.	

Leg			
Product	Support	Description	Image
Angel suit	Active	Motorized, custom-fitted knee-ankle-foot orthosis with controllers, sensors, and a battery pack. Weighs 20 lb and supports up to 80 kg. Operates for ~2 hours on a single charge. Allows 5° of knee extension and 115° of flexion, with 30° of hip extension and 130° of flexion.	
Ascend	Active	Battery-powered pneumatic device that supports the knee, eliminating quadricep muscle strain and improving mobility. With the battery and air compressor in the backpack, it weighs 11-12 pounds.	
Chairless Chair	Passive	Relieves muscle strain in the lower back, legs, and knees by allowing quick transitions between sitting, standing, and walking. Weighs 6.6 lb and features adjustable sitting angles.	
CX Soft Knee	Passive	Cushioning knee pads that protect knees from pressure and impact when kneeling on hard surfaces.	
Knee Brace	Passive	Device that prevents or supports the knee during injury recovery.	

Shoulder			
Product	Support	Description	Image
Ekso EVO	Passive	Adjustable spring device that provides customized support for overhead work, between 5-15 lb per arm.	
EXHAUSS Stronger	Passive	Shoulder flexor load reduction during lifting or holding objects above the waistline using spring-loaded arms, transferring the load to the harness.	
ExoActive	Active	Motorized device that supports overhead activities to reduce shoulder, arm, and neck loads. Features adjustable support areas (waist-up, chest-up, or overhead). Up to 50N/11 lb of assistive force.	
EXO-S	Passive	Redistributes weight during overhead work to reduce load on shoulder and neck muscles. Weighs 5 lb.	
Fawcett Exovest with zeroG2 arm	Passive	Acts as a third arm, supporting tool weight by transferring it to the pelvis. Uses pads to avoid compression of abdomen, spine, neck, and shoulders. Permits unrestricted breathing and arm movement by removing chest straps. Weighs 11 lb.	
H-Vex (Hyundai Vest Exoskeleton)	Passive	132 lb of relief during repetitive or heavy load overhead work by reducing strain on the musculoskeletal system. Weighs 6 lb.	
IX Shoulder Air	Passive	Reduces shoulder stress by up to 40% during overhead tasks by transferring load from shoulder to hips. Weighs 4.9 lb	

Paexo Shoulder	Passive	Supports the shoulder during overhead tasks by transferring the load to the hips. Adjustable support levels and accommodates heights between 160 and 190 cm. Weighs 4 lb.	
Shoulder Brace	Passive	Low-level support and compression to prevent injury or assist the shoulder during recovery.	
Skelex 360-XFR	Passive	Assists overhead work and adjusts between 1 and 9 lb of support per arm. Accommodates users between 150 and 200 cm. Weighs 5 lb.	

Appendix B: Mechanical-Trade Tasks – Field Images

This appendix presents field images of mechanical-trade tasks, grouped by the body region under primary load: back, leg, and shoulder. Full source details appear in the References list.

Back



Leg



Shoulder



Appendix C: Collected Experiment Data (Laboratory and Field)

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	1	Back	NP01	24	0	182	102	2	73	94	21	12	2.37	84	107	23	14	2.14	4	1	2	
Lab	2	Back	NP01	24	0	182	102	2	73	94	21	12	2.37	96	120	24	18	2.12	4	5	1	
Lab	3	Back	NP01	24	0	182	102	2	73	94	21	12	2.37	95	113	18	22	2.09	4	4	2	
Lab	6	Leg	NP01	24	0	182	102	2	70	82	12	17	9	96	102	6	18	9	3	4	2	
Lab	7	Leg	NP01	24	0	182	102	2	70	82	12	17	9	100	107	7	23	8	4	4	2	
Lab	8	Leg	NP01	24	0	182	102	2	70	82	12	17	9	81	98	17	39	9	3	3	3	
Lab	10	Shoulder	NP01	24	0	182	102	2	79	110	31	76	0.21	92	97	5	82	0.2	2	3	1	
Lab	11	Shoulder	NP01	24	0	182	102	2	79	110	31	76	0.21	100	94	10	56	0.22	1	2	1	
Lab	12	Shoulder	NP01	24	0	182	102	2	79	110	31	76	0.21	88	87	6	82	0.13	4	2	5	
Lab	1	Back	NP02	32	0	175	64	2	81	88	7	9	2.08	84	97	13	12	1.92	5	4	1	
Lab	2	Back	NP02	32	0	175	64	2	81	88	7	9	2.08	80	85	5	18	1.89	4	5	2	
Lab	3	Back	NP02	32	0	175	64	2	81	88	7	9	2.08	82	88	6	17	1.88	3	4	2	
Lab	6	Leg	NP02	32	0	175	64	2	79	90	11	12	8	79	82	3	9	8	3	4	2	
Lab	7	Leg	NP02	32	0	175	64	2	79	90	11	12	8	86	96	10	12	8	5	4	2	
Lab	8	Leg	NP02	32	0	175	64	2	79	90	11	12	8	87	93	6	16	8	5	5	2	
Lab	10	Shoulder	NP02	32	0	175	64	2	84	92	8	66	0.16	93	100	7	82	0.16	2	4	2	
Lab	11	Shoulder	NP02	32	0	175	64	2	84	92	8	66	0.16	88	94	6	68	0.15	5	3	1	
Lab	12	Shoulder	NP02	32	0	175	64	2	84	92	8	66	0.16	80	109	29	129	0.09	4	5	5	
Lab	1	Back	NP03	22	1	164	66	2	92	104	12	11	2.03	100	114	14	16	1.95	4	2	2	
Lab	2	Back	NP03	22	1	164	66	2	92	104	12	11	2.03	100	116	16	19	1.89	4	5	2	
Lab	3	Back	NP03	22	1	164	66	2	92	104	12	11	2.03	98	120	22	22	1.92	4	4	3	
Lab	6	Leg	NP03	22	1	164	66	2	82	95	13	44	7	103	113	10	53	7	4	4	2	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	7	Leg	NP03	22	1	164	66	2	82	95	13	44	7	108	115	7	79	6	4	5	3	
Lab	8	Leg	NP03	22	1	164	66	2	82	95	13	44	7	102	113	11	53	7	2	4	3	
Lab	10	Shoulder	NP03	22	1	164	66	1	84	95	11	69	0.18	103	113	10	57	0.18	3	3	1	
Lab	11	Shoulder	NP03	22	1	164	66	1	84	95	11	69	0.18	102	115	13	69	0.18	4	2	2	
Lab	12	Shoulder	NP03	22	1	164	66	1	84	95	11	69	0.18	102	113	11	85	0.11	3	4	5	
Lab	2	Back	NP04	24	0	178	73	3	109	110	20	60	1.92	102	100	21	45	1.83	2	3	1	
Lab	3	Back	NP04	24	0	178	73	3	109	110	20	60	1.92	106	108	2	62	1.79	3	2	2	
Lab	4	Back	NP04	24	0	178	73	3	109	110	20	60	1.92	105	110	5	50	1.28	3	3	2	
Lab	7	Leg	NP04	24	0	178	73	3	108	115	7	42	8	111	118	7	29	5	3	2	1	
Lab	8	Leg	NP04	24	0	178	73	3	108	115	7	42	8	100	102	2	28	4	2	3	2	
Lab	9	Leg	NP04	24	0	178	73	3	108	115	7	42	8	105	112	7	94	6	5	2	5	
Lab	11	Shoulder	NP04	24	0	178	73	3	112	113	13	161	0.19	104	103	10	98	0.19	3	5	1	
Lab	12	Shoulder	NP04	24	0	178	73	3	112	113	13	161	0.19	103	103	6.4	172	0.11	5	3	4	
Lab	2	Back	NP05	34	0	164	59	3	110	133	23	23	2.04	100	109	9	41	1.97	4	5	2	
Lab	3	Back	NP05	34	0	164	59	3	110	133	23	23	2.04	94	125	31	32	1.98	3	4	2	
Lab	4	Back	NP05	34	0	164	59	3	110	133	23	23	2.04	89	118	29	36	1.43	4	3	3	
Lab	7	Leg	NP05	34	0	164	59	2	102	114	12	24	8	103	111	8	28	8	4	3	1	
Lab	8	Leg	NP05	34	0	164	59	2	102	114	12	24	8	93	118	25	41	6	3	4	1	
Lab	9	Leg	NP05	34	0	164	59	2	102	114	12	24	8	88	100	12	224	7	5	2	5	
Lab	11	Shoulder	NP05	34	0	164	59	3	98	99	13	118	0.2	100	100	10	119	0.19	3	1	1	
Lab	12	Shoulder	NP05	34	0	164	59	3	98	99	13	118	0.2	98	96	6.4	126	0.12	5	2	5	
Lab	2	Back	NP06	34	1	177	59	2	99	117	18	30	2.36	89	127	38	34	2.3	4	5	2	
Lab	3	Back	NP06	34	1	177	59	2	99	117	18	30	2.36	84	116	32	34	2.34	4	4	2	
Lab	4	Back	NP06	34	1	177	59	2	99	117	18	30	2.36	81	85	4	31	1.61	4	4	4	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	7	Leg	NP06	34	1	177	59	2	92	105	13	13	8	88	101	13	23	8	3	4	1
Lab	8	Leg	NP06	34	1	177	59	2	92	105	13	13	8	90	99	9	33	7	3	4	1
Lab	9	Leg	NP06	34	1	177	59	2	92	105	13	13	8	101	98	7	62	7	4	3	4
Lab	11	Shoulder	NP06	34	1	177	59	2	81	98	17	106	0.2	100	103	3	115	0.2	3	3	2
Lab	12	Shoulder	NP06	34	1	177	59	2	81	98	17	106	0.2	93	93	0	120	0.12	5	3	4
Lab	1	Back	NP07	23	0	180	83	3	74	119	45	35	2.12	95	136	41	22	2.1	3	4	1
Lab	2	Back	NP07	23	0	180	83	3	74	119	45	35	2.12	103	132	29	30	1.98	2	2	1
Lab	3	Back	NP07	23	0	180	83	3	74	119	45	35	2.12	104	146	42	42	1.88	3	5	2
Lab	4	Back	NP07	23	0	180	83	3	74	119	45	35	2.12	103	142	39	29	1.54	3	2	4
Lab	7	Leg	NP07	23	0	180	83	3	91	111	20	40	7	105	106	1	35	7	3	2	2
Lab	8	Leg	NP07	23	0	180	83	3	91	111	20	40	7	105	112	7	22	7	1	3	2
Lab	9	Leg	NP07	23	0	180	83	3	91	111	20	40	7	123	106	7	40	6	1	1	3
Lab	10	Shoulder	NP07	23	0	180	83	3	92	97	5	86	0.2	105	95	11	35	0.19	3	2	2
Lab	11	Shoulder	NP07	23	0	180	83	3	92	97	5	86	0.2	108	94	10	94	0.19	2	4	2
Lab	12	Shoulder	NP07	23	0	180	83	3	92	97	5	86	0.2	97	93	6	73	0.13	5	3	5
Lab	1	Back	NP08	25	0	183	84	2	118	149	31	15	1.98	95	144	49	22	1.88	5	4	2
Lab	2	Back	NP08	25	0	183	84	2	118	149	31	15	1.98	106	141	35	24	1.86	5	5	1
Lab	3	Back	NP08	25	0	183	84	2	118	149	31	15	1.98	125	145	20	19	1.8	2	5	3
Lab	4	Back	NP08	25	0	183	84	2	118	149	31	15	1.98	111	141	30	19	1.57	4	2	4
Lab	7	Leg	NP08	25	0	183	84	2	115	134	19	53	8	105	123	18	26	7	5	4	2
Lab	8	Leg	NP08	25	0	183	84	2	115	134	19	53	8	113	133	20	28	8	1	5	2
Lab	9	Leg	NP08	25	0	183	84	2	115	134	19	53	8	126	128	2	53	6	1	1	5
Lab	11	Shoulder	NP08	25	0	183	84	2	116	117	13	53	0.22	118	111	10	69	0.21	5	1	1
Lab	12	Shoulder	NP08	25	0	183	84	2	116	117	13	53	0.22	113	114	1	64	0.14	5	5	5

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	1	Back	NP09	22	0	175	60	2	103	146	43	20	1.78	103	156	53	24	1.76	3	5	2
Lab	2	Back	NP09	22	0	175	60	2	103	146	43	20	1.78	106	142	36	28	1.78	4	4	2
Lab	3	Back	NP09	22	0	175	60	2	103	146	43	20	1.78	109	151	42	24	1.64	2	5	3
Lab	4	Back	NP09	22	0	175	60	2	103	146	43	20	1.78	101	138	37	22	1.41	4	3	3
Lab	7	Leg	NP09	22	0	175	60	2	104	119	15	31	7	104	113	9	34	7	3	4	2
Lab	8	Leg	NP09	22	0	175	60	2	104	119	15	31	7	119	125	6	12	7	1	5	2
Lab	9	Leg	NP09	22	0	175	60	2	104	119	15	31	7	112	127	15	57	6	4	2	4
Lab	11	Shoulder	NP09	22	0	175	60	2	117	118	13	60	0.16	100	109	9	77	0.17	3	4	1
Lab	12	Shoulder	NP09	22	0	175	60	2	117	118	13	60	0.16	112	112	0	65	0.1	5	4	4
Lab	1	Back	NP10	31	0	168	70	2	88	128	40	19	1.84	96	114	18	25	1.78	4	5	1
Lab	4	Back	NP10	31	0	168	70	2	88	128	40	19	1.84	89	114	25	17	1.41	2	4	2
Lab	6	Leg	NP10	31	0	168	70	2	90	100	10	11	8	94	95	1	25	8	4	3	1
Lab	9	Leg	NP10	31	0	168	70	2	90	100	10	11	8	96	106	10	65	7	4	5	3
Lab	10	Shoulder	NP10	31	0	168	70	2	86	93	7	44	0.19	96	96	0	77	0.19	4	2	1
Lab	12	Shoulder	NP10	31	0	168	70	2	86	93	7	44	0.19	88	94	6	108	0.11	4	4	4
Lab	1	Back	NP11	30	0	172	69	2	89	121	32	22	2.07	89	124	35	24	1.91	5	2	2
Lab	4	Back	NP11	30	0	172	69	2	89	121	32	22	2.07	102	119	17	15	1.58	3	5	2
Lab	6	Leg	NP11	30	0	172	69	2	86	118	32	22	8	103	96	8	30	8	5	4	1
Lab	9	Leg	NP11	30	0	172	69	2	86	118	32	22	8	86	98	12	86	6	4	4	3
Lab	10	Shoulder	NP11	30	0	172	69	2	95	105	13	48	0.15	100	88	11	83	0.15	5	2	1
Lab	12	Shoulder	NP11	30	0	172	69	2	95	105	13	48	0.15	86	103	17	104	0.08	4	5	5
Lab	1	Back	NP12	23	0	175	79	2	104	137	33	20	1.92	100	152	52	30	1.77	5	2	1
Lab	4	Back	NP12	23	0	175	79	2	104	137	33	20	1.92	102	150	48	23	1.68	4	5	2
Lab	6	Leg	NP12	23	0	175	79	2	110	125	15	30.12	8	119	129	10	31	8	4	4	1

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	9	Leg	NP12	23	0	175	79	2	110	125	15	30.12	8	107	113	6	67	6	3	4	4	
Lab	10	Shoulder	NP12	23	0	175	79	2	105	117	12	70	0.14	103	100	11	73	0.14	4	2	2	
Lab	12	Shoulder	NP12	23	0	175	79	2	105	117	12	70	0.18	106	103	6	92	0.1	5	4	2	
Lab	1	Back	NP13	31	0	181	95	3	76	88	12	13	1.98	88	101	13	13	1.75	4	4	1	
Lab	2	Back	NP13	31	0	181	95	3	76	88	12	13	1.98	77	90	13	15	1.94	4	4	1	
Lab	3	Back	NP13	31	0	181	95	3	76	88	12	13	1.98	78	89	11	15	1.82	4	4	2	
Lab	4	Back	NP13	31	0	181	95	3	76	88	12	13	1.98	82	91	9	16	1.81	4	4	3	
Lab	5	Back	NP13	31	0	181	95	3	76	88	12	13	1.98	83	89	6	22	1.45	3	4	5	
Lab	6	Leg	NP13	31	0	181	95	1	78	86	8	41	9	77	85	8	56	9	3	4	1	
Lab	7	Leg	NP13	31	0	181	95	1	78	86	8	41	9	75	81	6	51	10	2	4	2	
Lab	8	Leg	NP13	31	0	181	95	1	78	86	8	41	9	74	82	8	103	10	3	3	2	
Lab	9	Leg	NP13	31	0	181	95	1	78	86	8	41	9	78	83	5	185	8	4	2	5	
Lab	10	Shoulder	NP13	31	0	181	95	2	81	93	12	47	0.19	80	88	8	26	0.18	4	3	1	
Lab	11	Shoulder	NP13	31	0	181	95	2	81	93	12	47	0.19	78	89	11	28	0.18	3	2	1	
Lab	12	Shoulder	NP13	31	0	181	95	2	81	93	12	47	0.19	79	85	6	49	0.1	4	2	5	
Lab	1	Back	NP14	28	0	181	82	3	65	81	16	13	1.99	66	79	13	14	1.91	4	4	2	
Lab	2	Back	NP14	28	0	181	82	3	65	81	16	13	1.99	63	78	15	15	1.89	4	4	2	
Lab	3	Back	NP14	28	0	181	82	3	65	81	16	13	1.99	66	77	11	11	1.89	5	4	2	
Lab	4	Back	NP14	28	0	181	82	3	65	81	16	13	1.99	67	79	12	28	1.44	5	5	4	
Lab	5	Back	NP14	28	0	181	82	3	65	81	16	13	1.99	69	78	9	27	1.4	4	5	5	
Lab	6	Leg	NP14	28	0	181	82	3	63	72	9	182	10	65	74	9	267	9	5	5	2	
Lab	7	Leg	NP14	28	0	181	82	3	63	72	9	182	10	68	74	6	282	9	5	5	3	
Lab	8	Leg	NP14	28	0	181	82	3	63	72	9	182	10	65	72	7	289	9	5	5	4	
Lab	9	Leg	NP14	28	0	181	82	3	63	72	9	182	10	71	78	7	472	9	4	5	5	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	10	Shoulder	NP14	28	0	181	82	3	71	82	11	73	0.19	63	78	15	67	0.2	4	3	2
Lab	11	Shoulder	NP14	28	0	181	82	3	71	82	11	73	0.19	68	79	11	72	0.18	1	2	2
Lab	12	Shoulder	NP14	28	0	181	82	3	71	82	11	73	0.19	69	75	6	98	0.12	5	1	5
Lab	1	Back	NP15	31	1	155	63	1	81	95	14	10	2.27	76	85	9	8	2.3	4	4	1
Lab	2	Back	NP15	31	1	155	63	1	81	95	14	10	2.27	78	93	15	10	2.2	5	5	1
Lab	3	Back	NP15	31	1	155	63	1	81	95	14	10	2.27	77	90	13	10	2.22	5	5	1
Lab	4	Back	NP15	31	1	155	63	1	81	95	14	10	2.27	74	88	14	12	1.86	5	5	3
Lab	5	Back	NP15	31	1	155	63	1	81	95	14	10	2.27	76	84	8	21	1.75	4	5	4
Lab	6	Leg	NP15	31	1	155	63	3	77	85	8	74	9	75	82	7	65	9	5	4	1
Lab	7	Leg	NP15	31	1	155	63	3	77	85	8	74	9	76	83	7	76	8	1	5	2
Lab	8	Leg	NP15	31	1	155	63	3	77	85	8	74	9	79	84	5	99	7	1	2	2
Lab	9	Leg	NP15	31	1	155	63	3	77	85	8	74	9	75	82	7	284	8	3	1	4
Lab	10	Shoulder	NP15	31	1	155	63	2	77	88	11	36	0.19	75	85	10	38	0.18	5	1	1
Lab	11	Shoulder	NP15	31	1	155	63	2	77	88	11	36	0.19	81	88	7	32	0.17	5	3	1
Lab	12	Shoulder	NP15	31	1	155	63	2	77	88	11	36	0.19	74	82	8	82	0.1	5	3	5
Lab	1	Back	NP16	27	0	182	82	3	90	106	16	25	1.98	88	105	17	25	1.8	5	4	2
Lab	2	Back	NP16	27	0	182	82	3	90	106	16	25	1.98	85	99	14	21	1.66	5	4	1
Lab	3	Back	NP16	27	0	182	82	3	90	106	16	25	1.98	91	104	13	27	1.76	5	4	1
Lab	4	Back	NP16	27	0	182	82	3	90	106	16	25	1.98	88	106	18	31	1.7	4	4	3
Lab	5	Back	NP16	27	0	182	82	3	90	106	16	25	1.98	92	103	11	33	1.14	5	4	4
Lab	6	Leg	NP16	27	0	182	82	2	88	96	8	45	8	85	97	12	44	8	5	5	1
Lab	7	Leg	NP16	27	0	182	82	2	88	96	8	45	8	91	98	7	47	8	5	5	1
Lab	8	Leg	NP16	27	0	182	82	2	88	96	8	45	8	83	92	9	56	7	3	4	2
Lab	9	Leg	NP16	27	0	182	82	2	88	96	8	45	8	85	91	6	226	7	4	3	5

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	10	Shoulder	NP16	27	0	182	82	3	81	88	7	68	0.21	78	89	11	76	0.23	4	2	2
Lab	11	Shoulder	NP16	27	0	182	82	3	81	88	7	68	0.21	86	94	8	88	0.17	2	4	1
Lab	12	Shoulder	NP16	27	0	182	82	3	81	88	7	68	0.21	85	88	3	128	0.12	5	3	5
Lab	1	Back	NP17	27	1	164	70	2	81	103	22	18	2.29	87	96	9	21	2.16	5	4	1
Lab	2	Back	NP17	27	1	164	70	2	81	103	22	18	2.29	79	102	23	20	2.18	4	4	1
Lab	3	Back	NP17	27	1	164	70	2	81	103	22	18	2.29	82	104	22	25	1.82	3	5	2
Lab	4	Back	NP17	27	1	164	70	2	81	103	22	18	2.29	84	109	25	24	1.84	4	4	2
Lab	5	Back	NP17	27	1	164	70	2	81	103	22	18	2.29	86	98	12	22	1.2	5	4	5
Lab	6	Leg	NP17	27	1	164	70	3	87	98	11	79	9	81	95	14	83	9	5	5	2
Lab	7	Leg	NP17	27	1	164	70	3	87	98	11	79	9	82	92	10	109	8	3	5	2
Lab	8	Leg	NP17	27	1	164	70	3	87	98	11	79	9	84	93	9	137	8	4	4	1
Lab	9	Leg	NP17	27	1	164	70	3	87	98	11	79	9	83	89	6	162	7	5	4	4
Lab	10	Shoulder	NP17	27	1	164	70	3	76	89	13	75	0.18	94	105	11	70	0.17	5	5	1
Lab	11	Shoulder	NP17	27	1	164	70	3	76	93	17	75	0.18	87	102	15	89	0.16	3	4	1
Lab	12	Shoulder	NP17	27	1	164	70	3	76	93	17	75	0.18	83	88	5	130	0.11	5	4	4
Lab	1	Back	NP18	37	0	190	86	2	92	109	17	21	2.23	88	110	22	22	1.96	5	4	1
Lab	2	Back	NP18	37	0	190	86	2	92	109	17	21	2.23	86	104	18	24	2.18	4	5	2
Lab	3	Back	NP18	37	0	190	86	2	92	109	17	21	2.23	90	102	12	25	1.74	4	4	1
Lab	4	Back	NP18	37	0	190	86	2	92	109	17	21	2.23	85	102	17	30	1.72	4	3	2
Lab	5	Back	NP18	37	0	190	86	2	92	109	17	21	2.23	85	98	13	42	1.24	5	4	3
Lab	6	Leg	NP18	37	0	190	86	3	82	94	12	75	8	80	94	14	46	9	5	5	1
Lab	7	Leg	NP18	37	0	190	86	3	82	94	12	75	8	82	92	10	60	9	3	5	2
Lab	8	Leg	NP18	37	0	190	86	3	82	94	12	75	8	84	95	11	71	9	3	4	2
Lab	9	Leg	NP18	37	0	190	86	3	82	94	12	75	8	81	87	6	167	8	5	4	3

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	10	Shoulder	NP18	37	0	190	86	3	86	98	12	61	0.17	90	101	11	74	0.17	4	5	2	
Lab	11	Shoulder	NP18	37	0	190	86	3	86	98	12	61	0.17	85	94	9	88	0.16	4	4	2	
Lab	12	Shoulder	NP18	37	0	190	86	3	86	98	12	61	0.17	92	97	5	123	0.1	5	3	4	
Lab	1	Back	NP19	65	0	180	108	1	92	124	32	9	2.71	101	140	39	9	2.29	5	4	1	
Lab	2	Back	NP19	65	0	180	108	1	92	124	32	9	2.71	89	121	32	7	2.59	4	4	1	
Lab	3	Back	NP19	65	0	180	108	1	92	124	32	9	2.71	95	122	27	12	2.11	4	4	1	
Lab	4	Back	NP19	65	0	180	108	1	92	124	32	9	2.71	91	116	25	17	1.95	4	5	4	
Lab	5	Back	NP19	65	0	180	108	1	92	124	32	9	2.71	93	111	18	15	1.66	5	4	5	
Lab	6	Leg	NP19	65	0	180	108	1	89	102	13	32	10	91	106	15	35	9	5	4	2	
Lab	7	Leg	NP19	65	0	180	108	1	89	102	13	32	10	95	105	10	42	9	4	5	2	
Lab	8	Leg	NP19	65	0	180	108	1	89	102	13	32	10	88	99	11	40	9	4	3	3	
Lab	9	Leg	NP19	65	0	180	108	1	89	102	13	32	10	93	102	9	137	9	5	2	4	
Lab	10	Shoulder	NP19	65	0	180	108	2	86	95	9	54	0.31	82	92	10	62	0.25	4	2	1	
Lab	11	Shoulder	NP19	65	0	180	108	2	86	95	9	54	0.31	89	102	13	60	0.22	3	4	1	
Lab	12	Shoulder	NP19	65	0	180	108	2	86	95	9	54	0.31	86	91	5	102	0.18	5	2	4	
Lab	1	Back	NP20	61	1	157	64	1	86	106	20	10	2.81	79	98	19	12	2.68	3	4	1	
Lab	2	Back	NP20	61	1	157	64	1	86	106	20	10	2.81	82	106	24	10	2.7	4	4	2	
Lab	3	Back	NP20	61	1	157	64	1	86	106	20	10	2.81	81	101	20	17	2.15	4	3	2	
Lab	4	Back	NP20	61	1	157	64	1	86	106	20	10	2.81	85	106	21	20	2.09	3	4	3	
Lab	5	Back	NP20	61	1	157	64	1	86	106	20	10	2.81	84	98	14	22	1.85	5	4	5	
Lab	6	Leg	NP20	61	1	157	64	2	91	105	14	41	9	91	110	19	61	9	5	4	1	
Lab	7	Leg	NP20	61	1	157	64	2	91	105	14	41	9	86	100	14	56	9	4	5	2	
Lab	8	Leg	NP20	61	1	157	64	2	91	105	14	41	9	89	100	11	63	10	3	5	3	
Lab	9	Leg	NP20	61	1	157	64	2	91	105	14	41	9	85	94	9	91	8	5	3	5	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	10	Shoulder	NP20	61	1	157	64	1	79	98	19	62	0.23	85	101	16	61	0.21	5	4	1
Lab	11	Shoulder	NP20	61	1	157	64	1	79	98	19	62	0.23	95	108	13	83	0.19	4	4	1
Lab	12	Shoulder	NP20	61	1	157	64	1	79	98	19	62	0.23	88	96	8	118	0.15	5	3	5
Lab	1	Back	NP21	63	0	175	99	2	76	101	25	11	2.67	84	109	25	12	2.75	5	5	1
Lab	2	Back	NP21	63	0	175	99	2	76	101	25	11	2.67	86	104	18	9	2.48	5	5	1
Lab	3	Back	NP21	63	0	175	99	2	76	101	25	11	2.67	82	103	21	11	2.56	5	4	2
Lab	4	Back	NP21	63	0	175	99	2	76	101	25	11	2.67	79	95	16	14	2.2	5	5	4
Lab	5	Back	NP21	63	0	175	99	2	76	101	25	11	2.67	85	112	27	18	1.98	3	5	5
Lab	6	Leg	NP21	63	0	175	99	2	81	94	13	22	10	80	95	15	21	9	5	4	2
Lab	7	Leg	NP21	63	0	175	99	2	81	94	13	22	10	77	88	11	20	9	5	4	2
Lab	8	Leg	NP21	63	0	175	99	2	81	94	13	22	10	76	87	11	24	9	5	5	3
Lab	9	Leg	NP21	63	0	175	99	2	81	94	13	22	10	83	89	6	68	9	1	5	3
Lab	10	Shoulder	NP21	63	0	175	99	1	78	95	17	25	0.24	78	96	18	26	0.24	5	1	1
Lab	11	Shoulder	NP21	63	0	175	99	1	78	95	17	25	0.24	81	97	16	23	0.22	5	5	1
Lab	12	Shoulder	NP21	63	0	175	99	1	78	95	17	25	0.24	82	93	11	37	0.16	5	5	3
Lab	1	Back	NP22	58	1	136	60	1	77	98	21	8	2.56	84	109	25	10	2.44	4	4	2
Lab	2	Back	NP22	58	1	136	60	1	77	98	21	8	2.56	85	105	20	7	2.68	5	5	1
Lab	3	Back	NP22	58	1	136	60	1	77	98	21	8	2.56	87	110	23	9	2.48	5	5	2
Lab	4	Back	NP22	58	1	136	60	1	77	98	21	8	2.56	85	104	19	12	2.24	5	5	4
Lab	5	Back	NP22	58	1	136	60	1	77	98	21	8	2.56	78	92	14	13	1.78	5	5	5
Lab	6	Leg	NP22	58	1	136	60	2	77	91	14	22	9	80	95	15	31	10	5	5	1
Lab	7	Leg	NP22	58	1	136	60	2	77	91	14	22	9	83	93	10	26	9	5	5	1
Lab	8	Leg	NP22	58	1	136	60	2	77	91	14	22	9	86	98	12	28	8	5	5	2
Lab	9	Leg	NP22	58	1	136	60	2	77	91	14	22	9	81	91	10	89	8	3	5	5

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	10	Shoulder	NP22	58	1	136	60	2	82	94	12	47	0.22	86	96	10	57	0.24	5	3	3
Lab	11	Shoulder	NP22	58	1	136	60	2	82	94	12	47	0.22	79	87	8	56	0.2	5	5	3
Lab	12	Shoulder	NP22	58	1	136	60	2	82	94	12	47	0.22	77	81	4	65	0.16	5	5	5
Lab	3	Back	NP23	35	1	167	63	2	76	91	15	19	2.09	79	93	14	27	1.84	4	5	2
Lab	4	Back	NP23	35	1	167	63	2	76	91	15	19	2.09	83	96	13	31	1.78	4	4	2
Lab	5	Back	NP23	35	1	167	63	2	76	91	15	19	2.09	81	89	8	36	1.46	5	4	5
Lab	7	Leg	NP23	35	1	167	63	2	84	97	13	68	8	85	98	13	95	8	3	5	1
Lab	8	Leg	NP23	35	1	167	63	2	84	97	13	68	8	82	89	7	127	7	3	4	3
Lab	9	Leg	NP23	35	1	167	63	2	84	97	13	68	8	86	92	6	168	7	5	4	4
Lab	10	Shoulder	NP23	35	1	167	63	2	81	95	14	68	0.21	84	96	12	72	0.19	4	5	1
Lab	11	Shoulder	NP23	35	1	167	63	2	81	95	14	68	0.21	91	100	9	85	0.17	3	4	2
Lab	12	Shoulder	NP23	35	1	167	63	2	81	95	14	68	0.21	83	88	5	119	0.12	5	4	4
Lab	1	Back	NP24	26	1	139	55	3	73	86	13	12	2.04	69	88	19	10	2.09	5	4	1
Lab	2	Back	NP24	26	1	139	55	3	73	86	13	12	2.04	82	96	14	8	1.99	5	5	2
Lab	3	Back	NP24	26	1	139	55	3	73	86	13	12	2.04	71	82	11	10	2.02	5	5	1
Lab	4	Back	NP24	26	1	139	55	3	73	86	13	12	2.04	74	83	9	13	1.86	5	5	3
Lab	5	Back	NP24	26	1	139	55	3	73	86	13	12	2.04	73	79	6	17	1.52	4	5	5
Lab	6	Leg	NP24	26	1	139	55	1	75	82	7	35	9	71	85	14	51	9	5	4	1
Lab	7	Leg	NP24	26	1	139	55	1	75	82	7	35	9	75	83	8	46	8	5	4	2
Lab	8	Leg	NP24	26	1	139	55	1	75	82	7	35	9	72	80	8	43	9	4	5	2
Lab	9	Leg	NP24	26	1	139	55	1	75	82	7	35	9	77	82	5	248	8	2	4	5
Lab	10	Shoulder	NP24	26	1	139	55	2	72	80	8	42	0.2	77	84	7	36	0.2	5	2	1
Lab	11	Shoulder	NP24	26	1	139	55	2	72	80	8	42	0.2	75	86	11	45	0.2	5	5	1
Lab	12	Shoulder	NP24	26	1	139	55	2	72	80	8	42	0.2	81	86	5	108	0.14	5	5	3

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	1	Back	NP25	30	0	178	85	3	68	78	10	22	2.18	71	80	9	21	2.25	4	4	2
Lab	2	Back	NP25	30	0	178	85	3	68	81	13	22	2.18	75	89	14	17	2.12	5	5	1
Lab	3	Back	NP25	30	0	178	85	3	68	81	13	22	2.18	67	78	11	20	2.06	5	5	2
Lab	4	Back	NP25	30	0	178	85	3	68	81	13	22	2.18	72	79	7	25	1.98	5	5	3
Lab	5	Back	NP25	30	0	178	85	3	68	81	13	22	2.18	66	72	6	27	1.72	5	5	5
Lab	6	Leg	NP25	30	0	178	85	3	70	79	9	58	8	66	80	14	65	8	5	4	2
Lab	7	Leg	NP25	30	0	178	85	3	70	79	9	58	8	65	75	10	60	8	5	5	2
Lab	8	Leg	NP25	30	0	178	85	3	70	79	9	58	8	71	77	6	59	7	5	5	3
Lab	9	Leg	NP25	30	0	178	85	3	70	79	9	58	8	67	72	5	177	7	3	5	4
Lab	10	Shoulder	NP25	30	0	178	85	3	67	78	11	28	0.18	71	81	10	27	0.17	5	3	1
Lab	11	Shoulder	NP25	30	0	178	85	3	67	78	11	28	0.18	66	80	14	29	0.18	5	5	2
Lab	12	Shoulder	NP25	30	0	178	85	3	67	78	11	28	0.18	66	75	9	53	0.13	5	5	4
Lab	1	Back	NP26	25	0	186	96	3	92	107	15	19	2.14	85	102	17	17	2.18	4	4	2
Lab	2	Back	NP26	25	0	186	96	3	92	107	15	19	2.14	90	109	19	23	2.06	5	4	2
Lab	3	Back	NP26	25	0	186	96	3	92	107	15	19	2.14	87	99	12	21	1.82	5	5	2
Lab	4	Back	NP26	25	0	186	96	3	92	107	15	19	2.14	93	104	11	30	1.65	4	5	2
Lab	5	Back	NP26	25	0	186	96	3	92	107	15	19	2.14	85	96	11	38	1.44	5	4	3
Lab	6	Leg	NP26	25	0	186	96	3	84	94	10	57	8	91	104	13	65	8	5	5	2
Lab	7	Leg	NP26	25	0	186	96	3	84	94	10	57	8	83	91	8	61	8	4	5	2
Lab	8	Leg	NP26	25	0	186	96	3	84	94	10	57	8	87	98	11	59	8	3	4	2
Lab	9	Leg	NP26	25	0	186	96	3	84	94	10	57	8	84	89	5	215	7	5	3	5
Lab	10	Shoulder	NP26	25	0	186	96	3	83	92	9	81	0.18	82	94	12	92	0.18	4	2	1
Lab	11	Shoulder	NP26	25	0	186	96	3	83	92	9	81	0.18	79	90	11	101	0.18	3	4	1
Lab	12	Shoulder	NP26	25	0	186	96	3	83	92	9	81	0.18	83	85	2	149	0.12	5	4	4

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	User Perceived			
																			Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	1	Back	NP27	31	0	180	90	2	77	91	14	21	2.41	78	95	17	21	2.31	5	5	2	
Lab	3	Back	NP27	31	0	180	90	2	77	91	14	21	2.41	85	97	12	25	2.36	5	5	3	
Lab	4	Back	NP27	31	0	180	90	2	77	91	14	21	2.41	82	92	10	33	2.01	4	5	3	
Lab	5	Back	NP27	31	0	180	90	2	77	91	14	21	2.41	89	101	12	38	1.74	5	5	5	
Lab	7	Leg	NP27	31	0	180	90	3	79	88	9	58	8	80	90	10	61	9	5	5	2	
Lab	8	Leg	NP27	31	0	180	90	3	79	88	9	58	8	78	89	11	93	7	4	5	2	
Lab	9	Leg	NP27	31	0	180	90	3	79	88	9	58	8	85	92	7	243	7	4	5	5	
Lab	10	Shoulder	NP27	31	0	180	90	3	82	94	12	87	0.24	84	95	11	96	0.23	5	3	1	
Lab	11	Shoulder	NP27	31	0	180	90	3	82	94	12	87	0.24	91	101	10	99	0.24	4	5	1	
Lab	12	Shoulder	NP27	31	0	180	90	3	82	94	12	87	0.24	87	90	3	154	0.16	5	4	5	
Lab	3	Back	NP28	24	0	178	83	2	62	75	13	29	1.96	67	78	11	36	1.75	5	5	2	
Lab	4	Back	NP28	24	0	178	83	2	62	75	13	29	1.96	74	82	8	37	1.68	4	4	4	
Lab	5	Back	NP28	24	0	178	83	2	62	75	13	29	1.96	65	72	7	44	1.45	5	4	5	
Lab	6	Leg	NP28	24	0	178	83	2	67	74	7	92	9	65	77	12	88	9	4	5	1	
Lab	7	Leg	NP28	24	0	178	83	2	67	74	7	92	9	68	75	7	103	9	4	5	1	
Lab	8	Leg	NP28	24	0	178	83	2	67	74	7	92	9	65	73	8	101	9	3	5	1	
Lab	9	Leg	NP28	24	0	178	83	2	67	74	7	92	9	63	66	3	208	8	5	4	3	
Lab	10	Shoulder	NP28	24	0	178	83	2	63	71	8	74	0.19	68	75	7	79	0.16	4	5	2	
Lab	11	Shoulder	NP28	24	0	178	83	2	63	71	8	74	0.19	65	71	6	88	0.13	3	5	2	
Lab	12	Shoulder	NP28	24	0	178	83	2	63	71	8	74	0.19	64	67	3	115	0.1	5	4	5	
Lab	2	Back	NP29	42	0	174	105	1	82	106	24	16	2.46	76	107	31	18	2.51	5	4	1	
Lab	3	Back	NP29	42	0	174	105	1	82	106	24	16	2.46	81	107	26	15	2.42	5	5	1	
Lab	4	Back	NP29	42	0	174	105	1	82	106	24	16	2.46	77	100	23	19	2.33	5	5	2	
Lab	5	Back	NP29	42	0	174	105	1	82	106	24	16	2.46	76	95	19	23	2.02	4	5	3	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	6	Leg	NP29	42	0	174	105	1	79	93	14	19	9	78	95	17	31	9	5	4	1
Lab	7	Leg	NP29	42	0	174	105	1	79	93	14	19	9	80	92	12	26	9	5	4	2
Lab	8	Leg	NP29	42	0	174	105	1	79	93	14	19	9	83	92	9	42	9	4	5	3
Lab	9	Leg	NP29	42	0	174	105	1	79	93	14	19	9	81	90	9	78	9	2	4	3
Lab	10	Shoulder	NP29	42	0	174	105	1	80	91	11	38	0.24	78	91	13	36	0.22	5	2	1
Lab	11	Shoulder	NP29	42	0	174	105	1	80	91	11	38	0.24	82	93	11	39	0.2	5	5	1
Lab	12	Shoulder	NP29	42	0	174	105	1	80	91	11	38	0.24	75	83	8	89	0.18	5	5	2
Lab	1	Back	NP30	29	1	179	73	3	66	78	12	28	2.08	62	78	16	23	2.21	5	5	1
Lab	3	Back	NP30	29	1	179	73	3	66	78	12	28	2.08	71	83	12	21	2.06	5	5	2
Lab	4	Back	NP30	29	1	179	73	3	66	78	12	28	2.08	66	75	9	26	1.98	5	5	4
Lab	5	Back	NP30	29	1	179	73	3	66	78	12	28	2.08	68	74	6	31	1.72	5	5	5
Lab	6	Leg	NP30	29	1	179	73	3	71	78	7	52	8	72	80	8	43	8	5	5	2
Lab	7	Leg	NP30	29	1	179	73	3	71	78	7	52	8	69	75	6	60	8	5	5	2
Lab	8	Leg	NP30	29	1	179	73	3	71	78	7	52	8	67	76	9	59	7	5	5	3
Lab	9	Leg	NP30	29	1	179	73	3	71	78	7	52	8	73	75	2	177	7	3	5	5
Lab	10	Shoulder	NP30	29	1	179	73	3	69	75	6	68	0.18	73	78	5	27	0.16	5	3	1
Lab	11	Shoulder	NP30	29	1	179	73	3	69	75	6	68	0.18	68	75	7	29	0.18	5	5	1
Lab	12	Shoulder	NP30	29	1	179	73	3	69	75	6	68	0.18	72	75	3	56	0.13	5	5	3
Lab	3	Back	NP31	26	1	157	64	3	75	87	12	18	2.23	70	79	9	20	2.1	5	5	2
Lab	4	Back	NP31	26	1	157	64	3	75	87	12	18	2.23	71	79	8	22	1.93	4	5	3
Lab	5	Back	NP31	26	1	157	64	3	75	87	12	18	2.23	75	81	6	26	1.71	5	4	4
Lab	7	Leg	NP31	26	1	157	64	3	73	78	5	76	8	68	72	4	76	8	4	5	2
Lab	8	Leg	NP31	26	1	157	64	3	73	78	5	76	8	72	78	6	81	7	3	4	2
Lab	9	Leg	NP31	26	1	157	64	3	73	78	5	76	8	74	78	4	236	7	5	3	5

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	10	Shoulder	NP31	26	1	157	64	3	68	76	8	81	0.22	69	78	9	92	0.22	4	2	1
Lab	11	Shoulder	NP31	26	1	157	64	3	68	76	8	81	0.22	66	74	8	101	0.22	3	4	2
Lab	12	Shoulder	NP31	26	1	157	64	3	68	76	8	81	0.22	70	74	4	149	0.16	5	4	4
Lab	1	Back	P01	51	0	183	91	1	76	102	26	13	2.27	80	108	28	16	2.09	5	5	2
Lab	2	Back	P01	51	0	183	91	1	76	102	26	13	2.27	77	108	31	14	2.19	4	4	2
Lab	3	Back	P01	51	0	183	91	1	76	102	26	13	2.27	81	106	25	12	2.18	4	4	4
Lab	4	Back	P01	51	0	183	91	1	76	102	26	13	2.27	78	101	23	17	1.94	5	4	4
Lab	5	Back	P01	51	0	183	91	1	76	102	26	13	2.27	82	93	11	19	1.26	5	5	5
Lab	6	Leg	P01	51	0	183	91	2	84	98	14	47	9	79	92	13	47	9	5	5	2
Lab	7	Leg	P01	51	0	183	91	2	84	98	14	47	9	74	85	11	70	8	5	5	4
Lab	8	Leg	P01	51	0	183	91	2	84	98	14	47	9	75	82	7	75	8	4	5	3
Lab	9	Leg	P01	51	0	183	91	2	84	98	14	47	9	81	86	5	128	7	3	4	5
Lab	10	Shoulder	P01	51	0	183	91	2	79	91	12	58	0.2	77	89	12	69	0.2	5	5	2
Lab	11	Shoulder	P01	51	0	183	91	2	79	91	12	58	0.2	83	93	10	64	0.22	4	4	2
Lab	12	Shoulder	P01	51	0	183	91	2	79	91	12	58	0.2	79	81	2	88	0.12	3	4	5
Lab	3	Back	P02	54	0	185	88	2	74	95	21	20	2.16	78	98	20	21	2.1	3	4	3
Lab	4	Back	P02	54	0	185	88	2	74	95	21	20	2.16	73	92	19	26	1.9	3	5	4
Lab	5	Back	P02	54	0	185	88	2	74	95	21	20	2.16	81	93	12	32	1.57	5	5	5
Lab	6	Leg	P02	54	0	185	88	2	73	85	12	47	9	77	90	13	51	9	5	4	2
Lab	7	Leg	P02	54	0	185	88	2	73	85	12	47	9	71	80	9	71	8	2	4	2
Lab	8	Leg	P02	54	0	185	88	2	73	85	12	47	9	76	83	7	81	8	4	4	2
Lab	9	Leg	P02	54	0	185	88	2	73	85	12	47	9	74	80	6	118	7	4	5	5
Lab	10	Shoulder	P02	54	0	185	88	2	76	93	17	30	0.18	73	89	16	34	0.16	5	4	2
Lab	11	Shoulder	P02	54	0	185	88	2	76	93	17	30	0.18	79	92	13	37	0.16	5	5	2

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	12	Shoulder	P02	54	0	185	88	2	76	93	17	30	0.18	75	84	9	46	0.09	4	3	4	
Lab	1	Back	P03	39	0	175	102	2	80	99	19	24	2.28	82	98	16	30	2.26	5	4	2	
Lab	2	Back	P03	39	0	175	102	2	80	99	19	24	2.28	80	97	17	21	2.34	4	5	2	
Lab	3	Back	P03	39	0	175	102	2	80	99	19	24	2.28	78	93	15	25	2.28	3	2	3	
Lab	4	Back	P03	39	0	175	102	2	80	99	19	24	2.28	77	91	14	22	2.12	4	3	4	
Lab	5	Back	P03	39	0	175	102	2	80	99	19	24	2.28	81	94	13	33	1.63	4	3	5	
Lab	7	Leg	P03	39	0	175	102	1	77	95	18	42	9	75	88	13	65	8	3	4	2	
Lab	8	Leg	P03	39	0	175	102	1	77	95	18	42	9	80	87	7	68	8	4	4	2	
Lab	9	Leg	P03	39	0	175	102	1	77	95	18	42	9	74	80	6	118	8	3	3	4	
Lab	10	Shoulder	P03	39	0	175	102	2	81	96	15	55	0.17	79	91	12	59	0.17	4	4	1	
Lab	11	Shoulder	P03	39	0	175	102	2	81	96	15	55	0.17	80	90	10	57	0.16	3	3	2	
Lab	12	Shoulder	P03	39	0	175	102	2	81	96	15	55	0.17	83	90	7	71	0.12	5	4	5	
Lab	3	Back	P04	57	0	190	107	1	80	104	24	13	2.26	81	101	20	16	2.17	4	4	3	
Lab	4	Back	P04	57	0	190	107	1	80	104	24	13	2.26	75	96	21	17	2.06	4	4	4	
Lab	5	Back	P04	57	0	190	107	1	80	104	24	13	2.26	79	93	14	21	1.84	5	4	5	
Lab	6	Leg	P04	57	0	190	107	2	92	110	18	61	9	86	103	17	67	9	5	4	2	
Lab	7	Leg	P04	57	0	190	107	2	92	110	18	61	9	87	100	13	92	8	4	4	3	
Lab	8	Leg	P04	57	0	190	107	2	92	110	18	61	9	89	94	5	80	8	4	5	4	
Lab	9	Leg	P04	57	0	190	107	2	92	110	18	61	9	91	95	4	119	7	5	4	5	
Lab	10	Shoulder	P04	57	0	190	107	2	75	92	17	78	0.18	78	96	18	81	0.17	4	4	1	
Lab	11	Shoulder	P04	57	0	190	107	2	75	92	17	78	0.18	74	87	13	83	0.17	3	4	1	
Lab	12	Shoulder	P04	57	0	190	107	2	75	92	17	78	0.18	76	85	9	128	0.11	5	5	5	
Lab	1	Back	P05	51	0	183	98	1	84	103	19	11	2.62	75	93	18	13	2.68	5	4	2	
Lab	2	Back	P05	51	0	183	98	1	84	103	19	11	2.62	73	95	22	12	2.52	4	4	2	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	3	Back	P05	51	0	183	98	1	84	103	19	11	2.62	78	97	19	10	2.42	4	5	3	
Lab	4	Back	P05	51	0	183	98	1	84	103	19	11	2.62	76	91	15	11	2.29	5	4	3	
Lab	5	Back	P05	51	0	183	98	1	84	103	19	11	2.62	81	91	10	16	1.47	4	5	4	
Lab	6	Leg	P05	51	0	183	98	2	89	110	21	72	10	81	100	19	75	10	5	4	2	
Lab	7	Leg	P05	51	0	183	98	2	89	110	21	72	10	83	99	16	105	9	4	5	2	
Lab	8	Leg	P05	51	0	183	98	2	89	110	21	72	10	79	90	11	95	9	3	5	3	
Lab	9	Leg	P05	51	0	183	98	2	89	110	21	72	10	75	81	6	137	8	4	4	5	
Lab	10	Shoulder	P05	51	0	183	98	1	78	95	17	34	0.2	81	96	15	33	0.21	4	5	2	
Lab	11	Shoulder	P05	51	0	183	98	1	78	95	17	34	0.2	75	87	12	36	0.19	4	5	2	
Lab	12	Shoulder	P05	51	0	183	98	1	78	95	17	34	0.2	76	84	8	54	0.12	5	5	5	
Lab	3	Back	P06	60	0	175	100	2	78	89	11	6	2.34	77	89	12	7	2.28	5	5	2	
Lab	4	Back	P06	60	0	175	100	2	78	89	11	6	2.34	81	91	10	8	2.06	5	5	4	
Lab	5	Back	P06	60	0	175	100	2	78	89	11	6	2.34	76	82	6	10	1.74	5	4	5	
Lab	6	Leg	P06	60	0	175	100	2	72	88	16	65	10	76	94	18	64	10	5	4	2	
Lab	7	Leg	P06	60	0	175	100	2	72	88	16	65	10	74	88	14	95	9	4	5	2	
Lab	8	Leg	P06	60	0	175	100	2	72	88	16	65	10	79	90	11	81	9	4	4	3	
Lab	9	Leg	P06	60	0	175	100	2	72	88	16	65	10	77	86	9	118	8	2	4	5	
Lab	10	Shoulder	P06	60	0	175	100	1	75	84	9	24	0.22	77	85	8	23	0.21	5	5	2	
Lab	11	Shoulder	P06	60	0	175	100	1	75	84	9	24	0.22	74	84	10	26	0.22	3	5	2	
Lab	12	Shoulder	P06	60	0	175	100	1	75	84	9	24	0.22	72	80	8	44	0.16	4	4	4	
Lab	1	Back	P07	34	0	172	81	3	58	69	11	18	1.92	58	70	12	19	1.74	4	4	2	
Lab	2	Back	P07	33	0	172	81	3	58	69	11	18	1.92	57	70	13	20	1.89	5	4	2	
Lab	3	Back	P07	34	0	172	81	3	58	69	11	18	1.92	62	70	8	16	1.94	5	5	3	
Lab	4	Back	P07	33	0	172	81	3	58	69	11	18	1.92	61	71	10	20	1.8	5	5	3	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	User Perceived			
																			Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Lab	5	Back	P07	33	0	172	81	3	58	69	11	18	1.92	72	82	10	26	1.66	4	4	5	
Lab	6	Leg	P07	33	0	172	81	3	62	67	5	53	7	66	71	5	59	7	5	4	2	
Lab	7	Leg	P07	33	0	172	81	3	62	67	5	53	7	64	68	4	78	7	5	5	2	
Lab	8	Leg	P07	33	0	172	81	3	62	67	5	53	7	63	67	4	75	7	3	5	2	
Lab	9	Leg	P07	33	0	172	81	3	62	67	5	53	7	68	71	3	158	7	1	3	5	
Lab	10	Shoulder	P07	33	0	172	81	3	57	63	6	76	0.18	67	75	8	68	0.18	4	5	2	
Lab	11	Shoulder	P07	33	0	172	81	3	57	63	6	76	0.18	62	66	4	71	0.21	3	4	2	
Lab	12	Shoulder	P07	33	0	172	81	3	57	63	6	76	0.18	70	73	3	98	0.14	4	4	5	
Lab	1	Back	P08	39	0	177	84	2	72	84	12	13	2.26	75	86	11	12	2.16	4	4	2	
Lab	2	Back	P08	39	0	177	84	2	72	84	12	13	2.26	73	83	10	12	2.44	5	4	2	
Lab	3	Back	P08	39	0	177	84	2	72	84	12	13	2.26	78	87	9	15	2.24	5	5	2	
Lab	4	Back	P08	39	0	177	84	2	72	84	12	13	2.26	74	83	9	18	2.18	5	5	3	
Lab	5	Back	P08	39	0	177	84	2	72	84	12	13	2.26	64	73	9	21	2.02	3	4	4	
Lab	6	Leg	P08	39	0	177	84	2	75	84	9	51	9	71	82	11	54	9	4	4	1	
Lab	7	Leg	P08	39	0	177	84	2	75	84	9	51	9	63	70	7	74	8	4	5	2	
Lab	8	Leg	P08	39	0	177	84	2	75	84	9	51	9	72	77	5	64	8	4	5	3	
Lab	9	Leg	P08	39	0	177	84	2	75	84	9	51	9	67	71	4	95	7	2	3	5	
Lab	10	Shoulder	P08	39	0	177	84	1	69	76	7	24	0.22	69	78	9	26	0.24	3	4	1	
Lab	11	Shoulder	P08	39	0	177	84	1	69	76	7	24	0.22	73	81	8	25	0.2	3	4	2	
Lab	12	Shoulder	P08	39	0	177	84	1	69	76	7	24	0.22	72	77	5	48	0.18	5	5	3	
Lab	1	Back	P09	42	0	181	86	2	71	88	17	15	2.22	73	88	15	17	2.34	5	4	1	
Lab	2	Back	P09	42	0	181	86	2	71	88	17	15	2.22	70	86	16	12	2.31	5	5	2	
Lab	3	Back	P09	42	0	181	86	2	71	88	17	15	2.22	72	87	15	14	2.2	4	4	2	
Lab	4	Back	P09	42	0	181	86	2	71	88	17	15	2.22	74	88	14	16	2.12	4	3	4	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	5	Back	P09	42	0	181	86	2	71	88	17	15	2.22	69	83	14	20	1.92	4	2	5
Lab	6	Leg	P09	42	0	181	86	1	64	75	11	34	9	70	81	11	38	9	5	5	1
Lab	7	Leg	P09	42	0	181	86	1	64	75	11	34	9	64	72	8	55	8	5	5	3
Lab	8	Leg	P09	42	0	181	86	1	64	75	11	34	9	68	76	8	72	8	4	5	3
Lab	9	Leg	P09	42	0	181	86	1	64	75	11	34	9	71	76	5	145	8	2	3	5
Lab	10	Shoulder	P09	42	0	181	86	2	68	76	8	56	0.19	68	75	7	51	0.21	3	3	1
Lab	11	Shoulder	P09	42	0	181	86	2	68	76	8	56	0.19	66	77	11	62	0.18	2	1	1
Lab	12	Shoulder	P09	42	0	181	86	2	68	76	8	56	0.19	72	78	6	106	0.14	3	4	5
Lab	1	Back	P10	59	0	175	79	2	74	87	13	16	2.46	72	78	6	19	2.36	5	5	3
Lab	3	Back	P10	59	0	175	79	2	74	87	13	16	2.46	76	87	11	15	2.38	5	5	3
Lab	4	Back	P10	59	0	175	79	2	74	87	13	16	2.46	73	81	8	17	2.32	5	4	2
Lab	5	Back	P10	59	0	175	79	2	74	87	13	16	2.46	68	76	8	20	2.08	5	4	4
Lab	6	Leg	P10	59	0	175	79	2	72	82	10	22	9	69	79	10	23	9	4	4	1
Lab	7	Leg	P10	59	0	175	79	2	72	82	10	22	9	71	79	8	32	8	5	5	3
Lab	8	Leg	P10	59	0	175	79	2	72	82	10	22	9	66	72	6	47	8	4	5	3
Lab	9	Leg	P10	59	0	175	79	2	72	82	10	22	9	68	73	5	78	7	3	3	5
Lab	10	Shoulder	P10	59	0	175	79	2	68	77	9	36	0.22	72	82	10	35	0.2	3	2	1
Lab	11	Shoulder	P10	59	0	175	79	2	68	77	9	36	0.22	66	78	12	32	0.19	3	2	1
Lab	12	Shoulder	P10	59	0	175	79	2	68	77	9	36	0.22	69	77	8	92	0.14	3	4	4
Lab	1	Back	P11	37	0	175	93	2	65	75	10	17	2.24	67	75	8	16	2.11	5	4	1
Lab	2	Back	P11	37	0	175	93	2	65	75	10	17	2.24	61	73	12	18	2.17	5	4	2
Lab	3	Back	P11	37	0	175	93	2	65	75	10	17	2.24	62	71	9	19	2.17	4	5	2
Lab	4	Back	P11	37	0	175	93	2	65	75	10	17	2.24	68	75	7	21	2.14	3	3	4
Lab	5	Back	P11	37	0	175	93	2	65	75	10	17	2.24	64	71	7	26	1.86	4	4	5

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	6	Leg	P11	37	0	175	93	2	73	81	8	54	10	69	77	8	50	10	4	4	1
Lab	7	Leg	P11	37	0	175	93	2	73	81	8	54	10	71	76	5	90	9	4	4	2
Lab	8	Leg	P11	37	0	175	93	2	73	81	8	54	10	66	72	6	74	9	5	4	3
Lab	9	Leg	P11	37	0	175	93	2	73	81	8	54	10	73	79	6	85	9	2	3	5
Lab	10	Shoulder	P11	37	0	175	93	2	72	76	4	41	0.19	72	78	6	45	0.22	2	2	1
Lab	11	Shoulder	P11	37	0	175	93	2	72	76	4	41	0.19	64	72	8	49	0.18	3	2	1
Lab	12	Shoulder	P11	37	0	175	93	2	72	76	4	41	0.19	68	72	4	88	0.12	2	3	3
Lab	1	Back	P12	44	0	188	100	2	63	79	16	15	2.31	70	87	17	18	2.36	4	4	1
Lab	3	Back	P12	44	0	188	100	2	63	79	16	15	2.31	76	86	10	18	2.34	3	5	3
Lab	4	Back	P12	44	0	188	100	2	63	79	16	15	2.31	67	80	13	20	2.06	4	3	2
Lab	5	Back	P12	44	0	188	100	2	63	79	16	15	2.31	74	81	7	22	1.76	4	4	4
Lab	6	Leg	P12	44	0	188	100	2	71	81	10	34	8	69	82	13	34	8	5	4	1
Lab	7	Leg	P12	44	0	188	100	2	71	81	10	34	8	71	78	7	52	7	5	5	2
Lab	8	Leg	P12	44	0	188	100	2	71	81	10	34	8	63	71	8	58	7	5	4	3
Lab	9	Leg	P12	44	0	188	100	2	71	81	10	34	8	65	71	6	117	7	3	2	5
Lab	10	Shoulder	P12	44	0	188	100	1	68	77	9	46	0.19	69	76	7	51	0.18	3	3	1
Lab	11	Shoulder	P12	44	0	188	100	1	68	77	9	46	0.19	73	84	11	54	0.23	3	3	1
Lab	12	Shoulder	P12	44	0	188	100	1	68	77	9	46	0.19	63	69	6	101	0.15	5	4	5
Lab	1	Back	P13	48	0	177	93	2	59	78	19	13	2.46	61	75	14	15	2.32	4	4	1
Lab	2	Back	P13	48	0	177	93	2	59	78	19	13	2.46	67	85	18	13	2.43	5	4	2
Lab	3	Back	P13	48	0	177	93	2	59	78	19	13	2.46	62	83	21	17	2.39	4	5	3
Lab	4	Back	P13	48	0	177	93	2	59	78	19	13	2.46	65	82	17	17	2.18	4	5	4
Lab	5	Back	P13	48	0	177	93	2	59	78	19	13	2.46	58	72	14	20	2.14	4	4	5
Lab	6	Leg	P13	48	0	177	93	1	63	76	13	34	9	64	77	13	39	9	4	4	1

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Lab	7	Leg	P13	48	0	177	93	1	63	76	13	34	9	61	71	10	57	8	4	4	1
Lab	8	Leg	P13	48	0	177	93	1	63	76	13	34	9	59	68	9	54	8	3	4	3
Lab	9	Leg	P13	48	0	177	93	1	63	76	13	34	9	68	74	6	122	7	3	2	5
Lab	10	Shoulder	P13	48	0	177	93	1	62	68	6	22	0.22	62	71	9	25	0.22	4	3	1
Lab	11	Shoulder	P13	48	0	177	93	1	62	68	6	22	0.22	68	79	11	19	0.24	4	4	2
Lab	12	Shoulder	P13	48	0	177	93	1	62	68	6	22	0.22	57	62	5	61	0.16	5	4	5
Field	1	Back	P01	51	0	183	91	2	72	105	33	5	2.36	65	99	34	4	2.41	5	3	1
Field	2	Back	P01	51	0	183	91	1	72	105	33	5	2.36	69	102	33	5	2.37	3	4	2
Field	3	Back	P01	51	0	183	91	1	72	105	33	5	2.36	76	107	31	6	2.03	4	4	3
Field	4	Back	P01	51	0	183	91	2	72	105	33	5	2.36	81	103	22	8	1.48	5	4	3
Field	5	Back	P01	51	0	183	91	2	72	105	33	5	2.36	80	95	15	10	1.26	4	4	5
Field	6	Leg	P01	51	0	183	91	2	78	101	23	62	9	75	98	23	64	9	5	4	1
Field	7	Leg	P01	51	0	183	91	2	78	101	23	62	9	71	89	18	89	8	4	4	2
Field	8	Leg	P01	51	0	183	91	2	78	101	23	62	9	74	96	22	66	9	3	5	3
Field	9	Leg	P01	51	0	183	91	1	78	101	23	62	9	83	94	11	194	7	4	3	5
Field	10	Shoulder	P01	51	0	183	91	2	73	98	25	124	0.26	79	97	18	118	0.29	4	4	1
Field	11	Shoulder	P01	51	0	183	91	2	73	98	25	124	0.26	81	101	20	115	0.26	4	4	2
Field	12	Shoulder	P01	51	0	183	91	2	73	98	25	124	0.26	77	81	4	247	0.18	5	4	5
Field	1	Back	P02	54	0	185	88	2	65	83	18	11	2.14	74	94	20	9	2.21	5	3	2
Field	2	Back	P02	54	0	185	88	2	65	83	18	11	2.14	60	79	19	10	2.11	4	4	1
Field	3	Back	P02	54	0	185	88	2	65	83	18	11	2.14	77	95	18	11	2.1	4	4	3
Field	4	Back	P02	54	0	185	88	2	65	83	18	11	2.14	80	96	16	12	2.13	4	4	3
Field	5	Back	P02	54	0	185	88	2	65	83	18	11	2.14	75	85	10	15	1.68	4	4	5
Field	6	Leg	P02	54	0	185	88	2	74	87	13	71	8	79	93	14	70	8	4	4	1

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
									Measured					Measured					User Perceived			
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Field	7	Leg	P02	54	0	185	88	2	74	87	13	71	8	82	94	12	65	8	4	4	2	
Field	8	Leg	P02	54	0	185	88	2	74	87	13	71	8	73	85	12	75	8	4	4	2	
Field	9	Leg	P02	54	0	185	88	2	74	87	13	71	8	77	85	8	159	7	3	3	4	
Field	10	Shoulder	P02	54	0	185	88	2	68	92	24	57	0.2	82	103	21	46	0.19	4	3	1	
Field	11	Shoulder	P02	54	0	185	88	2	68	92	24	57	0.2	85	108	23	49	0.23	3	4	1	
Field	12	Shoulder	P02	54	0	185	88	2	68	92	24	57	0.2	71	87	16	110	0.14	5	4	4	
Field	1	Back	P03	39	0	175	102	2	77	111	34	7	2.31	60	94	34	8	2.45	4	3	1	
Field	2	Back	P03	39	0	175	102	2	77	111	34	7	2.31	69	100	31	10	2.29	3	4	1	
Field	3	Back	P03	39	0	175	102	2	77	111	34	7	2.31	75	104	29	11	2.4	5	5	2	
Field	4	Back	P03	39	0	175	102	2	77	111	34	7	2.31	71	96	25	12	2.18	5	4	3	
Field	5	Back	P03	39	0	175	102	2	77	111	34	7	2.31	83	102	19	16	1.94	4	4	5	
Field	6	Leg	P03	39	0	175	102	1	75	98	23	57	10	76	100	24	50	10	5	4	1	
Field	7	Leg	P03	39	0	175	102	1	75	98	23	57	10	74	96	22	52	9	4	4	2	
Field	8	Leg	P03	39	0	175	102	1	75	98	23	57	10	79	101	22	60	10	3	4	3	
Field	9	Leg	P03	39	0	175	102	1	75	98	23	57	10	72	86	14	146	7	3	3	4	
Field	10	Shoulder	P03	39	0	175	102	2	71	96	25	74	0.28	71	95	24	65	0.26	4	3	2	
Field	11	Shoulder	P03	39	0	175	102	2	71	96	25	74	0.28	80	108	28	80	0.26	3	4	1	
Field	12	Shoulder	P03	39	0	175	102	2	71	96	25	74	0.28	83	102	19	112	0.12	5	4	5	
Field	1	Back	P04	57	0	190	107	1	76	102	26	11	2.51	79	101	22	14	2.42	4	3	2	
Field	2	Back	P04	57	0	190	107	1	76	102	26	11	2.51	78	102	24	12	2.43	4	4	2	
Field	3	Back	P04	57	0	190	107	1	76	102	26	11	2.51	75	98	23	14	2.31	4	4	3	
Field	4	Back	P04	57	0	190	107	1	76	102	26	11	2.51	78	98	20	16	2.19	4	5	4	
Field	5	Back	P04	57	0	190	107	1	76	102	26	11	2.51	71	89	18	18	1.94	4	4	5	
Field	6	Leg	P04	57	0	190	107	2	89	110	21	52	9	71	90	19	59	9	4	4	1	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)								
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	User Perceived			
																			Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)	
Field	7	Leg	P04	57	0	190	107	2	89	110	21	52	9	82	100	18	63	8	4	4	2	
Field	8	Leg	P04	57	0	190	107	2	89	110	21	52	9	84	99	15	72	8	4	4	2	
Field	9	Leg	P04	57	0	190	107	2	89	110	21	52	9	76	93	17	82	8	3	3	4	
Field	10	Shoulder	P04	57	0	190	107	2	72	91	19	65	0.32	75	97	22	72	0.29	4	4	2	
Field	11	Shoulder	P04	57	0	190	107	2	72	91	19	65	0.32	79	95	16	73	0.29	3	4	2	
Field	12	Shoulder	P04	57	0	190	107	2	72	91	19	65	0.32	81	92	11	114	0.21	4	3	4	
Field	1	Back	P05	51	0	183	98	1	81	102	21	9	2.71	73	98	25	9	2.78	5	3	1	
Field	2	Back	P05	51	0	183	98	1	81	102	21	9	2.71	68	91	23	10	2.71	4	4	1	
Field	3	Back	P05	51	0	183	98	1	81	102	21	9	2.71	81	103	22	11	2.61	4	4	2	
Field	4	Back	P05	51	0	183	98	1	81	102	21	9	2.71	79	99	20	10	2.62	5	5	4	
Field	5	Back	P05	51	0	183	98	1	81	102	21	9	2.71	84	97	13	14	1.76	4	4	5	
Field	6	Leg	P05	51	0	183	98	2	78	100	22	65	10	81	101	20	68	9	4	4	1	
Field	7	Leg	P05	51	0	183	98	2	78	100	22	65	10	78	96	18	72	10	5	5	2	
Field	8	Leg	P05	51	0	183	98	2	78	100	22	65	10	78	93	15	87	9	3	4	2	
Field	9	Leg	P05	51	0	183	98	2	78	100	22	65	10	76	84	8	162	8	3	3	5	
Field	10	Shoulder	P05	51	0	183	98	1	85	104	19	23	0.35	79	96	17	26	0.32	4	3	1	
Field	11	Shoulder	P05	51	0	183	98	1	85	104	19	23	0.35	85	100	15	25	0.31	3	3	2	
Field	12	Shoulder	P05	51	0	183	98	1	85	104	19	23	0.35	79	88	9	44	0.19	5	4	5	
Field	1	Back	P06	60	0	175	100	2	75	90	15	4	2.46	75	90	15	3	2.46	5	3	1	
Field	2	Back	P06	60	0	175	100	2	75	90	15	4	2.46	61	74	13	4	2.43	4	4	2	
Field	3	Back	P06	60	0	175	100	2	75	90	15	4	2.46	77	88	11	6	2.37	5	4	2	
Field	4	Back	P06	60	0	175	100	2	75	90	15	4	2.46	74	82	8	6	2.22	4	4	3	
Field	5	Back	P06	60	0	175	100	2	75	90	15	4	2.46	83	92	9	7	1.93	4	4	5	
Field	6	Leg	P06	60	0	175	100	2	80	100	20	57	10	78	97	19	59	10	4	4	1	

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Field	7	Leg	P06	60	0	175	100	2	80	100	20	57	10	74	93	19	60	10	5	4	1
Field	8	Leg	P06	60	0	175	100	2	80	100	20	57	10	70	89	19	60	10	3	4	3
Field	9	Leg	P06	60	0	175	100	2	80	100	20	57	10	72	88	16	79	9	4	4	4
Field	10	Shoulder	P06	60	0	175	100	1	72	85	13	18	0.36	75	86	11	19	0.33	4	3	1
Field	11	Shoulder	P06	60	0	175	100	1	72	85	13	18	0.36	73	85	12	19	0.32	4	4	2
Field	12	Shoulder	P06	60	0	175	100	1	72	85	13	18	0.36	70	79	9	37	0.19	5	4	4
Field	1	Back	P07	34	0	172	81	3	60	75	15	15	2.11	77	91	14	15	2.1	4	4	1
Field	2	Back	P07	33	0	172	81	3	60	75	15	15	2.11	74	88	14	14	2.09	3	5	1
Field	3	Back	P07	34	0	172	81	3	60	75	15	15	2.11	72	84	12	16	2.01	4	5	3
Field	4	Back	P07	33	0	172	81	3	60	75	15	15	2.11	67	82	15	16	2.06	4	4	3
Field	5	Back	P07	33	0	172	81	3	60	75	15	15	2.11	68	84	16	23	1.59	4	5	5
Field	6	Leg	P07	33	0	172	81	3	64	73	9	42	8	68	77	9	46	8	4	5	1
Field	7	Leg	P07	33	0	172	81	3	64	73	9	42	8	77	87	10	48	9	5	4	2
Field	8	Leg	P07	33	0	172	81	3	64	73	9	42	8	72	80	8	73	8	3	4	2
Field	9	Leg	P07	33	0	172	81	3	64	73	9	42	8	78	84	6	162	7	3	3	4
Field	10	Shoulder	P07	33	0	172	81	3	62	74	12	63	0.29	66	77	11	65	0.24	4	4	2
Field	11	Shoulder	P07	33	0	172	81	3	62	74	12	63	0.29	74	83	9	91	0.23	4	4	1
Field	12	Shoulder	P07	33	0	172	81	3	62	74	12	63	0.29	69	73	4	92	0.19	5	3	5
Field	1	Back	P08	39	0	177	84	2	86	101	15	12	2.42	78	93	15	12	2.4	4	3	1
Field	2	Back	P08	39	0	177	84	2	86	101	15	12	2.42	80	93	13	11	2.39	3	5	2
Field	3	Back	P08	39	0	177	84	2	86	101	15	12	2.42	86	98	12	13	2.35	4	5	2
Field	4	Back	P08	39	0	177	84	2	86	101	15	12	2.42	74	84	10	15	2.23	5	4	3
Field	5	Back	P08	39	0	177	84	2	86	101	15	12	2.42	73	83	10	22	1.91	4	4	5
Field	6	Leg	P08	39	0	177	84	2	90	101	11	46	10	81	92	11	50	10	4	4	1

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Field	7	Leg	P08	39	0	177	84	2	90	101	11	46	10	85	97	12	56	10	4	4	1
Field	8	Leg	P08	39	0	177	84	2	90	101	11	46	10	82	91	9	64	9	4	4	3
Field	9	Leg	P08	39	0	177	84	2	90	101	11	46	10	78	86	8	67	9	3	3	5
Field	10	Shoulder	P08	39	0	177	84	1	89	97	8	19	0.38	71	82	11	22	0.36	5	3	1
Field	11	Shoulder	P08	39	0	177	84	1	89	97	8	19	0.38	78	85	7	17	0.35	3	3	2
Field	12	Shoulder	P08	39	0	177	84	1	89	97	8	23	0.38	82	89	7	42	0.21	5	4	4
Field	1	Back	P09	42	0	181	86	2	65	85	20	13	2.46	62	82	20	12	2.44	4	3	1
Field	2	Back	P09	42	0	181	86	2	65	85	20	13	2.46	79	98	19	13	2.38	3	4	2
Field	3	Back	P09	42	0	181	86	2	65	85	20	13	2.46	78	97	19	13	2.45	4	4	2
Field	4	Back	P09	42	0	181	86	2	65	85	20	13	2.46	70	88	18	14	2.38	4	4	3
Field	5	Back	P09	42	0	181	86	2	65	85	20	13	2.46	72	84	12	24	1.89	4	4	5
Field	6	Leg	P09	42	0	181	86	1	74	89	15	29	10	64	77	13	27	10	5	4	2
Field	7	Leg	P09	42	0	181	86	1	74	89	15	29	10	72	84	12	28	10	5	4	2
Field	8	Leg	P09	42	0	181	86	1	74	89	15	29	10	69	81	12	46	9	3	4	2
Field	9	Leg	P09	42	0	181	86	1	74	89	15	29	10	69	76	7	127	8	3	3	5
Field	10	Shoulder	P09	42	0	181	86	2	68	77	9	51	0.28	73	81	8	47	0.27	4	4	1
Field	11	Shoulder	P09	42	0	181	86	2	68	77	9	51	0.28	67	77	10	56	0.26	3	3	2
Field	12	Shoulder	P09	42	0	181	86	2	68	77	9	51	0.28	69	75	6	87	0.19	5	4	5
Field	1	Back	P10	59	0	175	79	2	70	86	16	14	2.61	62	76	14	13	2.59	4	3	2
Field	2	Back	P10	59	0	175	79	2	70	86	16	14	2.61	73	88	15	12	2.6	4	4	1
Field	3	Back	P10	59	0	175	79	2	70	86	16	14	2.61	70	83	13	14	2.51	4	4	3
Field	4	Back	P10	59	0	175	79	2	70	86	16	14	2.61	65	75	10	17	2.44	4	4	3
Field	5	Back	P10	59	0	175	79	2	70	86	16	14	2.61	75	88	13	22	1.88	4	5	5
Field	6	Leg	P10	59	0	175	79	2	73	85	12	20	10	77	88	11	21	10	4	4	1

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Field	7	Leg	P10	59	0	175	79	2	73	85	12	20	10	65	75	10	22	9	4	4	2
Field	8	Leg	P10	59	0	175	79	2	73	85	12	20	10	68	77	9	29	9	3	4	3
Field	9	Leg	P10	59	0	175	79	2	73	85	12	20	10	68	76	8	64	8	3	3	4
Field	10	Shoulder	P10	59	0	175	79	2	72	83	11	33	0.4	67	80	13	35	0.37	4	3	1
Field	11	Shoulder	P10	59	0	175	79	2	72	83	11	33	0.4	74	87	13	29	0.36	3	4	2
Field	12	Shoulder	P10	59	0	175	79	2	72	83	11	33	0.4	71	80	9	64	0.24	5	3	4
Field	1	Back	P11	37	0	175	93	2	66	79	13	14	2.38	72	86	14	13	2.45	5	3	1
Field	2	Back	P11	37	0	175	93	2	66	79	13	14	2.38	72	85	13	12	2.37	4	4	2
Field	3	Back	P11	37	0	175	93	2	66	79	13	14	2.38	71	83	12	14	2.32	4	4	2
Field	4	Back	P11	37	0	175	93	2	66	79	13	14	2.38	73	82	9	17	2.21	4	4	3
Field	5	Back	P11	37	0	175	93	2	66	79	13	14	2.38	68	76	8	16	1.72	4	4	5
Field	6	Leg	P11	37	0	175	93	2	74	84	10	47	10	67	78	11	51	9	4	4	1
Field	7	Leg	P11	37	0	175	93	2	74	84	10	47	10	69	80	11	48	10	4	4	1
Field	8	Leg	P11	37	0	175	93	2	74	84	10	47	10	73	83	10	57	9	3	4	2
Field	9	Leg	P11	37	0	175	93	2	74	84	10	47	10	65	72	7	102	8	3	3	4
Field	10	Shoulder	P11	37	0	175	93	2	71	79	8	38	0.27	65	72	7	41	0.25	4	4	2
Field	11	Shoulder	P11	37	0	175	93	2	71	79	8	38	0.27	65	75	10	42	0.25	3	4	1
Field	12	Shoulder	P11	37	0	175	93	2	71	79	8	38	0.27	73	79	6	64	0.18	5	4	5
Field	1	Back	P12	44	0	188	100	2	67	86	19	12	2.52	64	82	18	14	2.56	4	3	2
Field	2	Back	P12	44	0	188	100	2	67	86	19	12	2.52	74	88	14	15	2.34	4	4	1
Field	3	Back	P12	44	0	188	100	2	67	86	19	12	2.52	72	85	13	16	2.47	5	5	2
Field	4	Back	P12	44	0	188	100	2	67	86	19	12	2.52	74	84	10	19	2.28	4	4	3
Field	5	Back	P12	44	0	188	100	2	67	86	19	12	2.52	72	84	12	23	1.86	4	4	5
Field	6	Leg	P12	44	0	188	100	2	73	86	13	28	9	77	89	12	30	9	4	4	2

	Wearable Support		User Profile (NP = Non-Practitioner, P = Practitioner)						Without Wearable (Baseline Condition)					With Wearable (Intervention Condition)							
									Measured					Measured					User Perceived		
Exp. Setting	Device Code	Body Region	ID	Age (yr)	Sex (M=0, F=1)	Height (cm)	Weight (kg)	Health Score (1-3)	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	HR Before Task	HR After Task	HRC	Fatigue Thrsh.	Erg. Risk Score	Comf. (1-5)	ROM (1-5)	Fatigue Red. (1-5)
Field	7	Leg	P12	44	0	188	100	2	73	86	13	28	9	65	76	11	31	9	4	4	2
Field	8	Leg	P12	44	0	188	100	2	73	86	13	28	9	72	82	10	38	8	3	4	2
Field	9	Leg	P12	44	0	188	100	2	73	86	13	28	9	71	79	8	119	8	3	3	4
Field	10	Shoulder	P12	44	0	188	100	1	65	76	11	41	0.25	74	84	10	45	0.29	4	3	1
Field	11	Shoulder	P12	44	0	188	100	1	65	76	11	41	0.25	74	85	11	46	0.28	3	4	1
Field	12	Shoulder	P12	44	0	188	100	1	65	76	11	43	0.25	72	81	9	83	0.17	5	3	4
Field	1	Back	P13	48	0	177	93	2	69	90	21	11	2.63	67	88	21	12	2.62	4	3	1
Field	2	Back	P13	48	0	177	93	2	69	90	21	11	2.63	79	101	22	12	2.64	4	4	2
Field	3	Back	P13	48	0	177	93	2	69	90	21	11	2.63	62	82	20	13	2.53	4	5	2
Field	4	Back	P13	48	0	177	93	2	69	90	21	11	2.63	62	80	18	17	2.43	4	4	3
Field	5	Back	P13	48	0	177	93	2	69	90	21	11	2.63	68	84	16	13	2.31	5	4	4
Field	6	Leg	P13	48	0	177	93	2	62	79	17	28	10	64	79	15	38	9	4	4	1
Field	7	Leg	P13	48	0	177	93	2	62	79	17	28	10	63	77	14	43	9	4	5	2
Field	8	Leg	P13	48	0	177	93	2	62	79	17	28	10	62	75	13	51	8	3	4	3
Field	9	Leg	P13	48	0	177	93	2	62	79	17	28	10	68	77	9	104	7	3	3	5
Field	10	Shoulder	P13	48	0	177	93	1	61	72	11	19	0.38	70	84	14	21	0.37	4	3	1
Field	11	Shoulder	P13	48	0	177	93	1	61	72	11	19	0.38	67	80	13	16	0.35	3	4	2
Field	12	Shoulder	P13	48	0	177	93	1	61	72	11	19	0.38	65	72	7	37	0.22	5	4	5

Appendix D: Enumeration of the 60 Device Sets

No.	Device Codes (B, L, S)	LOS Provided (B, L, S)	Total Cost (\$)	Lowest-Cost Qualifying Set for Required LOS (B, L, S)
1	1, 6, 10	1, 1, 1	91.56	(1, 1, 1)
2	2, 6, 10	1, 1, 1	110.49	–
3	1, 6, 11	1, 1, 1	110.55	–
4	2, 6, 11	1, 1, 1	129.47	–
5	1, 7, 10	1, 1, 1	160.32	–
6	2, 7, 10	1, 1, 1	179.25	–
7	1, 7, 11	1, 1, 1	179.31	–
8	2, 7, 11	1, 1, 1	198.23	–
9	1, 9, 10	1, 3, 1	204.88	(1, 2, 1); (1, 3, 1)
10	3, 6, 10	1, 1, 1	206.95	–
11	2, 9, 10	1, 3, 1	223.80	–
12	1, 9, 11	1, 3, 1	223.86	–
13	3, 6, 11	1, 1, 1	225.93	–
14	2, 9, 11	1, 3, 1	242.79	–
15	1, 8, 10	1, 2, 1	275.46	–
16	3, 7, 10	1, 1, 1	275.71	–
17	2, 8, 10	1, 2, 1	294.38	–
18	1, 8, 11	1, 2, 1	294.44	–
19	3, 7, 11	1, 1, 1	294.69	–
20	2, 8, 11	1, 2, 1	313.37	–
21	3, 9, 10	1, 3, 1	320.26	–
22	3, 9, 11	1, 3, 1	339.25	–
23	3, 8, 10	1, 2, 1	390.84	–
24	3, 8, 11	1, 2, 1	409.83	–
25	4, 6, 10	2, 1, 1	525.49	(2, 1, 1)
26	4, 6, 11	2, 1, 1	544.47	–
27	4, 7, 10	2, 1, 1	594.25	–
28	4, 7, 11	2, 1, 1	613.23	–
29	4, 9, 10	2, 3, 1	638.80	(2, 2, 1); (2, 3, 1)
30	4, 9, 11	2, 3, 1	657.79	–
31	4, 8, 10	2, 2, 1	709.38	–
32	4, 8, 11	2, 2, 1	728.37	–
33	1, 6, 12	1, 1, 3	2,061.73	(1, 1, 2); (1, 1, 3)
34	2, 6, 12	1, 1, 3	2,080.66	–
35	1, 7, 12	1, 1, 3	2,130.49	–
36	2, 7, 12	1, 1, 3	2,149.42	–
37	1, 9, 12	1, 3, 3	2,175.05	(1, 2, 2); (1, 2, 3); (1, 3, 2); (1, 3, 3)
38	3, 6, 12	1, 1, 3	2,177.12	–
39	2, 9, 12	1, 3, 3	2,193.97	–
40	1, 8, 12	1, 2, 3	2,245.63	–

No.	Device Codes (B, L, S)	LOS Provided (B, L, S)	Total Cost (\$)	Lowest-Cost Qualifying Set for Required LOS (B, L, S)
41	3, 7, 12	1, 1, 3	2,245.88	–
42	2, 8, 12	1, 2, 3	2,264.55	–
43	3, 9, 12	1, 3, 3	2,290.43	–
44	3, 8, 12	1, 2, 3	2,361.01	–
45	4, 6, 12	2, 1, 3	2,495.66	(2, 1, 2); (2, 1, 3)
46	5, 6, 10	3, 1, 1	2,560.49	(3, 1, 1)
47	4, 7, 12	2, 1, 3	2,564.42	–
48	5, 6, 11	3, 1, 1	2,579.47	–
49	4, 9, 12	2, 3, 3	2,608.97	(2, 2, 2); (2, 2, 3); (2, 3, 2); (2, 3, 3)
50	5, 7, 10	3, 1, 1	2,629.25	–
51	5, 7, 11	3, 1, 1	2,648.23	–
52	5, 9, 10	3, 3, 1	2,673.80	(3, 2, 1); (3, 3, 1)
53	4, 8, 12	2, 2, 3	2,679.55	–
54	5, 9, 11	3, 3, 1	2,692.79	–
55	5, 8, 10	3, 2, 1	2,744.38	–
56	5, 8, 11	3, 2, 1	2,763.37	–
57	5, 6, 12	3, 1, 3	4,530.66	(3, 1, 2); (3, 1, 3)
58	5, 7, 12	3, 1, 3	4,599.42	–
59	5, 9, 12	3, 3, 3	4,643.97	(3, 2, 2); (3, 2, 3); (3, 3, 2); (3, 3, 3)
60	5, 8, 12	3, 2, 3	4,714.55	–

Note. B, L, S = back, leg, shoulder; device codes as in Figure 6.29-a; LOS 1, 2, 3 = Low, Medium, High; costs in \$ CAD, computed from the unrounded catalogue unit costs. The sets are listed in order of total cost, so the first set whose LOS provided meets a combination's required LOS in every region is that combination's lowest-cost qualifying set. The last column gives the combinations of required LOS for which the set is the lowest-cost qualifying set.

Appendix E: Exact-Solver Verification Script

AID Statement: *Artificial Intelligence Tool:* Claude Fable 5.1 (Anthropic), used in October 2026; *Data Analysis:* Claude was used to write the Python script below, which solves the optimization model of Section 6.6 exactly with the HiGHS solver and enumerates all 60 device sets, and the author reviewed and ran the script and checked its results against the Excel implementation.

```
"""Exact-solver verification of the DSS device-selection model with HiGHS (highspy), Section 6.6.

Solves the binary form of the model (Eqs. 20-24, tie-breaker linearized exactly) for all 27
combinations of required LOS at the workbook's budget, cross-checks every answer by exhaustive
enumeration of the 60 device sets with the workbook's own formulas, and prints the listing shown in
Figure 6.39.

Usage:  python3 highs_verify.py "/path/to/Optimization Model.xlsm"
Needs:  python3 -m pip install highspy openpyxl

Workbook cells read (sheet "New"; the file is opened read-only and never modified):
    B8:D12  back catalogue (device code, LOS provided, device cost)
    B16:D19  leg catalogue          B23:D25  shoulder catalogue
    I15      budget (Max. Total Cost)      I25  cost-equivalence threshold tau
The enumeration replicates the workbook formulas: I23 surplus, I24 max surplus,
I26 epsilon = tau*(I23/I24)*cost, I27 objective = cost - epsilon, and table (f) (cheapest device
meeting the LOS in each region) for the minimum budget.
"""
import functools
import itertools
import operator
import os
import sys
import time
from decimal import Decimal, ROUND_HALF_UP

import highspy
import openpyxl

REGIONS = ("back", "leg", "shoulder") # listing order (B, L, S), as in Tables 6.10 and 6.12
CAT_ROWS = {"back": range(8, 13), "leg": range(16, 20), "shoulder": range(23, 26)} # sheet "New"
BUDGET_CELL, TAU_CELL = "I15", "I25"

def load_catalogue(path, sheet="New"):
    wb = openpyxl.load_workbook(path, data_only=True, keep_vba=True, read_only=True)
    if sheet not in wb.sheetnames:
        sys.exit(f"Sheet {sheet!r} not found in {os.path.basename(path)} (sheets: {wb.sheetnames})")
    ws = wb[sheet]
    cat = {}
    for r in REGIONS:
        rows = []
        for i in CAT_ROWS[r]:
            code, los, cost = ws[f"B{i}"].value, ws[f"C{i}"].value, ws[f"D{i}"].value
            if code is None or los is None or cost is None:
                sys.exit(f"Row {i} of sheet {sheet!r} has no device code / LOS / cost (B{i}:D{i}) "
                        f"- is this the right workbook?")
            rows.append((int(code), int(los), float(cost)))
        cat[r] = rows
    budget, tau = ws[BUDGET_CELL].value, ws[TAU_CELL].value
    if budget is None or tau is None:
        sys.exit(f"Budget ({BUDGET_CELL}) or tau ({TAU_CELL}) is empty - save the workbook in "
                f"Excel once and run again.")
    wb.close()
    return cat, float(budget), float(tau)

def money(x):
    """Two decimals, rounded half up as in Excel (value taken to 6 decimals first),
    e.g. 2175.045 -> 2,175.05."""
    return f"{Decimal(str(round(x, 6))).quantize(Decimal('0.01'), rounding=ROUND_HALF_UP):,}"

def lin_sum(h, terms):
    terms = list(terms)
    if not terms:
        return 0
    if hasattr(h, "qsum"):
        try:
            return h.qsum(terms)
```

```

        except Exception:
            pass
    return functools.reduce(operator.add, terms)

def value(h, var):
    """Value of a variable in the current solution (the highspy API differs between versions)."""
    try:
        return float(h.val(var))
    except Exception:
        return float(h.getSolution().col_value[var.index])

def solve_highs(cat, req, budget, tau, with budget=True, tiebreak=True):
    """req: dict region -> required LOS (1-3). Returns (status, codes dict, cost, seconds)."""
    h = highs.Highs()
    try:
        h.silent()
    except Exception:
        h.setOptionValue("output_flag", False)
    devs = [(r, code, los, cost) for r in REGIONS for code, los, cost in cat[r]]
    x = {}
    for r, code, los, cost in devs:
        try:
            x[(r, code)] = h.addBinary()
        except Exception:
            x[(r, code)] = h.addVariable(lb=0, ub=1, type=highspy.HighsVarType.kInteger)
    # exactly one device per region (Eq. 20); LOS sufficiency (Eq. 22)
    for r in REGIONS:
        h.addConstr(lin_sum(h, [x[(r, c)] for c, _, _ in cat[r]]) == 1)
        h.addConstr(lin_sum(h, [1 * x[(r, c)] for c, l, _ in cat[r]]) >= req[r])
    cost_expr = lin_sum(h, [k * x[(r, c)] for r, c, _, k in devs])
    if with budget:
        h.addConstr(cost_expr <= budget)
    objective = cost_expr
    if tiebreak:
        dmax = sum(max(1 for _, l, _ in cat[r]) - req[r] for r in REGIONS)
        if dmax > 0:
            scale = tau / dmax
            terms = []
            # same-region products reduce to x itself (Eq. 20)
            for r, c, l, k in devs:
                coef = scale * (1 - req[r]) * k
                if coef != 0:
                    terms.append(coef * x[(r, c)])
            # cross-region products -> continuous auxiliaries
            for (ra, ca, la, ka), (rb, cb, lb_, kb) in itertools.combinations(devs, 2):
                if ra == rb:
                    continue
                y = h.addVariable(lb=0, ub=1)
                h.addConstr(y - x[(ra, ca)] <= 0)
                h.addConstr(y - x[(rb, cb)] <= 0)
                h.addConstr(y - x[(ra, ca)] - x[(rb, cb)] >= -1)
                coef = scale * ((la - req[ra]) * kb + (lb_ - req[rb]) * ka)
                if coef != 0:
                    terms.append(coef * y)
            if terms:
                objective = cost_expr - lin_sum(h, terms)
    t0 = time.perf_counter()
    h.minimize(objective)
    secs = time.perf_counter() - t0
    status = h.modelStatusToString(h.getModelStatus())
    if status != "Optimal":
        return status, None, None, secs
    codes = {}
    for r in REGIONS:
        chosen = [c for c, _, _ in cat[r] if value(h, x[(r, c)]) > 0.5]
        codes[r] = chosen[0]
    cost = sum(k for r, c, _, k in devs if codes[r] == c)
    return status, codes, cost, secs

def enumerate_exact(cat, req, budget, tau):
    """Workbook formulas over all 60 sets: objective = cost - tau*cost*(surplus/max surplus);
    minimum budget (cheapest qualifying set) if none fits."""
    dmax = sum(max(1 for _, l, _ in cat[r]) - req[r] for r in REGIONS)
    best, best_obj, min_cost = None, None, None
    for combo in itertools.product(*[cat[r] for r in REGIONS]):
        los = {r: combo[i][1] for i, r in enumerate(REGIONS)}
        cost = sum(c[2] for c in combo)
        if any(los[r] < req[r] for r in REGIONS):

```

```

        continue
    if min_cost is None or cost < min_cost[0]:
        min_cost = (cost, {r: combo[i][0] for i, r in enumerate(REGIONS)})
    if cost > budget:
        continue
    surplus = sum(los[r] - req[r] for r in REGIONS)
    eps = 0.0 if dmax == 0 else tau * cost * surplus / dmax
    obj = cost - eps
    if best_obj is None or obj < best_obj - 1e-9:
        best, best_obj = {r: combo[i][0] for i, r in enumerate(REGIONS)}, obj
    return best, min_cost

def main(path):
    print(f"Workbook: {os.path.basename(path)} (sheet New)", file=sys.stderr)
    cat, budget, tau = load_catalogue(path)
    los_of = {r: {c: 1 for c, l, _ in cat[r]} for r in REGIONS}
    try:
        version = highs.Highs().version()
    except Exception:
        version = getattr(highspy, "__version__", "unknown")
    n_pairs = sum(len(cat[a]) * len(cat[b]) for a, b in itertools.combinations(REGIONS, 2))
    n_sets = len(cat["back"]) * len(cat["leg"]) * len(cat["shoulder"])
    print("EXACT-SOLVER VERIFICATION OF THE DEVICE-SELECTION MODEL (binary form, Eqs. 20-24)")
    print(f"Solver: HiGHS {version} (highspy); branch and cut; proven optimality or proven "
          f"infeasibility")
    print(f"Catalogue: back 1-5, leg 6-9, shoulder 10-12 ({n_sets} device sets); "
          f"budget ${budget:,.2f}; tau = {tau:.0%}")
    n_bin = sum(len(cat[r]) for r in REGIONS)
    print(f"Variables per instance: {n_bin} binary + {n_pairs} continuous (linearized products); "
          f"instances: 27")
    print()
    print(" #   Required LOS   HiGHS status   Selected set   LOS provided   Total cost   ")
    print("Minimum budget   Time")
    print("      (B, L, S)                      (B, L, S)      (B, L, S)      ($)          ")
    print("      ($)                      (ms)")
    print("-" * 104)
    n_opt = n_inf = agree = 0
    for i, (b, lg, s) in enumerate(itertools.product((1, 2, 3), repeat=3), 1):
        req = {"back": b, "leg": lg, "shoulder": s}
        status, codes, cost, secs = solve_highs(cat, req, budget, tau)
        enum_best, enum_min = enumerate_exact(cat, req, budget, tau)
        if status == "Optimal":
            n_opt += 1
            agree += int(enum_best == codes)
            cb, cl, cs = codes["back"], codes["leg"], codes["shoulder"]
            cost_s, mb_s = money(cost).rjust(9), "-".rjust(9)
        else:
            n_inf += 1
            st2, codes2, mincost, secs2 = solve_highs(cat, req, budget, tau,
                                                       with_budget=False, tiebreak=False)
            secs += secs2
            if st2 != "Optimal":
                sys.exit(f"Instance {i}: unexpected status {st2!r} without the budget constraint")
            agree += int(enum_best is None and codes2 == enum_min[1]
                        and abs(mincost - enum_min[0]) < 1e-6)
            cb, cl, cs = codes2["back"], codes2["leg"], codes2["shoulder"]
            cost_s, mb_s = "-".rjust(9), money(mincost).rjust(9)
        print(f"{i:>2}   ({b}, {lg}, {s})           {status:<12}   {cb:>2}, {cl:>2}, {cs:>2}      "
              f"   {los_of['back'][cb]}, {los_of['leg'][cl]}, {los_of['shoulder'][cs]}      "
              f"   {cost_s}      {mb_s}      {secs * 1000:5.1f}")
    print("-" * 104)
    print(f"Result: {n_opt} instances optimal within budget, {n_inf} proven infeasible "
          f"(minimum budget from a second solve without the budget constraint).")
    print(f"Cross-check: exhaustive enumeration of all 60 device sets with the workbook formulas "
          f"agreed in {agree}/27 instances.")

if __name__ == "__main__":
    if len(sys.argv) < 2:
        sys.exit("Usage: python3 highs_verify.py <path to the .xslm>")
    main(sys.argv[1])

```

Appendix F: Field Survey Questionnaire

Survey on Smart Tools for Managing Assets and Projects

Respondent Information (optional)

Company Type (Owner / Contractor / Asset Management):

Position & Job Function:

Years of Experience & Comments:

Survey on Smart Tools for Managing Assets and Projects

Main Menu

Once you have answered all of the applicable sections below, please select 'Submit Survey' and click 'Next' to submit the survey.

*** Please select the area that you are involved in (A, B, or C) and click 'Next' to proceed to that section. Once finished with that section, you will automatically be taken back to this page. You may then proceed to the next applicable section in the same manner, or submit the survey by following the above instructions.**

☐ **A: Managing a
Portfolio of Assets**

☐ **B: Managing a
Portfolio of
Projects**

☐ **C: Managing
Individual Projects**

☐ **Submit Survey**

Survey on Smart Tools for Managing Assets and Projects

Part A: Managing a Portfolio of Assets

Schools - Campus Buildings - Hospitals - Roads - Parks - Factories - Real Estate - Oil & Gas, etc.

We would like your help identifying how smart technologies can support the following functions:

- 1. Inspection & Performance Analysis**
- 2. Operations & Maintenance**
- 3. Prioritizing Capital Renewal Works**

General Information

You participate in function 1, 2, 3, or other (specify):

Your organization's asset types (e.g., campus buildings):

No. of assets (e.g., buildings) your organization manages:

No. of components (e.g., boilers, roofs, windows) per asset (e.g., 100 components per asset):

Yearly Maintenance Budget (\$):

Yearly Capital Renewal Budget (\$):

Survey on Smart Tools for Managing Assets and Projects

Part A: Managing a Portfolio of Assets

A1: Inspection & Performance Analysis

At your organization, how is this function (Inspection & Performance Analysis) performed?

- ☐ Internally
- ☐ External consultants

How much is spent on this function?

Budget (% of Annual Maintenance Budget):

Staff Effort (Low, Med, Hi)

What challenges do you currently face in this function?

Which assets/components are most challenging to assess and why?

Does your system consider multiple factors (e.g., social impact), in addition to physical condition, in the performance of assets?

- ☐ Yes
- ☐ No

If yes, how?

Existing Software

What software does your organization use for Inspection & Performance Analysis (e.g., VFA, SAP)?

What is your level of satisfaction with the above software's features?

- ☐ Very satisfied
- ☐ Satisfied
- ☐ Neither satisfied nor dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

What are the main drawbacks of the above software (e.g., manual/needs training/not accurate/time consuming/no drawing markups)?

Potential Improvements

I would consider a system/software to be smart if it could perform the following functions for Inspection & Performance Analysis (e.g., auto-analysis of asset deterioration patterns):

What features would you like to see in a system/software used in Inspection & Performance Analysis (e.g., identification of asset with top inspection priority)?

In your opinion, could smart tools such as robotics and AI improve this function?

- ☐ Significant potential
- ☐ Minor potential
- ☐ Not at all

Is there any part of Inspection & Performance Analysis that you would prefer to be automated (e.g., a robot performing certain tasks, a chart showing certain information)?

If a smart robot could be developed to assist you in this function, what task would you give it?

Other comments:

Survey on Smart Tools for Managing Assets and Projects

Part A: Managing a Portfolio of Assets

A2: Operations & Maintenance

At your organization, how is this function (Operations & Maintenance) performed?

- ☐ Internally
- ☐ External consultants

How much is spent on this function?

Budget (% of Annual Maintenance Budget):

Staff Effort (Low, Med, Hi)

What challenges do you currently face in Operations & Maintenance?

Which assets/components are most challenging and why?

Existing Software

What software does your organization use for Operations & Maintenance (e.g. VFA, SAP)?

What is your level of satisfaction with the above software's features?

- ☐ Very satisfied
- ☐ Satisfied
- ☐ Neither satisfied nor dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

What are the main drawbacks of the above software (e.g., manual/needs training/not accurate/time consuming/no drawing markups)?

Does your system share maintenance data with other functions (e.g., to prioritize inspections or assets to renew)?

☐ Yes

☐ No

If yes, how?

Potential Improvements

I would consider a system/software to be smart if it could perform the following functions for Operations & Maintenance:

What features would you like to see in a system/software for Operations & Maintenance (e.g., identification of asset with top maintenance priority, preventative maintenance scheduling)?

In your opinion, could smart tools such as robotics and AI improve this function?

☐ Significant potential

☐ Minor potential

☐ Not at all

Is there any part of Operations & Maintenance that you would prefer to be automated (e.g., a robot performing certain tasks, a chart showing certain information highlighting maintenance needs)?

If a smart robot could be developed to assist you in Operations & Maintenance, what task would you give it?

Other comments:

Survey on Smart Tools for Managing Assets and Projects

Part A: Managing a Portfolio of Assets

A3: Prioritizing Capital Renewal Works Under a Limited Budget

At your organization, how is this function (Prioritizing Capital Renewals) performed?

- ☐ Internally
- ☐ External consultants

How much is spent on this function?

Budget (% of Capital Budget):

Staff Effort (Low, Med, Hi)

What challenges do you currently face with Prioritizing Capital Renewals?

How do you consider the different types of assets that compete for funding (e.g., roof vs HVAC system)?

- ☐ Weighting for different asset types
- ☐ Health and Safety
- ☐ Impact on building operation

Does your system use a worst-first strategy for prioritizing renewals?

- ☐ Yes
- ☐ No

If no, please explain your approach:

Existing Software

What software does your organization use for Prioritizing Capital Renewals (e.g. VFA, SAP)?

What is your level of satisfaction with the above software's features?

- ☐ Very satisfied
- ☐ Satisfied
- ☐ Neither satisfied nor dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

What are the main drawbacks of the above software (e.g., manual process, requires training, not accurate, time consuming to use, no drawing markups, no accurate reports, time consuming to update)?

Potential Improvements

I would consider a system/software to be smart if it could perform the following functions (e.g., auto-analysis of asset deterioration patterns, prediction of asset deterioration, automatic calculation of renewal costs):

What features would you like to see in a system/software for capital renewal prioritization (e.g., optimization function for maximum benefits, developing annual program for given budget, selecting priority projects based on multiple criteria)?

In your opinion, could smart tools such as robotics and AI improve the prioritization of capital renewals?

- ☐ Significant potential
- ☐ Minor potential
- ☐ Not at all

Is there any part of prioritizing capital renewals that you would prefer to be automated (e.g., a robot performing certain tasks such as inspection, a chart showing certain information)?

If a smart tool could be developed to assist you in prioritizing capital renewal, what task would you expect?

Other comments:

Survey on Smart Tools for Managing Assets and Projects

Part B: Managing a Portfolio of Projects

This section refers to managing a group of potentially similar projects together (applicable to a portfolio manager or department manager job function).

Part B: General Information

Which of the following functions do you perform for your organization?

- | | | |
|---|--|--|
| ☐ Design | ☐ Procurement | ☐ Progress Monitoring |
| ☐ Work Packaging & Contracting | ☐ Detailed Scheduling | ☐ Construction |
| ☐ Other (please specify) | | |

Your organization's project types (e.g., roads, schools, utilities):

Project Info:

Avg No.
Projects/Year:

Avg No. of
Tasks/Project

Avg Project Size (\$)

Avg Project Duration
(days)

Survey on Smart Tools for Managing Assets and Projects

Part B: Managing a Portfolio of Projects

This section refers to managing a group of potentially similar projects together (applicable to a portfolio manager or department manager job function).

At your organization, which types of projects are most challenging and why (interior renovation, additions, equipment replacement, etc)?

At your organization, which functions are performed internally and which ones are performed using consultants (if applicable)?

	Internally	Consultants	Both
Design	☐	☐	☐
Work Packaging & Contracting	☐	☐	☐
Procurement	☐	☐	☐
Detailed Scheduling	☐	☐	☐
Progress Monitoring	☐	☐	☐
Construction	☐	☐	☐

What challenges do you currently face in these functions?

Design	<input type="text"/>
Work Packaging & Contracting	<input type="text"/>
Procurement	<input type="text"/>
Detailed Scheduling	<input type="text"/>
Progress Monitoring	<input type="text"/>
Construction	<input type="text"/>

How much of the construction work is performed by in-house trades and how much is performed by contractors/subcontractors (if selected "both" above)?

In-house (%):	<input type="text"/>
Contract (%):	<input type="text"/>
Reason:	<input type="text"/>

Do you bundle smaller rehabilitation works together into one contract?

☐ Yes

☐ No

Please explain

Existing Software

Which software does your organization use for managing a portfolio of projects (e.g. MS Project, Primavera P6)?

Do you use this software's features for multi-project management?

☐ Yes

☐ No

Do you use repetitive scheduling tools to manage projects at different locations?

☐ Yes

☐ No

Can this software optimize multi-project schedules to meet deadlines?

☐ Yes

☐ No

Does this software update the schedule dynamically and support your corrective action planning?

☐ Yes

☐ No

Do you use Earned Value analysis to monitor cost and schedule performance?

☐ Yes

☐ No

Does this software provide a sufficient level of documentation for progress events that is suitable for verifying claims for project extension?

☐ Yes

☐ No

What is your level of satisfaction with the software's features?

- ☐ Very satisfied
- ☐ Satisfied
- ☐ Neither satisfied nor dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

What are the main drawbacks of the software?

Potential Technologies

I would consider a system/software to be smart if it could perform the following functions:

In your opinion, can smart tools such as robotics and AI improve project management functions?

- ☐ Significant Potential
- ☐ Minor Potential
- ☐ Not at all

Which project management job functions do you think robotics or AI could improve at your organization? How significantly (0-10)?

Site Inspection	<input type="text"/>
Contract Management	<input type="text"/>
Scope Definition	<input type="text"/>
Reporting	<input type="text"/>
Locating Materials	<input type="text"/>
Progress Monitoring	<input type="text"/>

Which technologies do you think would be helpful for improving efficiency in your role (select all that apply)?

- | | |
|---|---|
| ☐ Building Information Modelling | ☐ Unmanned Aerial Vehicles |
| ☐ Wearable Sensing Data | ☐ Image Analysis |
| ☐ Robotics & Automation | ☐ Augmented Reality |

What features would you like to see in a system/software used for managing a portfolio of projects (e.g., a map showing the status of all of your projects at different locations, overall schedule for entire portfolio, relationships/dependencies between projects)?

Is there any part of your role that you would prefer to be automated?

Which project phases have the most potential for efficiency improvements using advanced technologies?

- ☐ Planning and Design
- ☐ Procurement
- ☐ Construction, Commissioning
- ☐ Closeout

How much support do you get from your existing software tools for the following aspects?

	None	Low	Med	High
Safety Planning	☐	☐	☐	☐
Sustainability	☐	☐	☐	☐
Waste Reduction	☐	☐	☐	☐
Green Projects	☐	☐	☐	☐
Energy Savings	☐	☐	☐	☐

Other Comments:

Survey on Smart Tools for Managing Assets and Projects

Part C: Managing Individual Projects

This section refers to the functions involved in managing a single project at a time (applicable to a project manager job function).

Part C: General Information

Which of the following functions do you perform for your organization?

- | | | |
|---|--|--|
| ☐ Design | ☐ Procurement | ☐ Construction |
| ☐ Contracting | ☐ Detailed Scheduling | ☐ Progress Monitoring |
| ☐ Other (please specify) | | |

Your organization's project types (e.g., roads, schools, utilities):

Project Info:

Avg No. of
Tasks/Project

Avg Project Size (\$)

Avg Project Duration
(days)

Survey on Smart Tools for Managing Assets and Projects

Part C: Managing Individual Projects

This section refers to the functions involved in managing a single project at a time (applicable to a project manager job function).

At your organization, which types of projects are most challenging and why (interior renovation, new construction, additions, equipment replacement, etc)?

At your organization, which functions are performed internally and which ones are performed using consultants (if applicable)?

	Internally	Consultants	Both
Design	☐	☐	☐
Contracting	☐	☐	☐
Procurement	☐	☐	☐
Detailed Scheduling	☐	☐	☐
Construction	☐	☐	☐
Progress Monitoring	☐	☐	☐

What challenges do you currently face in these functions?

Design	<input type="text"/>
Contracting	<input type="text"/>
Procurement	<input type="text"/>
Detailed Scheduling	<input type="text"/>
Construction	<input type="text"/>
Progress Monitoring	<input type="text"/>

How much of the construction work is performed by in-house trades and how much is performed by contractors/subcontractors (if selected "both" above)?

In-house (%):	<input type="text"/>
Contract (%):	<input type="text"/>
Reason:	<input type="text"/>

Software

Which software does your organization use for managing individual projects (e.g. MS Project, Primavera P6)?

Can this software optimize the work schedule to meet deadlines, minimize cost, and efficiently manage resources?

☐ Yes

☐ No

Does this software update the schedule dynamically and support your corrective action planning?

☐ Yes

☐ No

Does this software provide a sufficient level of documentation for progress events that is suitable for verifying claims for project extension?

☐ Yes

☐ No

What is your level of satisfaction with the software's features?

☐ Very satisfied

☐ Satisfied

☐ Neither satisfied nor dissatisfied

☐ Dissatisfied

☐ Very dissatisfied

What are the main drawbacks of the software?

Do you use Earned Value analysis to monitor cost and schedule performance?

☐ Yes

☐ No

Potential Technologies

I would consider a system/software to be smart if it could perform the following functions:

In your opinion, can smart tools such as robotics and AI improve project management functions?

- ☐ Significant Potential
- ☐ Minor Potential
- ☐ Not at all

Which project management job functions do you think robotics or AI could improve at your organization? How significantly (0-10)?

Site Inspection	<input type="text"/>
Contract Management	<input type="text"/>
Scope Definition	<input type="text"/>
Reporting	<input type="text"/>
Locating Materials	<input type="text"/>
Progress Monitoring	<input type="text"/>

Which technologies do you think would be helpful for improving efficiency in your role (select all that apply)?

- | | |
|---|---|
| ☐ Building Information Modelling | ☐ Unmanned Aerial Vehicles |
| ☐ Wearable Sensing Data | ☐ Image Analysis |
| ☐ Robotics & Automation | ☐ Augmented Reality |

Which technologies do you think would be helpful for managing occupational health and safety (select all that apply)?

- | | |
|---|---|
| ☐ Building Information Modelling | ☐ Unmanned Aerial Vehicles |
| ☐ Wearable Sensing Data | ☐ Image Analysis |
| ☐ Robotics & Automation | ☐ Augmented Reality |

What features would you like to see in a system/software used in managing individual projects?

Is there any part of your role that you would prefer to be automated?

Which project phases have the most potential for efficiency improvements using advanced technologies?

- ☐ Planning and Design
- ☐ Procurement
- ☐ Construction, Commissioning
- ☐ Closeout

How much support do you get from your existing software tools for the following aspects?

	None	Low	Med	High
Safety Planning	☐	☐	☐	☐
Sustainability	☐	☐	☐	☐
Waste Reduction	☐	☐	☐	☐
Green Projects	☐	☐	☐	☐
Energy Savings	☐	☐	☐	☐

Other Comments:

Survey on Smart Tools for Managing Assets and Projects

Main Options

Thank you for completing the survey!