Development of AI-based ergonomics risk assessment tools for harmonization of industrial work systems

by

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Abstract

Manufacturing industry workers face significant ergonomic risks due to poorly designed work systems. Consequently, it is crucial to periodically assess work systems to identify areas for improvement. However, the assessment process is often disregarded due to the absence of user-friendly ergonomics risk assessment tools. The primary objective of this study is to address this issue by leveraging artificial intelligence to develop convenient ergonomics risk assessment tools for occupational injury management. The study identified four significant challenges that hamper the effectiveness of ergonomics risk assessment: (1) a lack of versatile physical-ergonomic tools; (2) the fragmented nature of existing ergonomic tools that fails to provide an integrated assessment of work systems; (3) the challenge of developing an interpretable data analytics framework for risk diagnosis; and (4) the inability to develop human-centered ML-powered ergonomics risk assessment tools. To address these challenges, the study pursued four objectives. First, a versatile physical-ergonomics risk assessment tool is developed using the Pattern Search optimization algorithm to simplify tool selection for improving work systems. Second, a fuzzy logic-based Decision Support System is developed to provide an integrated assessment of the ergonomic performance of work systems by blending physical, environmental, and sensory risk factors. Third, an effective and interpretable machine learning-based data analytics framework is developed for diagnosing safety and ergonomics risk factors in work systems. Finally, a literature review is conducted to uncover the many design challenges that hinder the development of human-centered ML-powered ergonomics risk assessment tools. Overall, this study aims to demonstrate the effectiveness of AI as a valuable technology for developing convenient ergonomics risk assessment tools that aid health and safety specialists in mitigating ergonomic risks by facilitating the harmonization of industrial work systems.

Preface

This thesis is the original work of the author, Aswin Ramaswamy Govindan. The research presented in this thesis has been conducted in accordance with ethical guidelines and has received approval from the Human Research Ethics Board at the University of Alberta. The ethics approval number for this research is Pro00123306. Six research papers related to this thesis have been submitted, accepted, or published. They are as follows:

Journal Publications

1. Govindan, A., & Li, X. (2022). Revamped Physical Load Index. *Human Factors and Ergonomics in Manufacturing and Service Industries.* [Submitted]
2. Govindan, A., & Li, X. (2023). Fuzzy logic-based decision support system for automating ergonomics risk assessments. *International Journal of Industrial Ergonomics.* [Accepted]
3. Govindan, A., & Li, X. (2023). A data analytics framework for identifying and characterizing incident clusters in the diagnosis of risk factors in manufacturing. *International Journal of Occupational Safety and Ergonomics.* [Submitted].
4. Govindan, A., & Li, X. (2023). Current status, challenges, and opportunities in the application of machine learning for the improvement of physical ergonomics in manufacturing industries: a human-centered design perspective. *International Journal of Industrial Ergonomics.* [Submitted].

Conference Publications

1. Govindan, A., & Li, X. (2022). Revamped PLI: An ergonomics risk assessment technique for assessing Work-Related Musculoskeletal Disorders in Manufacturing and Modular

Construction Operations. *Global Summit and Expo on Industrial and Manufacturing Engineering. [Accepted].*

2. Govindan, A., & Li, X. (2022). Design and Implementation of a Fuzzy Expert System for an Ergonomic Performance Assessment in Modular Construction Operations Using the DMAIC Approach. *In Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021: CSCE21 Construction Track Volume 1 (pp. 409-421). Singapore: Springer Nature Singapore.* [Accepted].

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List of Abbreviations

DSS	Decision Support System
EHR	Extremely High Risk
ERI	Ergonomic Risk Indicator
FES	Fuzzy Expert System
HR	High Risk
HSE	Health and Safety Executive
LR	Low Risk
MAC	Manual Handling Assessment Charts
ML	Machine Learning
MR	Medium Risk
NR	Negligible Risk
NIOSH	National Institute for Occupational Safety and Health
OSHA	Occupational Safety and Health Administration
OWAS	Ovako Working Posture Analysing System
PCA	Principal Component Analysis
PLI	Physical Load Index
REBA	Rapid Entire Body Assessment
RULA	Rapid Upper Limb Assessment
WBGT	Wet Bulb Globe Temperature
WMSD	Work-related Musculoskeletal Disorders

Chapter 1: INTRODUCTION

1.1 Background and motivation

Ergonomics is the study of human-workplace interactions, with the goal of optimizing safety, human well-being, and system performance through the use of theory, concepts, data, and design (International Ergonomics Association, 2003). In a manufacturing facility, workers at each workstation are responsible for performing a set of job tasks. These tasks involve interacting with other system elements to transform raw materials into finished products. However, when ergonomic discomfort leads to errors or unproductive activities, these issues can propagate to downstream workstations, resulting in production fluctuations and losses that can impact system throughput and product quality (Lee et al., 2021).

To improve interactions between workers and system elements on the shop floor, manufacturing companies must focus on improving the ergonomic performance of their industrial work systems. By doing so, they can minimize injury rates, increase worker productivity, reduce product defects, and lower manufacturing costs (Resnick, 1997; Wilson, 2000; Shikdar, 2002; Shikdar, 2003; Krishna et al., 2015; Zare et al., 2016; Martin Lebeau et al., 2013). A variety of ergonomics risk assessment methods have been proposed by ergonomics researchers to evaluate different physical, environmental, and sensory aspects of workplace design. These researchers have introduced many conventional manual ergonomics risk assessment tools for assessing the ergonomic performance of work systems (Lynn et al., 1993; Waters et al., 1993; Moore et al., 1995; Karhu et al., 1977; Hol et al., 1999, McAtamney et al., 2004; Health and Safety Executive, 2006; Freivalds et al., 2013; Health and Safety Executive, 2020; Occupational Safety and Health Administration, 2020; Hart et al., 1988; Reid et al., 1988; Li et al., 2015; Li et al., 2019a).

Despite the significant benefits of prioritizing health and safety in manufacturing (Hendrick, 2003; Dul et al., 2009), businesses often overlook ergonomic performance assessments due to the lack of convenient tools (Kahraman et al., 2003; Azadeh et al., 2008). Therefore, the primary objective of this research is to leverage artificial intelligence to develop convenient ergonomics risk assessment tools that can help health and safety specialists mitigate ergonomic risks in the workplace and harmonize industrial work systems. In this context, harmonization refers to the intricate process of aligning and seamlessly integrating individuals with their work environments, ultimately ensuring not only their ease and comfort but also optimizing the efficiency and effectiveness of their job tasks.

1.2 Problem statement

Four significant challenges, which make the ergonomics risk assessment process less convenient for health and safety specialist based on the current state of art, are discovered in this research:

Problem 1: lack of versatile physical-ergonomic tools

The existing physical-ergonomic tools available for assessing workplace risks are often specialized and not versatile enough to be compatible with different data collection methods to suit their time and budget constraints (David, 2005). Additionally, the requirement for practitioners to learn new tools for assessing diverse work systems further hinders the progress of enhancing work systems. To address this challenge, there is a need for a versatile physical-ergonomics risk assessment tool that can simplify tool selection for work system improvement.

Problem 2: the fragmented nature of existing ergonomic tools that fail to provide an integrated assessment of work systems

Current ergonomics risk assessment tools assess physical, environmental, and sensory work system components individually, which does not provide an integrated assessment of work systems. A comprehensive ergonomics risk assessment tool should incorporate physical, environmental, and sensory factors and consider their interplay. However, due to a lack of literature on the interplay between these factors, developing a standard logical decision support system (DSS) for this scenario proves to be a challenging task. Fortunately, a fuzzy logic-based DSS can address problems with incomplete, partial, or inaccurate knowledge (Zadeh et al. 2013; Novak et al. 2012; Kayacan et al. 2016). Therefore, there is a need to develop a fuzzy logic-based DSS that incorporates physical, environmental, and sensory elements to assess the ergonomic performance of work systems.

Problem 3: the challenge of developing an interpretable data analytics framework for risk diagnosis

Managing occupational risks in the manufacturing industry can reduce injuries, workers' compensation costs, and improve productivity and product quality (Pawłowska et al. 2011; Li et al. 2019; Lee et al. 2021). However, occupational risks can be difficult to understand and require a risk classification system. Researchers have developed several supervised machine learning (ML) models to classify and diagnose risk factors (Sarkar et al. 2020; Lee et al. 2021; Chan et al. 2022), but these models can be difficult for non-expert users to understand. Moreover, these models require labeled datasets, which may not always be available. To address this issue, an effective and interpretable ML-based data analytics framework that can diagnose occupational risk factors using worker incident data without needing pre-labeled datasets needs to be developed.

Problem 4: the inability to develop human-centered ML-powered ergonomics risk assessment tools

The objective of ergonomics in manufacturing is to maintain worker comfort and safety, which can lead to positive outcomes in various contexts, including financial, technical, legal, social, organizational, political, and professional, resulting in decreased costs and increased productivity. While researchers have demonstrated the viability of several ML-powered ergonomics risk assessment tools in manufacturing ergonomics (Parsa et al., 2020; Arora et al., 2021; Ciccarelli et al., 2022; Arora et al., 2022; Lee et al., 2022; Kwon et al., 2022; Fernandes et al., 2022; Generosi et al., 2022; Kunz et al., 2022), the dominance of research-focused machine learning (ML) tools in the literature highlights various challenges that researchers encounter. Therefore, there is a need to propose strategic visions to bridge the gap between research-focused ML tools and practical ML systems for manufacturing ergonomics.

1.3 Research objectives

To solve the research problems, the following objectives are pursued in this research:

1. Develop a versatile physical-ergonomics risk assessment tool to simplify tool selection for work system improvement.
2. Develop a fuzzy logic-based DSS that integrates the Physical, Environmental, and Sensory aspects to assess the ergonomic performance of work systems.

3. Develop an interpretable data analytics framework for effective occupational injury management through occupational risk diagnosis.
4. Develop strategic visions for bridging the gap between research-focused ML tools and practical ML systems in manufacturing ergonomics.

Specifically, Objective 1 aims to revamp a pre-existing physical ergonomics risk assessment tool called the Physical Load Index (PLI) that has the potential to be compatible with Self-reports, Observational methods, and Direct Measurements. Objective 2 intends to craft a fuzzy logic-based DSS that portrays overall ergonomic risk in the workplace (including physical, environmental, and sensory risk factors) by blending different ergonomics risk assessment tools to develop a composite key performance indicator (KPI) called the ergonomic risk indicator (ERI). Objective 3 aims to develop a data analytics framework for occupational risk diagnosis to facilitate better occupational injury management. Finally, Objective 4 aims to conduct a detailed literature review of ML research in manufacturing ergonomics and propose strategic visions for future research to bridge the gap between research-focused ML tools and practical ML systems.

1.4 Thesis organization

This thesis comprises seven distinct chapters, each contributing to the advancement of ergonomic risk assessment in industrial work systems, which are represented on a high-level in Figure 1-1. Figure 1-1 visually represents the structure of the thesis and how each chapter contributes to the overarching goal of improving ergonomic risk assessment. It serves as a roadmap, guiding through the various aspects and stages of the research undertaken to address the challenges and objectives discussed earlier.

Chapter 1 serves as an introduction, outlining the background, motivation, and essential context for this research. It highlights the significance of harnessing AI for the development of efficient ergonomics risk assessment tools that align with industrial work systems' needs. This chapter also articulates the problem statement and research objectives guiding this endeavor.

Chapter 2 provides a literature review outlining five essential concepts for understanding subsequent chapters. It emphasizes key trends and challenges identified in the literature, pinpointing gaps to address in the following sections.

In Chapter 3, the conventional Physical Load Index (PLI), a tool for evaluating physical-ergonomics risks, undergoes a transformation to create a versatile tool. The revamped version, known as Revamped PLI, emerges as a versatile instrument capable of assisting health and safety experts in enhancing work systems. Revamped PLI capitalizes on the strengths of its predecessor while addressing its limitations. This chapter substantiates the efficacy of Revamped PLI by comparing it with the widely-used Rapid Entire Body Assessment (REBA) tool.

Chapter 4 recognizes the importance of a comprehensive assessment encompassing various ergonomic risk factors. Beyond physical aspects, environmental and sensory factors are integrated into a fuzzy logic-based Decision Support System (DSS). This innovative DSS amalgamates different ergonomics risk assessment tools to generate a composite risk score, referred to as ERI. Real-life validation attests to the effectiveness of the proposed DSS.

Chapter 5 extends the focus to risk interpretation alongside quantification. An interpretable Machine Learning (ML) data analytic framework is conceived for identifying and characterizing clusters of worker incidents, facilitating improved management of occupational injuries. This framework combines unsupervised ML, supervised ML, and Explainable AI techniques for diagnosing occupational risk factors. A real-life case study verifies the framework's utility.

In Chapter 6, the influence of ML on ergonomic risk assessments is recognized, prompting an extensive literature review of existing ML research in the context of manufacturing ergonomics. The review underscores a bias towards research-oriented tools rather than human-centered solutions. This imbalance is attributed to four distinct design challenges. In response, the chapter proposes four strategic visions to address design challenges and enhance the development of human-centered, practical ML solutions.

Finally, Chapter 7 offers a synthesis of the thesis's findings and contributions. It encapsulates the outcomes of the research journey, reflecting upon its significance. Additionally, this chapter acknowledges the limitations of the study and delineates potential avenues for future research.

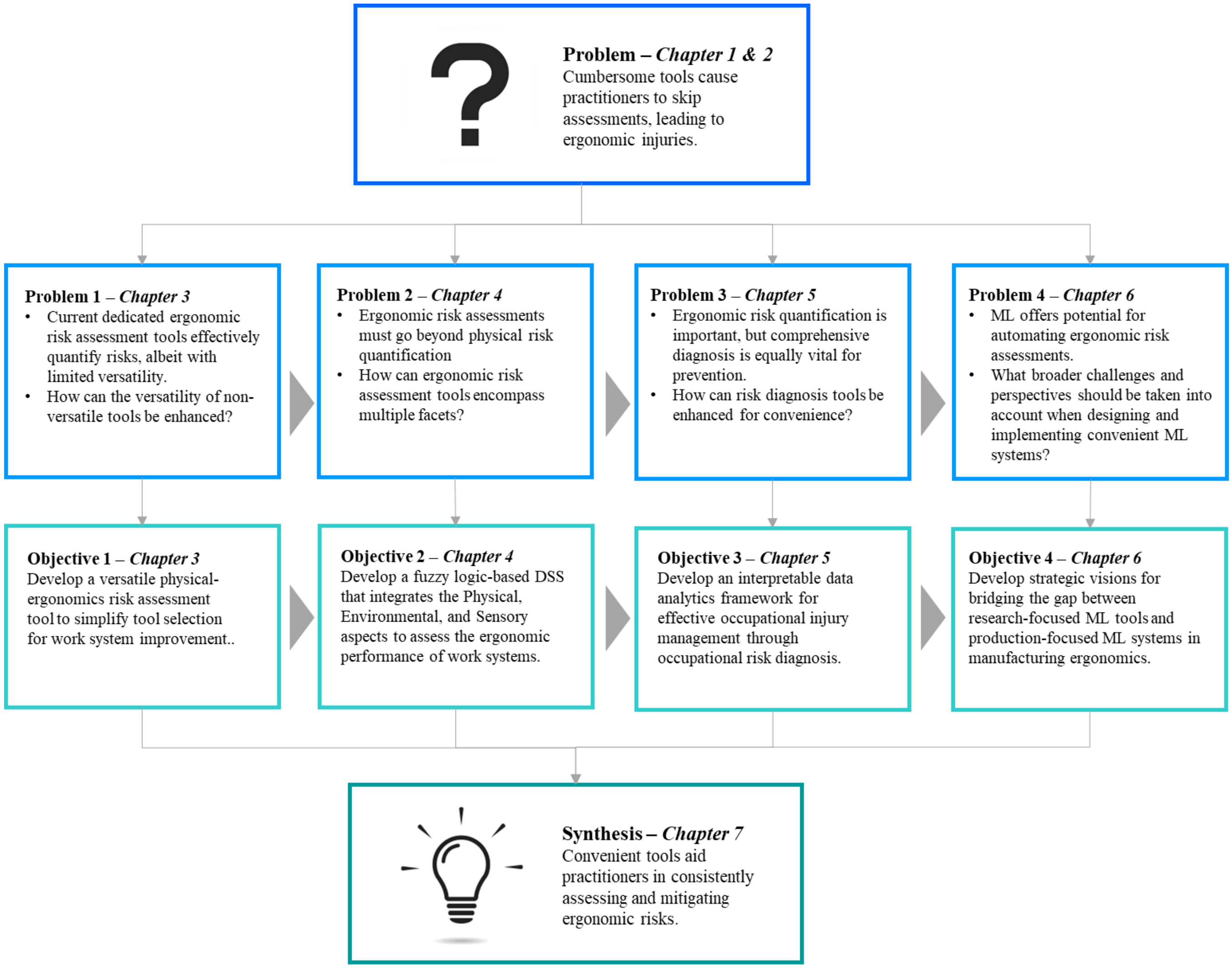

Figure 1-1 Thesis Structure

Chapter 2: LITERATURE REVIEW

This chapter offers a comprehensive exploration of five pivotal topics that play a crucial role in achieving the harmonization of work systems. Section 2.1 focuses on the classification of ergonomic data collection methods, exploring the different approaches used to gather data in this field. Section 2.2 examines conventional physical ergonomics risk assessment tools commonly employed for evaluating industrial job tasks, highlighting their significance in assessing ergonomic risks and their impacts on workers' well-being. This section reviews the assessed ergonomics risk assessment tools, emphasizing their limitations and narrow specializations, which present challenges for health and safety specialists when selecting tools that align with their organization's specific needs and limitations. Section 2.3 explores the applications of fuzzy logic in ergonomics risk assessment, highlighting its widespread use in various industries while emphasizing the need for an integrated fuzzy logic-based decision support system to address all relevant hazards in work systems. Section 2.4 explains how ML can be used to diagnose risk factors in manufacturing occupational safety and health. It emphasizes the need for easier-to-understand model interpretation techniques, the challenges of labeling datasets, and the importance of integrating safety and ergonomics research. Lastly, Section 2.5 provides a broader overview of the state-of-the art ML-powered ergonomic risk assessment tools in manufacturing ergonomics. By comprehensively addressing the following five areas, this chapter strives to delve into essential concepts to enhance the harmonization of work systems.

2.1 Data collection methods for ergonomics risk assessments

Various ergonomic data collection methods are available for conducting ergonomics risk assessments. David (2005) conducted an in-depth review of the ergonomic methods that have been developed for assessing exposure to risk factors for work-related musculoskeletal disorders (WMSDs). As David notes, the methods for assessing WMSD risk factors can be understood in terms of three main categories: (1) self-reports, where workplace exposure data is collected and assessed based on physical and psychosocial factors through interviews and questionnaires; (2) observational methods, which can be subcategorized as either "simple observational methods" (where the observer methodically records and assesses workplace exposure data using manual observational techniques) or "advanced observational methods" (where workplace postural variation in highly dynamic activities are observed using computer vision algorithms or other dedicated software); and (3) direct measurements, where workplace exposure data is collected using monitoring instruments that typically rely on sensors or optical markers attached directly to the individual under observation (David, 2005; Inyang et al., 2012). Given the diverse range of methods available, the data acquisition costs, maintenance costs, training strategies, time requirements, and assessment precision will vary depending on the particular method being employed. Accordingly, the type of assessment method to be employed is chosen by the practitioner based on the resources available to the organization, as illustrated in Figure 2-1 (David, 2005; Li et al., 2018; Humadi et al., 2021; Yantao Yu et al., 2019; Nath et al., 2017).

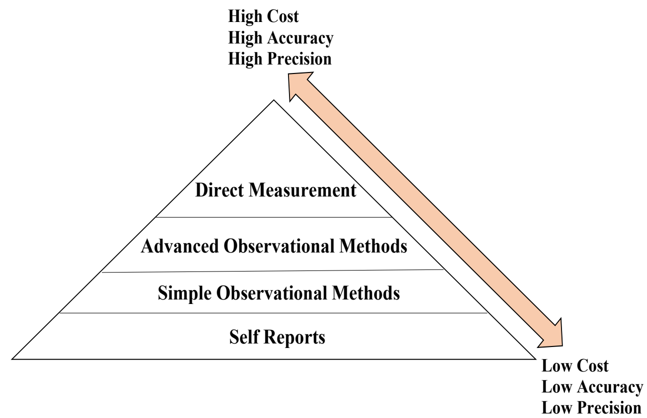

Figure 2-1 Classification of human data collection methods

2.2 Prominent tools for ergonomics risk assessments

A range of tools have been developed in the last decades for assessing various aspects of physical ergonomic risk. The reviewed literature suggests that the spine, which connects different parts of the musculoskeletal system, is the most affected region in the human body when performing any type of strenuous activity (Punnett et al., 2005; Trinkoff et al., 2003; Cole et al., 2001; Ebraheim et al., 2004; Bridger, 1991; Pope et al., 2002, Straker 1999). Thus, Hollmann et al. (1999) developed Physical Load Index (PLI), which focuses on evaluating risk factors primarily based on the posture of the trunk and the mechanical load it carries and the frequency of postures while performing dynamic and continuous activities. Pascual et al. (2008) investigated and found that the National Institute for Occupational Safety and Health (NIOSH) Lifting Equation, Rapid Upper Limb Assessment (RULA), and REBA are the tools recommended most by certified ergonomists. To be more specific, Waters et al. (1993) have noted that the NIOSH Lifting Equation is "designed to assist in the identification of ergonomic solutions for reducing the physical stresses associated with manual lifting by identifying the features of the lifting task that contribute the most to the hazard for low back injuries”. Lynn et al. (1993) have indicated that RULA is designed to “assess operators who may be exposed to musculoskeletal loading which is known to contribute to upper limb disorders”. McAtamney et al. (2004), meanwhile, mentioned that REBA is a tool specifically designed to be sensitive to erratic working postures observed in health care and other service industries as part of entire body assessments. In addition to these prominent tools, there are other credible ergonomics risk assessment tools currently in use in industry. For instance, Moore et al. (2010) developed a tool, called 'The strain index’, that measures six task variables by (1) assigning an ordinal rating for each task variable based on the exposure data; and (2) then assigning a multiplier value for each task variable. This tool is used to identify jobs associated with distal upper extremity disorders (Moore et al., 2010). In a much earlier study, Karhu et al. (1971) devised a pragmatic method, called Ovako working posture analyzing system (OWAS), for detecting and assessing poor working postures. OWAS was developed to evaluate worker performance as a function of the discomfort brought on by poor working postures. This tool was developed with the purpose of facilitating work sampling, offering insights into the frequency and duration of various postures assumed by workers (Karhu et al., 1971). As another example, manual handling assessment charts (MAC) is a checklist used by safety inspectors and professional health inspectors when analyzing the common risk factors associated with lifting, lowering, and individual or group lugging, although it should be noted that the method of assessment differs depending on which of the three operations is being assessed (Health and Safety Executive, 2014). Furthermore, Chapter 3 will provide a comprehensive and in-depth analysis of various tools, offering a more extensive and detailed comparison between them.

Overall, conventionally used ergonomics risk assessment tools such as REBA, RULA, the National Institute for Occupational Safety and Health (NIOSH) Lifting Equation, the strain index, the Ovako working posture analyzing system (OWAS), and manual handling assessment charts (MAC), are best suited to specific human data collection method such as simple observational methods. Moreover, these tools have narrow specializations that prevent them from being comprehensive tools that can be used for assessing all types of industrial job tasks. This makes it challenging for health and safety specialists to quickly find ergonomics risk assessment tools that fit their organization's needs and limits (David, 2005). Moreover, when selecting an ergonomics risk assessment tool, health and safety specialists are also required to consider execution time and costs associated with the selected tool. In addition, the health and safety specialists must also become acquainted with the selected tool. Therefore, selecting and acquainting oneself with an appropriate tool for assessing the performance of industrial job tasks delay the improvement of industrial work systems.

2.3 Fuzzy-Logic based ergonomics risk assessment tools

Many expert systems use dual-logic inference engines, but the fuzzy expert system (FES) uses fuzzy logic and approximate reasoning (Pal et al. 1991). Fuzzy logic seeks to reflect the imprecise forms of thinking that helps humans to make rational decisions in an uncertain and imprecise world. Thus, performance of an Fuzzy Expert System (FES) depends on human ability to deduce an approximate solution to a problem in the presence of an imperfect, incomplete, or unreliable body of knowledge (Hall et al. 1988; Zadeh et al. 2013; Novak et al. 2012; Kayacan et al. 2016). Hall et al. (1988) assert that FESs are applicable to multiple domains because the theory of imprecision handling for fuzzy sets is well-developed. Accordingly, fuzzy logic has been successfully used in several areas, such as control systems engineering, image processing, power engineering, industrial automation, robotics, consumer electronics, and optimization.

In addition, the application of fuzzy logic to the assessment of ergonomic risk has been widely adopted in a variety of industries. Azadeh et al. (2008) designed a FES for assessing the performance of health, safety, environment (HSE) and ergonomics system factors in a gas refinery. Nunes et al. (2009) created a FES to aid Occupational Health and Safety professionals in the identification, evaluation, and control of ergonomic risks associated with the development of musculoskeletal disorders. Azadeh et al. (2015) proposed a neuro-fuzzy algorithm for measuring and improving health, safety, environment, and ergonomics programs through performance evaluation of operators for management planning and control activities in a large petrochemical plant. Jablonski et al. (2018) designed a system that assesses environmental conditions related to occupant comfort in indoor and built environments using sensor data. Falahati et al. (2019) used the fuzzy logic approach to predict musculoskeletal disorders among automotive assembly workers based on self-reported questionnaires and REBA assessment using the MATLAB software.

Fuzzy logic has also been widely used to assess ergonomic risk in the construction industry. Fayek et al. (2005) showed how fuzzy logic and FESs can model industrial construction labor productivity with realistic constraints, such as subjective assessments, multiple contributing factors, and limited datasets. Aluclu et al. (2008) developed a fuzzy logic-based model for noise control in industrial workplaces. Golabchi et al. (2015) applied automated FES for ergonomics assessment in the form of a quick, simple, and reliable tool by which to identify unsafe worker actions and address them to reduce work-related musculoskeletal disorders. Debnath et al. (2015) developed an FES for assessing occupational risks on construction sites. Golabchi et al. (2016), in another study, proposed a fuzzy logic posture-based ergonomic analysis tool for field observation and assessment of manual construction operations using RULA. Wang et al. (2020) proposed a fuzzy-integrated automated post-3D visualization ergonomic analysis framework to assess dynamic motion-based ergonomic risk in existing and proposed workplace designs. Wang et al. (2021) also proposed a 3D fuzzy ergonomic analysis method for the rapid design and modification of construction workplaces. In summary, the usefulness of FESs in conducting ergonomics risk assessments in the construction industry is evident.

Nonetheless, it is important to note that the fuzzy logic-based systems proposed in the literature focus on the physical aspects of ergonomics for construction industries. Moreover, it has been noted in the literature that risk factors such as awkward posture, force, repetition, static loading, contact stress, lack of recovery, monotony of tasks, work duration, illumination, noise, extreme temperatures, vibration, auditory information demands, and visual information demands all contribute to hazardous work systems (Damaj et al. 2016; Parsons 2000; Freivalds et al. 2013, Jaffar et al. 2011; Li et al. 2015; Li et al., 2019a; Schifferstein et al. 2007). Consequently, it is evident that work systems are hazardous not only because of physical risks, but also because of environmental demands and sensory information overload (Freivalds et al. 2013). This necessitates the development of a fuzzy logic-based DSS that can automate ergonomics risk assessments in a comprehensive manner, considering the physical, environmental, and sensory hazards associated with work systems.

2.4 Occupational risk factor diagnosis using ML

ML can be a valuable technology for occupational risk factor diagnosis. Several risk classification models have been used as predictive tools in a range of industries (Sasikumar et al. 2018; Amiri et al. 2016; Aliabadi et al. 2020; Macedo et al. 2022) the use of classification models for OSH management is a relatively new notion. In the context of this study, there have been a few research studies on the prediction of risk classes in manufacturing. For instance, Baghdadi et al. (2018) used a Support Vector Machine to classify gait parameters measured by wearable sensors as either fatigued or non-fatigued following an occupational task. Darbandy et al. (2020) proposed a k-nearest neighbors' model that uses heart rate signals to classify workers' physical fatigue. In addition, researchers have created several ML models to classify the level of risk of occupational lower-back disorders (Asensio-Cuesta et al. 2010; Akay et al. 2011; Ganga et al. 2012; Zurada et al. 2012; Erdem et al. 2016). Although these tools can diagnose risk factors, they do not focus on the input–output variable relationships; instead, they place a greater emphasis on risk class prediction. However, relying solely on predictive models is inadequate for diagnosing risk factors, as it's the interpretation of the relationship between input and output variables that truly aids in risk diagnosis.

Recent research on OSH in manufacturing has examined not only building classification models, but also model interpretability for the diagnosis of ergonomic risks and safety risks. For instance, Maman et al. (2020) introduced a data analytics framework that uses wearable sensors to detect physical fatigue occurrence in simulated manufacturing tasks in order to classify fatigue states (Yes/No) over time. They demonstrated that the sequential application of predictive models when combined with visual analytics tools can help with diagnosing root causes. Moreover, Conforti et al. (2020) estimated biomechanical risk during lifting tasks via postural pattern recognition (correct/incorrect) using ML models driven by kinematic data from wearable sensors and incorporating a Support Vector Machine classifier. They then performed statistical analysis in order to better understand the relationship between kinematic data and the recognized postural patterns. Krishna et al. (2015), finally, developed a Decision Tree classifier to classify and interpret the prevalence of musculoskeletal disorders (Yes/No) among crane operators in an Indian steel plant using Nordic Musculoskeletal Questionnaire survey data.

Following the Krishna et al. (2015) study, several statistical methods have been integrated with the Decision Tree classifier for model interpretation. For instance, Sarkar et al. (2016) developed text mining-based classification ML models using both Fault Tree Analysis and Bayesian Network that can assist in identifying the root causes of steel plant accidents. They performed a sensitivity analysis on the developed classification ML models to further examine the causes of risk factors, and employed standard statistical tests to interpret the SVM classifier. Shirali et al. (2018) used Decision Trees to predict the outcomes of occupational accidents (minor/severe/fatal) in the steel industry. They then applied the Chi-square Automatic Interaction Detection algorithm to understand the input–output variable relationships. Overall, despite the utility of these studies, they all use model interpretation techniques that can be challenging for non-technical personnel, such as business stakeholders and health and safety specialists, to interpret and implement in safety intervention policies. This necessitates techniques for easier model interpretation.

Given the complexity of the predominant model interpretation techniques available, OSH researchers have begun seeking comparably simple model interpretation techniques, such as the plotting of feature importance, where feature importance plots simply represent the predictive power of input variables to predict output variables. For instance, using workers' compensation data, Kakhki et al. (2020) constructed a Random Forest Decision Tree classifier and a Naive Bayes classifier to categorize the injury severity level (low/medium) of occupational incidents in grain elevator Agro-manufacturing operations in the United States. In addition, the evaluation of feature importance using the Chi-squared method has been used for model interpretation. Sarkar et al. (2018a) predicted incident outcomes using Decision Tree and AdaBoost classifier on a mixed dataset comprising both reactive and proactive data. They then used the Decision Tree classifier to generate rules for determining which risk factors are most strongly associated with occurrences of work-related risks. Finally, as the basis for model interpretation, they evaluated feature importance using the Boruta feature selection and Chi-square method. In another study, Sarkar et al. (2018b) also used Expectation Maximization-based text clustering to carry out unstructured text analysis and pass it to a Deep Neural Network for the classification of injury risk using the accident data collected from a steel plant in India. Subsequently, they implemented the Chi-squared method for the evaluation of feature importance as a means of model interpretation. Finally, Sarkar et al. (2019) developed a novel method for the classification of Slip-Trip-Fall (STF) occurrences that uses Decision Tree classifiers and generates a set of rules to determine which risk factors are most strongly associated with STF occurrences. Yet again they employed the Chi-square method for the model interpretation. In summary, the studies in this area have generally favored the plotting of feature importance, especially using the Chi-square method, as a means of simplifying the model interpretation. However, the plotting of feature importance only indicates the predictive power of input variables with respect to output variables. As a result, there is still potential for improvement with regard to intuitive model interpretation.

Overall, the publications analyzed demonstrate the manner in which classification ML models can be used for risk factor diagnosis in manufacturing OSH research, but there remain some gaps and deficiencies. First, the model interpretation techniques that have been used in these studies may be easy for ML developers to understand, but they can be difficult for non-experts to grasp in practice. Therefore, it is challenging to persuade personnel who are not technical experts in this area to implement safety intervention policies rooted in ML, as they see these models as lying within a 'black box'. In this regard, it is well known that the recently developed interpretable ML techniques can make the 'black-box' of ML models simpler to unpack. Linardatos et al. (2020) examined numerous ML model interpretation techniques, including local interpretable model-agnostic explanations (LIME) (Riberio et al. 2016) and Shapley Additive Explanations (SHAP) (Lundberg et al. 2017), among others, and asserted that SHAP is the most comprehensive and intuitive technique for model interpretation currently available. Rather than merely demonstrating feature importance (as other techniques have done), SHAP highlights not only the predictive power of input variables but also the importance of each input variable in predicting multiple risk classes. Despite this, the application of SHAP to diagnose risk factors in manufacturing OSH research has not yet been explored. Second, classification ML models by definition must be developed using labeled datasets. While the works cited above have demonstrated the effective use of pre-labeled datasets in the development of classification ML models, pre-labeled datasets are not always readily available for ML model development. In such circumstances, substantial effort must be directed toward labeling the datasets, and this task can be time-consuming and can delay the diagnosis of risk factors. While the effectiveness of clustering algorithms in addressing the dataset, labeling problem is widely recognized (Madhulatha et al., 2012), no previous manufacturing OSH study utilizing clustering algorithms for this objective has been identified. Moreover, despite the fact that the goal of OSH management is to prevent all work-related injuries, illnesses, and fatalities, safety research and ergonomics research are frequently detached in terms of risk factor diagnosis. For these reasons, an interpretable ML-based data analytics framework is presented for safety and ergonomics risk factor diagnosis using incident data that does not require pre-labeled datasets in this study.

2.5 A broader overview of ML-powered ergonomics risk assessment tools

The recent growth of ML in the manufacturing ergonomics domain, several researchers have designed several ML-powered tools in order to make ergonomics risk assessments more convenient for health and safety experts. This section discusses the current status of ML-powered ergonomics risk assessment tools. Table 2-1 provides an overview of literature on state-of-the-art ML-powered ergonomics risk assessment tools.

Table 1-1 State of the art ergonomics risk assessment tools in manufacturing ergonomics

Citation	Purpose of ML	Data sample	ML algorithm(s) used	ML technique(s) used	Data collection method	Application
Abobakr et al., (2019)	Developed a semi-automated ergonomic posture assessment that makes use of a convolutional neural network to analyze the articulated posture and predict body joint angles from a single depth image.	RGB-D pictures and motion capture kinematic data synthesized utilizing six virtual human models (2 men, 2 women, 2 neutral).	**Convolutional neural network**	Regression	Direct Measurement	Posture identification
Abobakr et al., (2017)	The proposed method uses a low-cost Kinect sensor and a deep convolutional neural network model for joint angles regression.	168,000 colorized depth images for training and 42,000 images for testing	**Convolutional neural network**	Regression	Advanced Observational Method	Posture identification
Abubakar et al., (2020)	Developed an artificial neural network to model the relationship between safety climate, safety behavior, and workplace injuries in metal casting industry employees using survey data from metal casting industry employees.	306 workers from central Anatolia's metal casting industry.	**Artificial neural network**	Regression	Self-report	Identification of risk factors
Agostinelli et al., (2021)	Proposed a tool called RGB motion analysis system, to fasten the human joint angle extraction and RULA calculation for static postures by exploiting open-source deep neural network model from Carnegie Mellon University, from the tf-pose-estimation project.	6 participants (4 men, 2 women) were instructed to hold five distinct poses for 5 seconds each.	**Deep neural network**	Regression	Advanced Observational Method	Posture identification

Akay (2011)	Developed and compared Grey relational analysis, logistic regression, decision tree, artificial neural network, and ensemble models to classify industrial jobs related to occupational low back disorders risks.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**Grey relational analysis**, Logistic, regression, Decision tree, Artificial neural network, and Ensemble models	Binary classification	Dataset	Risk classification
Akay et al., (2009)	A classification model based on ant colony optimization entitled ACOCLASS was proposed for classifying the risk of low back disorder.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**ACOCLASS**	Binary classification	Dataset	Risk classification
Asadi et al., (2020)	Created deep neural network model for classifying musculoskeletal injuries by detecting isometric grip exertions with facial videos and wearable photoplethysmograms.	18 participants (8 men, 10 women)	**DeepFace** algorithm to process faces in images; **Deep neural network**	Binary classification; Multiclass classification	Advanced Observational Method	Risk classification
Asensio-Cuesta et al., (2010)	Developed a feedforward neural network to classify industrial jobs related to occupational low back disorders risks.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**Feedforward neural network**	Binary classification	Dataset	Risk classification
Baghdadi et al., (2018)	Created a support vector machine model to classify gait parameters measured by wearable sensors as fatigued or non-fatigued after an occupational task.	20 subjects (14 men, 6 women), chosen from the local labor force and students with physical labor experience.	**Support vector machine**	Binary classification	Direct Measurement	Risk classification
Baghdadi et al., (2018)	Presented a framework for kinematics estimation and fatigue monitoring that employs a small number of sensors and data.	20 subjects (14 men, 6 women), chosen from the local	**Support vector machine**	Binary classification	Direct Measurement	Risk classification

		labor force and students with physical labor experience.				
Bortolini et al., (2018)	Presented an original hardware-software architecture, called Motion Analysis System (MAS) to quantitatively measure body joint angles followed by ergonomic risk index calculation using conventional risk assessment tools such as NIOSH, OWAS, RULA, and REBA.	An operator is engaged in assembly operations in an automotive assembly line	**Artificial neural network**	Regression	Advanced Observational Method	Posture identification
Chen et al., (2000)	Developed a feedforward neural network to classify industrial jobs related to occupational low back disorders risks.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**feedforward neural network**	Binary classification	Dataset	Risk classification
Chen et al., (2004)	Using feedforward neural network, developed a method to reliably classify the risk of injuries in industrial tasks based on datasets that do not match the assumptions of parametric statistical tools or are incomplete.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**Feedforward neural network**	Binary classification	Dataset	Risk classification
Chung et al., (2002)	Presented a multi-layer perceptron neural network model to classify macro-postural workload based on perceived discomforts and postural stress levels for several joint motions.	19 male auto assembly line employees	**Multi-layer perceptron neural network**	Multiclass classification	Simple Observational Method	Risk classification

Conforti et al., (2020)	Estimated biomechanical risk during lifting operations using postural pattern identification utilizing ML powered by kinematic data from wearable sensors and support vector machine classifier.	26 healthy participants	**Support vector machine**	Binary classification	Direct Measurement	Risk classification
Darbandy et al., (2020)	Using heart rate signals, propose a k-nearest neighbors' model that can detect physical fatigue in workers.	8 members of the local community (5 men, 3 women); 2 employed in manufacturing.	**k-nearest neighbors**	Binary classification	Dataset	Risk classification
Erdem et al., (2016)	Employed support vector machine model to classify occupational lower back disorder risks for manual material handling tasks.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**Support vector machine**	Binary classification	Dataset	Risk classification
Ganga et al., (2012)	Developed a model based on linear discriminant analysis and artificial neural network to classify industrial jobs related to occupational low back disorders risks.	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	Linear discriminant analysis, A**rtificial neural network**	Binary classification	Dataset	Risk classification
Greene et al., (2019)	A computer vision method is shown for automatically classifying lifting postures such as standing, stooping, and squatting at the lift origin and destination utilizing a decision tree algorithm and an elastic rectangular bounding box drawn tightly around the body.	Mannequin poses systematically generated using 3DSSPP for various hand locations and lifting postures.	**Decision tree**	Multiclass classification	Advanced Observational Method	Posture identification

Kakhki et al., (2019)	Investigated the effectiveness of multi-layer perceptron neural network, and Radial basis function neural network, to classify injury root-causes in Agro-manufacturing operations in the USA	5400 opened and closed workers' compensation claims from 2008 to 2016, were used	**Multi-layer perceptron neural network, and Radial basis function neural network**	Multiclass classification	Dataset	Identification of risk factors
Konstantinidis et al., (2021)	Propose a unique method employing the 3D pose estimation algorithm known as Video Inference for Human Body Pose and Shape Estimation and deep neural network to assess the ergonomic risk of any work-related job in real-time using the REBA framework.	TUM Kitchen dataset and UW IOM dataset; Both datasets were split into 4 subsets and each time 3 subsets (15 videos) were selected for training and the remaining subset (5 videos were selected for testing.	**Video Inference for Human Body Pose and Shape Estimation (VIBE); Deep neural network**	Regression	Advanced Observational Method	Risk Quantification
Krüger et al., (2015)	Presented a method for the extraction of features from depth images using a low-cost depth sensor and a random forest classifier trained on manually labeled videos for posture classification.	8 participants working in an industrial setting	**Random forest**	Multiclass classification	Advanced Observational Method	Posture identification
Li et al., (2020)	Developed an algorithm that takes normal RGB images as input and outputs the RULA action level (4 levels), which is a further division of RULA grand score based on deep neural network and a RULA score estimator	Human3.6M (public human pose dataset with full-body kinematics marker data)	**Deep neural network**	Multiclass classification	Dataset	Risk classification

Maman et al., (2017)	Investigated the usage of wearable sensors to detect physical fatigue in simulated industrial jobs and evaluated the level of physical fatigue across time utilizing penalized logistic regression and multiple linear regression.	8 members of the local community (5 men, 3 women); 2 employed in manufacturing.	**Penalized logistic regression, Multiple linear regression**	Binary classification; Regression	Direct Measurement	Identification of risk factors
Maman et al., (2020)	Introduced a data analytic framework for managing fatigue in physically demanding workplaces using wearable sensor data to capture different fatigue modes and modules. This framework also investigated the performance of Logistic regression, penalized logistic regression, decision tree, naive Bayes, k nearest neighbors, random forest, bagging, and boosting algorithms.	24 healthy people were used, including manufacturing workers and students with some physical work experience; 15 used for analysis.	Logistic regression, Penalized logistic regression, Decision tree, Naive Bayes, k nearest neighbors, and three ensemble models **(Random forest**, Random forest with Bagging, and Random forest with Boosting)	Binary classification	Direct Measurement	Risk classification
Massiris Fernández et al., (2020)	Using the OpenPose Convolutional neural networks, a method was created to automatically compute RULA scores from digital video or still images.	Simulated 3D model, one author, and five videos of workers plastering walls, hammering, felling trees, drilling, and marshal signs.	**OpenPose** algorithm for posture detection	Regression	Advanced Observational Method	Posture identification
Mgbemena et al., (2016)	Presented an application developed to detect gestures towards triggering real-time human motion data capture on the shop floor for ergonomic evaluations and risk assessment using the Microsoft Kinect using AdaBoost algorithm	2742 occurrences of lowering gestures and 3079 occurrences of lifting gestures were recorded.	**AdaBoost**	Binary classification	Advanced Observational Method	Posture identification

Nath et al., (2018)	Developed a support vector machine-based method to unobtrusively evaluate the ergonomic risk levels caused by overexertion. This is accomplished by collecting time-stamped motion data from body-mounted smartphones (i.e. accelerometer, linear accelerometer, and gyroscope signals), automatically detecting workers' activities through a classification framework, and estimating activity duration and frequency data.	2 employees engaged in warehouse operations involving manual material handling activities.	**Support vector machine**	Multiclass classification	Direct Measurement	Identification of risk factors
Parsa et al., (2019)	Presented a method for the automatic prediction of ergonomic risks levels using REBA for material handling human activities for an automobile manufacturer based on the integration of a low-cost body sensor network and ML algorithms for tracking working operations. This is accomplished by learning spatial features using Convolutional neural networks. Subsequently, encoder decoder-temporal convolutional networks, dilated-temporal convolutional networks, bi-directional long short-term memory, and support vector machines were compared for video segmentation.	TUM Kitchen dataset with 24,052 training and 5,290 testing samples; UW IOM dataset with 27,539 training 6,052 testing samples, respectively	**Convolutional neural networks; Encoder decoder-temporal convolutional networks**, Dilated-temporal convolutional networks (D-TCN), Bi-directional long short-term memory (Bi-LSTM), and Support vector machines	Multiclass classification	Dataset	Risk classification

Parsa et al., (2020)	Presented a real time Spatio-temporal pyramid graph convolutional network for action recognition that enables the use of features from all levels of the skeleton feature hierarchy. In addition, the proposed method is also compatible with REBA score computation.	TUM Kitchen dataset; UW IOM dataset; Kinetics; and NTU-RGBD datasets	**Spatio-temporal pyramid graph convolutional network**	Multiclass classification	Dataset	Posture identification
Petz et al., (2021)	Developed a sensor system that can be used as universal platform for recording and classifying movement. A Long-short term memory neural network is used to demonstrate the classification of learned motion sequences.	The constructed sensor system collected 6030 training instances and 670 testing instances.	**Long-short term memory**	Multiclass classification	Direct Measurement	Posture identification
Zurada et al., (2012)	Developed and compared logistic regression, neural networks, radial basis function neural network, support vector machines, k-nearest neighbor, decision trees, and random forest classifier models to classify the risk of low back disorders	235 manual material handling activities taken from several manufacturing companies (Marras et al., 1993)	**Neural networks, support vector machines, k-nearest neighbour**, Logistic regression, Radial basis function neural network, Decision trees, and Random Forest	Binary classification	Dataset	Risk classification

Chapter 3: REVAMPED PHYSICAL LOAD INDEX (PLI)

3.1 Introduction

In current practice, practitioners choose an appropriate ergonomics risk assessment tool on a case-by-case basis considering the tools compatibility with data collection method (self-report, observational methods, direct measurements). Then, they choose an appropriate tool for assessing a specific industrial work activity, taking their time and budget constraints into consideration (David, 2005). To assess the ergonomic performance of a different industrial work activity, they may need to repeat the entire procedure, as different ergonomics risk assessment tools have different specializations. There is no global ergonomics risk assessment tool to comprehensively evaluate the ergonomic performance of work systems. Consequently, it must be understood that different ergonomics risk assessment tools are preferred for evaluating work systems based on the nature of the industrial work activity. Nevertheless, there is utility in developing a comprehensive ergonomics risk assessment tool that is compatible with all types of data collection methods.

This chapter describes a reinvention of an ergonomics risk assessment tool, the Physical Load Index (PLI), which was initially developed by Hollman et al. (1999), in order to present a versatile and near comprehensive ergonomics risk assessment tool. The PLI is specifically chosen for revision because of three reasons: (1) PLI has the potential for compatibility with all types of data collection methods (self-reports, observational methods, and direct measurements) as opposed to some other physical ergonomics risk assessment tools; (2) PLI includes assessment of entire body posture, weight of the load, and repetition/frequency as inputs, thereby, serving as a single tool for a near comprehensive assessment of both dynamic and continuous worker activities; and (3)

Numerous research studies have indicated that occupational injuries, often stemming from factors like heavy lifting, uncomfortable lifting postures, repetitive lifting, and sustained muscle loading, predominantly impact the back region (Qiu et al., 2021; Straker, 1999; Punnett et al., 2005; Trinkoff et al., 2003; Cole et al., 2001; Ebraheim et al., 2004; Bridger, 1991; Pope et al., 2002; Boulila et al., 2018). Therefore, it may be beneficial to revise a tool like PLI that was created by integrating information from a biomechanical model of lumbar load. Here, a lumbar load model is valuable because it helps address the prevalent issue of back-related occupational injuries caused by various factors, as evidenced by extensive research (Qiu et al., 2021; Straker, 1999; Punnett et al., 2005; Trinkoff et al., 2003; Cole et al., 2001; Ebraheim et al., 2004; Bridger, 1991; Pope et al., 2002; Boulila et al., 2018), warranting a revision of tools like PLI integrating biomechanical lumbar load information. Moreover, the Enhanced PLI capitalizes on the original version's strengths, adapting the framework to align with diverse objective data collection methods. It further integrates AI approaches like mathematical optimization to establish a revised scoring range, reflecting alterations in the PLI structure. Additionally, it introduces risk categories for simpler interpretation of PLI risk scores. The proposed Revamped PLI has been preliminary validated using data collected from manufacturing and construction industries and compared to the Rapid Entire Body Assessment (REBA) scores.

Overall, the existing physical-ergonomic tools available for assessing workplace risks are often specialized and not versatile enough to be compatible with different data collection methods to suit their time and budget constraints (David, 2005). The requirement for practitioners to learn new tools for assessing diverse work systems further hinders the progress of enhancing work systems.

Therefore, to address this challenge, this chapter proposes revising PLI to become a versatile and near-comprehensive physical-ergonomics risk assessment tool.

3.2 Research method

The detailed methodology for developing Revamped PLI is displayed in Figure 3-1 with three phases included. In order to develop Revamped PLI, three phases are required: (1) Tool selection for Revision – This phase discusses the research and exploration of numerous tools, as well as the rationale for selecting PLI for redevelopment in order to make it a versatile instrument; (2) Revision of PLI – This phase discusses the revisions made to PLI to develop Revamped PLI; and (3) Implementation and validation – This section discusses the use of Revamped PLI to assess the ergonomic performance of real-world industrial job tasks, followed by a comparison of the proposed tool to REBA (a well-known ergonomics risk assessment tool) to determine the validity of Revamped PLI.

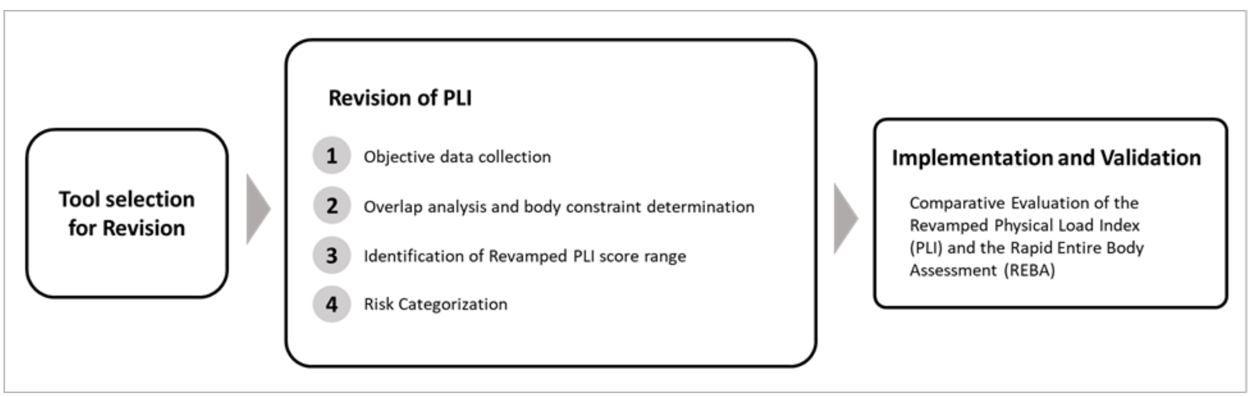

Figure 3-1 Methodological framework for development of the Revamped PLI

3.2.1 Tool selection for Revision

A range of quantitative risk assessment tools have been developed in the last decades for assessing various ergonomic risk factors in industrial job tasks such as awkward posture, material handling factors, and repetition/frequency body movement. Here, awkward posture involves uncomfortable body positions that can lead to musculoskeletal strain. Material handling factors encompass how objects are lifted, carried, pushed, or pulled, impacting musculoskeletal health. Repetition/frequency of body movement refers to the repetitive nature of certain actions, which can lead to overuse injuries.

These tools use varied input data to generate their risk indexes. Some of the commonly used tools to assess the ergonomic performance of industrial job tasks are PLI, REBA, RULA, NIOSH Lifting Equation, The strain index, OWAS, and MAC (McAtamney et al. 2004, Lynn et al. 1993, Waters et al. 1993, Moore et al. 2010, Karhu et al. 1971, Health and Safety Executive 2014). Therefore, these tools are investigated in Table 3-1 to determine the best tool for revampment. As a result, it has been determined that, among the tools presented in Table 3-1, PLI is the ideal tool for revision. PLI is deemed more suitable for revision than the other tools because, (1) PLI has the potential for compatibility with all types of data collection methods (self-reports, observational methods, and direct measurements) as opposed to some other physical ergonomics risk assessment tools; (2) PLI includes assessment of entire body posture, weight of the load, and repetition/frequency as primary inputs, thereby, serving as a single tool for a near comprehensive assessment. Specifically, PLI utilizes a comprehensive set of input factors to assess ergonomic risks. These factors include trunk postures (T) such as T1 (straight, upright), T2 (slightly inclined), T3 (strongly inclined), T4 (twisted), and T5 (laterally bent). Arm postures (A) include both arms below shoulder height (A1), one arm above shoulder height (A2), and both arms above shoulder height (A3). Leg postures (L) encompass sitting (L1), standing (L2), squatting (L3), kneeling (L4), and walking/moving (L5). Weight lifting activities (W) are classified into weight categories, including Wu1 (light up to 10 kg), Wu2 (10-20 kg), Wu3 (more than 20 kg) for non-inclined lifting, and Wi1 (light up to 10 kg), Wi2 (10-20 kg), Wi3 (more than 20 kg) for inclined lifting. By considering these specific postures along with weight load, in tandem with repetition/frequency of postures the PLI provides a holistic evaluation of physical ergonomic risks; and (3) Heavy lifting, awkward lifting positions, repetitive lifting, and static muscle loading, which affect the back, are a leading cause of occupational injuries, according to several research studies (Qiu et al., 2021; Straker, 1999; Punnett et al., 2005; Trinkoff et al., 2003; Cole et al., 2001; Ebraheim et al., 2004; Bridger, 1991; Pope et al., 2002; Boulila et al., 2018). Therefore, it may be beneficial to revise a tool like PLI that was created by integrating information from a biomechanical model of lumbar load. For these reasons, PLI is regarded as the optimal choice for enhancement, contrasting with tools such as REBA or NIOSH Lifting equation. While REBA and NIOSH equations align well with observational methods, they lack seamless compatibility with self-reports, fail to encompass all critical risk factors as primary inputs, and are not structured around lumbar load like PLI, thus rendering them less fitting for the revampment process. Consequently, the aim is to streamline the tool selection process for health and safety specialists by establishing the foundation for a versatile and near-comprehensive ergonomics risk assessment tool, named Revamped PLI. This tool exhibits the potential to accommodate diverse data collection methods, thereby offering users the flexibility to choose a method that aligns with their time and budget constraints.

Table 3-1 Comparison of ergonomics risk assessment tools

Tools	Inputs	Outputs	Analysis			Reference
			Compatibility	Pros	Cons	
PLI	**Primary inputs:** • Entire Body Posture • Weight of the Load • Repetition/ Frequency **Secondary inputs:** • N/A	• Risk Index	**with data collection methods:** • Self-report **with activities:** • For dynamic and continuous activities	• Non-Cumbersome tool • Includes all primary information necessary for assessing occupational tasks	• Risk index is not classified into risk categories • Results may not be accurate unless study includes large number of samples	Hollman et al. (1999)
REBA	**Primary inputs:** • Entire Body Posture **Secondary inputs:** • Repetition / Frequency • Load / Force	• Risk Score • Risk Category • Risk Description and Response Plan	**with data collection methods:** • Simple Observational Methods **with activities:** • For static or single postures	• Specialized in assessing the entire body posture	• No sufficient weight allocated to capture the weight of the handled load • Needs to be paired with advanced observational methods, direct measurements for dynamic and continuous activities	McAtamney et al. (2004)
RULA	**Primary inputs:** • Upper Body Posture **Secondary inputs:** • Repetition / Frequency • Load / Force	• Risk Score • Risk Category • Risk Description and Response Plan	**with data collection methods:** • Simple Observational Methods **with activities:** • For static or single postures	• Specialized in assessing the upper body posture	• Considers only the upper body posture • No sufficient weightage allocated for weight of the handled load • Needs to be paired with advanced observational methods, direct measurements for dynamic and continuous activities	Lynn et al. (1993)
NIOSH Lifting Equation	**Primary inputs:** • Material Handling Factors • Weight of the Load **Secondary inputs:** • Repetition/ Frequency	• Load acceptance	**with data collection methods:** • Simple Observational Methods • Direct Measurements **with activities:** • For dynamic activities	• Specialized in assessing job tasks that highly involve material handling tasks	• No sufficient emphasis on entire body posture • Accurate physical measurements are usually required	Waters et al. (1993)

The strain index	**Primary inputs:** • Intensity of exertion • Duration of exertion • Exertions per minute • Hand/wrist Posture • Speed of Work • Duration of task per day **Secondary inputs:** • N/A	• Strain Index	**with data collection methods:** • Simple Observational Methods **with activities:** • For dynamic and continuous activities	• Specialized in assessing jobs for risk of distal upper extremity disorders derived from physiological model of localized muscle fatigue	• Not based on quantitative relationship between a task variable and some physiological, biomechanical, or epidemiological responses • Task variables are limited • Three task variables rely on subjective judgement • Requires professional judgment • Requires training and experience to use	Moore et al. (2010)
OWAS	**Primary inputs:** • Entire Body Posture **Secondary inputs:** • N/A	• Posture Rating • Risk Category • Risk Description and Response Plan	**with data collection methods:** • Simple Observational Methods **with activities:** • For static and dynamic single postures	• Non-cumbersome tool specialized in rapidly assessing entire body posture	• Does not accurately reflect the ergonomic risks based on entire body posture	Karhu et al. (1971)
MAC	**Primary inputs:** • Material handling Factors • Weight of the Load • Repetition/ Frequency **Secondary inputs:** • N/A	• Numerical score • Risk band • Risk Description and Response Plan	**with data collection methods:** • Simple Observational Methods **with activities:** • For static and dynamic single postures	• Specialized in assessing job tasks that highly involve material handling tasks	• Does not provide sufficient emphasis on entire body posture • No action level is provided	Health and Safety Executive (2014)

3.2.2 Revision of PLI

This section explains the methodical approach taken to revise the computational framework of Revamped PLI. Prior to that, it's critical to categorize Revamped PLI in accordance with data collection methods used:

- the conventional PLI is compatible with self-reports and is still referred to as PLI;
- a revamped version of PLI when paired with observational methods is called PLI II;
- a revamped version of PLI when paired with direct measurements is called PLI III.

Thus, this revampment makes PLI compatible with all types of human data collection methods. Based on the time and budgetary availability, the practitioner can select the most suitable data collection method for the assessment and identify the associated tool (PLI, PLI II, PLI III). The underlying framework of Revamped PLI (including posture codes, weights, and linguistic categories of postures and frequencies) remains the same as in conventional PLI. However, certain revisions are made to the underlying framework of conventional PLI to which will be discussed in sections 3.2.2.1, 3.2.2.2, and 3.2.2.3.

3.2.2.1 Objective data collection

As aforementioned, one of the critical limitations of conventional PLI was the accuracy and imprecision of collected data in self-reports due to subjectivity. Referring to Figure 2-1, when moving towards the top of the data collection methods pyramid, the collected data exhibits comparatively higher levels of accuracy and precision. The reason for the increase in accuracy and precision is that observational methods and direct measurements are objective in nature, whereas self-reports are subjective in nature. Therefore, the limitations of conventional PLI can be overcome if conventional PLI is compatible with observational methods or direct measurements. As elaborated in section 3.1, observational methods can be carried out either using a human based observation (simple observational method) or computer-based observation (advanced observational method), while direct measurements can be carried out using monitoring instruments such as sensors or optical markers directly attached to the individual under observation (David, 2005; Inyang et al., 2012). Consequently, this section discusses how PLI input data can be collected objectively either using observational methods or direct measurements:

1. The 19 postures included in Revamped PLI can be identified by using joint angles (the angle between the two segments on either side of the human joint) and joint coordinates (the xyz position of joints) via observations (simple or advanced observational methods) or direct measurements. Moreover, if the determination of the workers postures in three-dimensional space is required, it can be referred from the "3D static strength prediction program", proposed by the University of Michigan, Center of Ergonomics (2012).
2. The material weights are the weight of tools, objects, and equipment handled by the worker during a job task. These weights can be measured directly or referred to the item's specifications when using simple observational methods. Nevertheless, when employing advanced observational methods or direct measurements, computer vision algorithms or weight sensors can be used to determine the weights lifted by human workers.
3. Referring to the research conducted by Li et al. (2019a, 2019b) and the Workers' Compensation Board – Alberta (2019), a proposal is made to enhance the conventional PLI approach. Instead of relying solely on linguistic descriptions, the suggestion is to quantify

the frequencies of postures using numerical percentages. These percentage values can then be categorized into five distinct ranges, known as frequency percentages (FP): Never (0%), Seldom (1%–5%), Sometimes (6%–33%), Often (34%–66%), and Very often (67%–100%).

$$FP = D_i / D_{total} \times 100\% \quad \textbf{(3-1)}$$

where

D_i: Total duration of a specific Posture Code (e.g. T1, T2, etc.) in one cycle of the job task

D_{total}: Total duration for one cycle of the job task

i: Specific Posture Code selected for assessment

Moreover, it is also important to note that the material handling frequency data is synchronous to the posture frequency data, but it is recorded only during material handling activities. Finally, the upcoming sections in this chapter center on developing the Revamped PLI framework, ensuring compatibility with both simple and advanced observational techniques as well as direct measurements, albeit validation being limited to simpler observational method.

3.2.2.2 Overlap analysis and body constraint determination

Conventional PLI allows for overlapping of any two postures in the list of available postures, even though in reality some postures cannot practically overlap with one another due to the body constraints. This is because conventional PLI was developed to suit the subjective nature of self-reports. For example, walking (L5) and sitting (L1) cannot overlap with one another, however, conventional PLI allows the overlap of walking (L5) and sitting (L1) postures. Therefore, an overlap analysis matrix is developed to identify the possible and impossible postural overlaps.

Based on this overlap analysis matrix, a total of 33 constraint equations are developed and applied in the Revamped PLI. The benefits of establishing and complying with constraint equations not only serve to eliminate impractical body postures from consideration in the assessment, but also allow practitioners to cross-check the reliability and the conformance of body postures to reality for the human motion data collected. For example, if the human data collected for trunk straight, upright (T1), trunk slightly inclined (T2), and trunk strongly inclined (T3) result in a sum of 200%, this finding violates conformance to reality, i.e. it is impossible for a worker to have his trunk both in upright and inclined positions. Therefore, the appropriate constraint equation, ‘T1 + T2 + T3 = 100%’, is proposed in this case. Thus, in total 33 constraint equations are developed to ensure the reliability and the conformance to reality of the collected data.

3.2.2.3 Identification of Revamped PLI score range

With the identification of possible and impossible postural overlaps, Revamped PLI is no longer subjected to the index range of 0-56 as in conventional PLI. The inclusion of constraint equations in Revamped PLI naturally has an impact on the final index range. Consequently, the Pattern Search optimization algorithm available on the Global Optimization Toolbox on MATLAB is used to identify the new index range of Revamped PLI. Consequently, it is determined that the index range for Revamped PLI is 0-32. To provide further insight, the Pattern Search algorithm employs the PLI equation as its objective function, with the 33 constraints detailed in section 3.2.2.2 established as constraint equations. These constraints serve to narrow down the search space, enabling the identification of the highest achievable value through the PLI equation, which is determined to be 32. On the other hand, when only neutral postures defined by the PLI equation are seen during a job task, the PLI equation gives a value of zero.

3.2.2.4 Risk Categorization

A major drawback of conventional PLI is the lack of risk categories, which entails that the index can only express the severity of risk in comparative terms (higher or lower risk). Health and safety specialists may benefit from risk categories for the following reasons: (1) it makes the risk index more interpretable; (2) it simplifies the process of communicating the severity of ergonomic risk to management and employees using risk labels; and (3) it helps determine which category of risks must be addressed immediately. Consequently, the continuous PLI scores obtained from the research execution and validation phase (section 3.2.3) for 92 real-world industrial job tasks are binned into five discrete bins of equal width that are representative of five risk categories, as shown in Table 3-2.

On the basis of the discussion in the preceding sections, a computational framework is proposed for Revamped PLI. This application of the framework is illustrated in Section 3.2.3.1 with respect to PLI II (simple observational method) along with computation steps. Although the application of this framework is shown with reference to PLI II (simple observational method), the computational framework of Revamped PLI can be easily adapted for PLI II (advanced observational methods) and PLI III (direct measurements) by simply changing the method of data collection in Step (1). This can be accomplished with the help of theoretical foundations of objective data collection discussed in section 3.2.2.1.

3.2.3 Implementation and validation

3.2.3.1 Implementation

The significant improvements made in Revamped PLI by revising the framework of conventional PLI is elaborated in this section. The Revamped PLI assessment form created by revising the conventional PLI form is displayed in Figure 3-2 as a partial sample. The full template of the Revamped PLI is given in the Appendix.

STEP (1)

Posture Code	Activities	Start time	Stop time	Time (s)	%	total %
T1	straight, upright	02:53:28	02:53:52	00:00:24	17.91	25.37
	straight, upright	02:52:50	02:52:58	00:00:08	5.97	
	straight, upright	02:52:28	02:52:30	00:00:02	1.49	
T2	slightly inclined	02:52:03	02:52:50	00:00:47	35.07	55.97
	slightly inclined	02:53:59	02:54:21	00:00:22	16.42	
	slightly inclined	02:53:21	02:53:27	00:00:06	4.48	
T3	strongly inclined	02:52:59	02:53:20	00:00:21	15.67	18.66
	strongly inclined	02:52:31	02:52:35	00:00:04	2.99	

STEP (2)

Posture Code	Weight	Linguistic Categories	NEVER	SELDOM	SOMETIMES	OFTEN	VERY OFTEN	SUM OF SCORES
		Frequency %	0%	1-5%	6-33%	34-66%	67-100%	
T1	0	straight, upright			25.37			25.37
T2	0.974	slightly inclined				55.97		55.97
T3	1.104	strongly inclined			18.66			18.66
T4	0.068	twisted						0
T5	0.173	laterally bent						0

STEP (3)

Posture Code	Weight	Linguistic Categories	NEVER	SELDOM	SOMETIMES	OFTEN	VERY OFTEN	SUM OF SCORES
		SCORES ASSIGNABLE	0	1	2	3	4	
T1	0	straight, upright			2			2
T2	0.974	slightly inclined				3		3
T3	1.104	strongly inclined			2			2
T4	0.068	twisted						0
T5	0.173	laterally bent						0

STEP (4)

	Score
PLI	6

Figure 3-2 Sample procedure visualization for calculating PLI II score – T postures

The computational methodology proposed for obtaining the Revamped PLI score can be explained using the following four steps:

1. In this step, the total duration of repeating postures over the duration of the job task are recorded for all posture codes based on observational methods or direct measurements. The recorded time for each posture is converted into frequency percentages (FP) by using Equation (3-1).
2. The form is then populated based on five quantitative FP ranges: Never (0%), Seldom (1%–5%), Sometimes (6%–33%), Often (34%–66%), and Very often (67%–100%). This step is to fill the form by assigning an FP value to each posture code.
3. In this step, the FPs are converted into frequency code scores (FCS) using the equational logic expressed as Equation (3-2) below.
4. Finally, Equation (3-3) is used to obtain the Revamped PLI score.

PLI Score Computation:

if FP = 0% AND FP <1%, then, FCS = 0

if FP ≥ 1% AND FP <6%, then, FCS = 1

if FP ≥ 6% AND FP <34%, then, FCS = 2

if FP ≥ 34% AND FP <67%, then, FCS = 3

if FP ≥ 67% AND FP <100%, then, FCS = 4 **(3-2)**

PLI = 0.974 × T2 score + 1.104 × T3 score + 0.068 × T4 score + 0.173 × T5 score + 0.157 × A2 score + 0.314 × A3 score + 0.405 × L3 score + 0.152 × L4 score + 0.152 × L5 score + 0.549 × Wu1 score + 1.098 × Wu2 score + 1.647 × Wu3 score + 1.777 × Wi1 score + 2.416 × Wi2 score + 3.056 × Wi3 score. (Hollman et al., 1999) **(3-3)**

With the identification of possible and impossible postural overlaps, the Revamped PLI index range is determined to be 0-32. Table 3-2 displays the five discrete risk categories of Revamped PLI index.

Table 3-2 Classification of Revamped PLI risk categories

Risk Category	Revamped PLI Score	Risk Description & Response Plan
NR	≤3	negligible risk, no action required
LR	≤6	low risk, change may be needed
MR	≤9	medium risk, investigate and implement change
HR	≤12	high risk, investigate and implement change soon
EHR	≥13	extremely high risk, implement change now

Overall, this section provided an overview of using the computational methodology of Revamped PLI. At this stage, it is important to recollect that the computational methodology of Revamped PLI is applicable for both PLI II (Revamped PLI that is compatible with simple and advanced observational methods) and PLI III (Revamped PLI that is compatible with Direct measurements). Although this study lays the theoretical groundwork for the development of a near comprehensive ergonomics risk assessment tool that is compatible with all types of data collection methods, it has only developed and validated PLI II (Revamped PLI compatible with simple observational method) for the assessment of ergonomic performance of industrial job tasks.

3.2.3.2 Validation

In this phase, Revamped PLI is compared with a well-established, valid, and reliable entire body assessment tool, REBA, for the purpose of preliminary validation of the proposed tool. For this purpose, PLI II and REBA data regarding 92 job tasks is collected from manufacturing and construction industries. Due to the disparate score ranges of REBA and PLI, direct comparison of risk indexes between the two tools is not possible. Consequently, using PLI II and REBA risk indexes, both tools are compared to see if they are aligned closely. If PLI II is in close agreement with REBA, then, PLI II will be recognized as a valid method for conducting ergonomics risk assessments. However, if PLI II scores contradict REBA scores, they will be deemed invalid for conducting ergonomics risk assessments.

3.3 Validation Results

In this section, PLI II's performance is compared with the REBA's performance using risk categories, for preliminarily validating the proposed tool. The validation dataset consists of scores and risk categories obtained from evaluating 92 job tasks in manufacturing and construction facilities. Considering the risk categories and risk descriptions of PLI II (Table 3-2) and REBA, ground rules (i.e., match criteria) are established for validating PLI II. The Match criteria Logic for validating PLI II with REBA are presented in Table 3-3. Despite the fact that the two tools use different inputs to evaluate risk severity, it is anticipated that PLI II will represent similar risk categories as REBA regardless of the industrial job task being assessed. If PLI II is in close agreement with REBA, then, PLI II will be recognized as a valid method for conducting ergonomics risk assessments. However, if PLI II scores entirely contradict REBA scores, then PLI II will be deemed invalid for conducting ergonomics risk assessments. The Match criteria Logic for validating PLI II with REBA (Table 3-3) is easier to comprehend with the help of an example. For instance, if a package handling job task in a warehouse shows an HR in both PLI II and REBA, this is a 'Match' and is considered an ideal result. In contrast, if the same job task shows an HR in PLI II but an NR in REBA, the result is 'Miss-Match', meaning that the risk severity results generated by the two tools are contradictory. Finally, if there is an instance in which the same job task shows an HR in PLI II and an LR in REBA, meaning that the tools have narrowly missed a 'Match', this can be considered to be a 'Semi-Match'. Overall, if the majority of the Match criteria Logic for PLI II and REBA (Table 3-3) depict a 'Match' or a 'Semi-Match,' then PLI II can be considered to be in close agreement with REBA, and therefore can be regarded as an acceptable tool for conducting ergonomics risk assessments.

Table 3-3 Match criteria Logic for PLI II and REBA

Outcomes	Descriptions	Match Criteria
Match	The tools show the same type of risk severity	if PLI II (NR) = REBA (NR) or if PLI II (LR) = REBA (LR) or if PLI II (MR) = REBA (MR) or if PLI II (HR) = REBA (HR) or if PLI II (EHR) = REBA (EHR)
Semi-Match	The tools are approximately similar, but are not radically different (PLI II minorly "overestimates" or "underestimates" risk categories in comparison to REBA)	if PLI II (NR) = REBA (LR) or if PLI II (LR) = REBA (NR, MR) or if PLI II (MR) = REBA (LR, HR) or if PLI II (HR) = REBA (MR, EHR) or if PLI II (EHR) = REBA (HR)
Miss-Match	The tools are contradictory	Other Cases

Among 92 industrial job tasks that were assessed, there were 37 'Match' cases (40%), 41 'Semi-Match' cases (45%), and 14 'Miss-Match' cases (15%), as displayed in Figure 3-3. At this stage it is imperative to recall that, the Revamped PLI focuses on the lumbar load present in the human body for a variety of postures and material handling tasks, while REBA focuses only on awkward postures. Since, majority of the cases (45%) are ‘Semi-Match’ cases, these cases are explored further and categorized as “overestimates” or “underestimates”. In addition, further data analysis reveals that "overestimates" and "underestimates" are caused by the predominant trunk posture of the worker. In particular, it is found that PLI II typically overestimates REBA scores when the worker is required to frequently use inclined trunk postures, and that PLI II typically underestimates REBA scores when the worker is required to predominantly use a straight upright trunk posture. In addition, industrial job tasks that involved lifting weights in an inclined trunk position typically fell in the overestimate category. This important discovery revealed that PLI II penalized industrial job tasks more than REBA when the trunk was frequently stressed by inclination. In addition, PLI II penalized industrial job tasks more than REBA if they required prolonged lifting of weights, specifically in an inclined position. The collected validation data also revealed a strong positive linear correlation of 0.73 between PLI II and REBA scores.

Considering these factors, it is reasonable to conclude that PLI II's risk categories are valid, closely aligning with REBA. Both tools demonstrate meaningful risk categories for whole-body awkward postures. Notably, PLI II excels over REBA, particularly in assessing material handling tasks. This is evident from PLI II generating higher risk scores for such tasks, whereas REBA tends to underestimate risks. This underscores PLI II's potential as a more comprehensive tool, offering more accurate, actionable insights for both awkward postures and material handling tasks. And therefore, the validation results also indicate that PLI II can be used to assess any type of industrial job task due to its comparative comprehensiveness when compared to REBA.

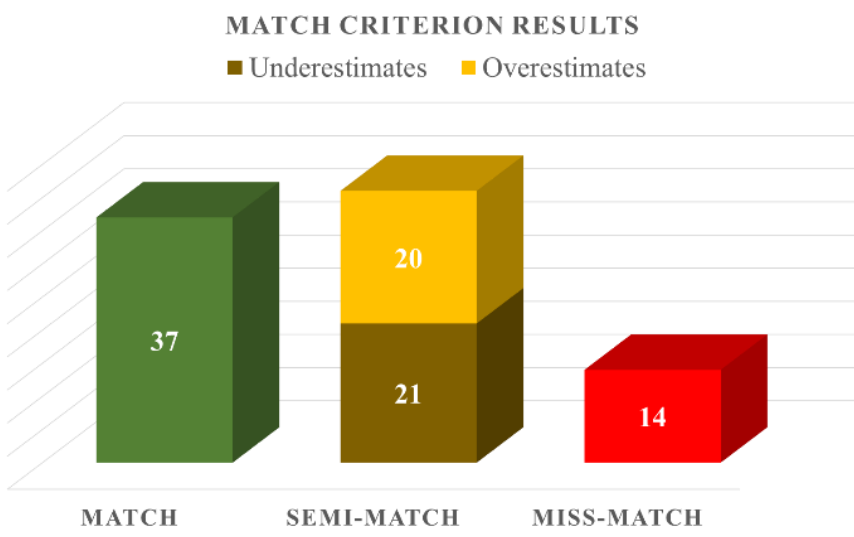

Figure 3-3 Match Criteria Results

3.4 Discussion and Conclusion

The Revamped PLI framework builds on the traditional PLI method, leveraging its strengths such as entire posture, load weight, and repetition/frequency as inputs while addressing its limitations by objectively collecting human motion data. This study compared the Revamped PLI against the widely-used REBA tool and demonstrated its effectiveness.

The key highlights of this study are:

- The theoretical and computational framework proposed for PLI II (simple observational method) sets the foundation for the development of PLI II (advanced observational methods) and PLI III (direct measurements).
- PLI II eliminates impossible overlapping postures and incorporates a time study component, removing subjectivity in the collection of human motion data. This feature results in better accuracy and precision than conventional PLI.

- PLI II scores are categorized into five risk categories using human motion data from 92 industrial job tasks. The added descriptive risk categories make Revamped PLI scores more interpretable than conventional PLI scores.

Overall, this study represents a significant step in the development of a versatile physical-ergonomics risk assessment tool. It has the potential to simplify tool selection for work system improvement. However, further research is necessary to fully evaluate the effectiveness of the theoretical foundations and computational framework proposed for PLI II (which uses advanced observational methods for data collection) and PLI III (which uses direct measurements for data collection). Actual implementation of these tools would provide valuable insights and feedback for the improvement and refinement of the proposed physical-ergonomics risk assessment tool.

Chapter 4: FUZZY LOGIC-BASED DSS FOR AUTOMATING ERGONOMIC RISK ASSESSMENTS

4.1 Introduction

Ergonomics is the scientific discipline focused on the interactions between humans and other elements of a system (people, environment, and objects) (ACE 2018). Ergonomists fit work systems to people's needs, skills, and limitations. Quantification and risk assessment of physical, environmental, and sensory risks associated with work system design can improve occupational health and safety. Specifically, the term risk assessment is used to describe the following processes: (1) hazard identification—finding risk factors; (2) risk analysis—understanding the nature of risk factors and estimating the severity of risk; (3) risk evaluation—estimating the significance of risk (Canadian Centre for Occupational Health and Safety, 2016). A variety of ergonomics risk assessment methods that evaluate different physical, environmental, and sensory aspects of workplace design have been proposed by ergonomics researchers. Specifically, ergonomics researchers have brought about advancements by introducing many manual ergonomics risk assessment methods for assessing the ergonomic performance of work systems (Lynn et al. 1993; Waters et al. 1993; Moore et al. 1995; Karhu et al. 1977; Hol et al. 1999, McAtamney et al. 2004; Health and Safety Executive 2006; Freivalds et al. 2013; Health and Safety Executive 2020; Occupational Safety and Health Administration 2020; Hart et al., 1988; Reid et al., 1988; Li et al. 2015; Li et al. 2019a). However, despite the beneficial effects of ergonomics risk assessments in terms of enhancing organizational health and safety by optimizing work systems (Hendrick, H. W. 2007, Li et al. 2019b, Ryu et al. 2020, Getuli et al. 2020; Silverstein 1997, Hendrick, H. W. 2007, ACE 2018, Golabchi et al. 2018, Li et al. 2019b), many organizations disregard ergonomics risk assessments due to the lack of convenient tools (Kahraman et al. 2003, Azadeh et al. 2008).

To address this issue, Pokorádi et al. (2009) argue for the wider adoption of fuzzy logic in today's technical management decision-making because it has been demonstrated to be helpful in risk assessment for human activities. Accordingly, other researchers have suggested a number of fuzzy logic-based ergonomics risk assessment tools over the years to enhance health and safety in the construction industry (Fayek et al. 2005; Aluclu et al. 2008; Debnath et al. 2015; Golabchi et al. 2015; Golabchi et al. 2016; Wang et al. 2020; Wang et al. 2021). Although a number of robust automated tools have been proposed by researchers in manufacturing ergonomics, these focus on physical ergonomic risk factors, and no tool has been proposed that simultaneously evaluates the physical, environmental, and sensory aspects of work systems. Therefore, this article proposes an integrated fuzzy logic-based Decision Support System (DSS) that enables the simultaneous assessment of physical, environmental, and sensory aspects of work systems. The key outcome of the proposed DSS is the ergonomics risk indicator (ERI), a composite risk score that reflects the combined physical, environmental, and sensory risk levels in work systems. Rather than relying on historical data to solve ergonomics problems in work systems, the proposed DSS can be used to proactively assess the level of ergonomic risk in work systems. To prove its validity, the proposed DSS is validated using a real-world case study in a modular construction facility by comparing the results of the overall DSS with the facility's occupational injury reports. Overall, the proposed DSS is intended to provide an automated and integrated ergonomics risk assessment that can assist practitioners in improving occupational health and safety.

4.2 Identifying appropriate existing ergonomics risk assessment tools for DSS development

In order to create an integrated automated ergonomics risk assessment system, it is necessary to integrate physical, environmental, and sensory assessment tools. The integration of physical, environmental, and sensory ergonomics risk assessment tools, in turn, requires knowledge of the interactions among physical, environmental, and sensory factors in work systems. However, these relationships can be difficult to characterize, and there is no reliable literature on the interaction of such factors and their impact on work systems. Therefore, it is difficult to design logical systems that incorporate existing physical, environmental, and sensory assessment tools. FESs are capable of overcoming the challenge of having incomplete, partial, or unreliable information (Zadeh et al. 2013; Novak et al. 2012; Kayacan et al. 2016). Thus, this study introduces a fuzzy logic-based DSS that incorporates existing physical, environmental, and sensory risk factors to generate an Ergonomic Risk Indicator (ERI) that can be used to comprehensively assess the ergonomic performance of a work system.

There are several existing ergonomics risk assessment tools in the literature that can be incorporated together to develop a fuzzy logic-based DSS capable of assessing the physical, environmental, and sensory aspects of work systems. In order to architect such a integrated ergonomics risk assessment tool, this study adapts individual comprehensive tools for assessing the physical, environmental, and sensory aspects of work systems when available. For aspects for which individual comprehensive tools are not available, multiple tools are blended together. In such cases, the multiple tools are selected with simplicity of design in mind. The high-level architecture of the proposed DSS is depicted in Fig. 4-1.

First, the risk assessment tool, Physical Load Index (PLI), developed by Hollmann et al. (1999), is selected for obtaining the Physical Indicator. In this regard, several ergonomics risk assessment tools, such as REBA (McAtamney et al. 2004), RULA (Lynn et al. 1993), and the National Institute for Occupational Safety and Health (NIOSH) Lifting Equation (Waters et al. 1993), were reviewed and are considered but are deemed to be too specialized (either in assessing postures or in assessing material handling tasks) for the purpose of the present study. PLI, it should be noted, is a questionnaire created by integrating information from a biomechanical model of the lumbar load. The PLI questionnaire aids in assessing the worker's entire body posture, the weight of the load carried, and the repetition/frequency of activities while performing job duties, all within the same assessment (Hollmann et al. 1999). Thus, the PLI questionnaire can comprehensively and easily assess physical ergonomic risks in a work system. Consequently, the PLI is selected in the present study for the assessment of the physical aspects of work systems.

Although there is no comprehensive individual tool for environmental risk assessment tool available in the literature, several separate tools are available that can be combined to comprehensively predict the environmental conditions of work systems. Therefore, a number of different environmental risk assessment tools are combined to generate an Environmental Indicator. Parsons (2000) states that illumination, heat hazard, noise, vibration, and wind chill are key environmental risk factors with regard to assessing work systems. Therefore, the illumination sub-indicator is obtained from 'recommended illumination levels for use in interior lighting design' charts using the age of workers, the reflectance of task/surface background, speed and accuracy required, and range of illuminance as inputs (Freivalds et al. 2013); the noise sub-indicator is obtained from the 'permissible noise exposure' chart (Freivalds et al. 2013); and the wind chill sub-indicator is obtained from 'equivalent wind chill temperature of cold environments under calm conditions' chart using air temperature and wind speed as inputs (Freivalds et al. 2013). The heat hazard sub-indicator is obtained from the Heat Stress standards recommended by Occupational Safety and Health Administration (OSHA) using workers' metabolic rate and Wet Bulb Globe Temperature (WBGT) as inputs (OSHA 2020). Finally, the vibration sub-indicator is obtained from the Health and Safety Executive (HSE)'s recommended limits for hand–arm vibration (HSE 2020).

Li et al. (2015) analyze sensory demands in modular construction plants using only visual and auditory demand data, as they regard visual and auditory demand to be the most important components of sensory risk in modular construction plants. In their work, a questionnaire with the following frequency categories is used to record workers' sensory demands: (1) Never (0%); (2) Rare (1%–5%); (3) Occasional (6%–33%); (4) Frequent (34%–66%); (5) Continuous (67%–100%). The reasoning underlying their study is that greater sensory demand corresponds with greater ergonomic risk. The tool proposed by Li et al. (2015) is used in the present study for evaluating the sensory aspects of work systems.

Developing a fuzzy logic-based DSS that incorporates the physical, environmental, and sensory aspects of work systems necessitates the development of a complex system, which in turn necessitates the modeling of multiple FESs that form the basis of the DSS. However, complex expert systems can be difficult to develop and interpret. To reduce the complexity of the expert system, emphasis is placed on selecting tools that prioritize simplicity and relevance to the modular construction industry. This approach leads to the selection of near-comprehensive subjective tools for assessing the Physical and Sensory indicators, while incorporating a diverse array of objective tools for evaluating the Environmental indicator.

4.3 Methodology

The methodology devised to design a integrated DSS entails a two-phase approach: firstly, defining the high-level architecture of the DSS, and secondly, constructing distinct FESs that collectively form the DSS. This approach aims to seamlessly incorporate established tools for assessing physical, environmental, and sensory ergonomics risks within the developed system.

4.3.1 Architecture of DSS

Constructing a single FES that incorporates existing physical, environmental, and sensory ergonomics risk assessment tools is a challenging task due to the numerous variables involved. In particular, it is difficult to construct a single FES to comprehensively automate ergonomics risk assessment since a considerable amount of time is required to precisely design a large number of rules. Consequently, in this study, a DSS is developed to overcome the curse of dimensionality by hierarchically interconnecting FESs, where each FES is an individual expert system performing a narrow function beneficial to the overall system. Fig. 4-1 depicts the high-level architecture of the proposed DSS. As can be seen, each FES in the proposed DSS accepts inputs and passes outputs, which in turn serve as inputs for the next FES in the chain. Fig. 4-1 depicts the pale blue boxes representing the inputs that must be supplied to the DSS by the practitioner using the data collected from the work system under investigation.

At this juncture it is important to note that, despite the fact that this study proposes the development of a fuzzy logic-based DSS for automating ergonomics risk assessments, the proposed DSS can only automate the process of risk estimation through the generation of ERI when the practitioner manually supplies the DSS with the collected ergonomics data. Collectively, the hierarchically interconnected FESs are able to estimate the ergonomic performance of any hypothetical work system by generating a composite risk score, referred to as an ERI, provided that the collected ergonomic data for the hypothetical work system is relayed to the appropriate FESs.

There are several ergonomics risk assessment tools in the literature that can be used to assess the physical, environmental, and sensory aspects of work systems separately. However, an integrated ergonomics risk assessment tool must be capable of assessing the physical, environmental, and sensory aspects of work systems simultaneously. In order to architect an integrated ergonomics risk assessment tool, this study looked for and adapted individually comprehensive tools for assessing the physical, environmental, and sensory aspects of work systems when they were available. However, when individually comprehensive tools were not available, separate tools were blended together. The high-level architecture of the proposed DSS is depicted in Figure 4-1. In addition, it is essential to note that the proposed DSS's diverse array of separate tools was selected with simplicity of design in mind.

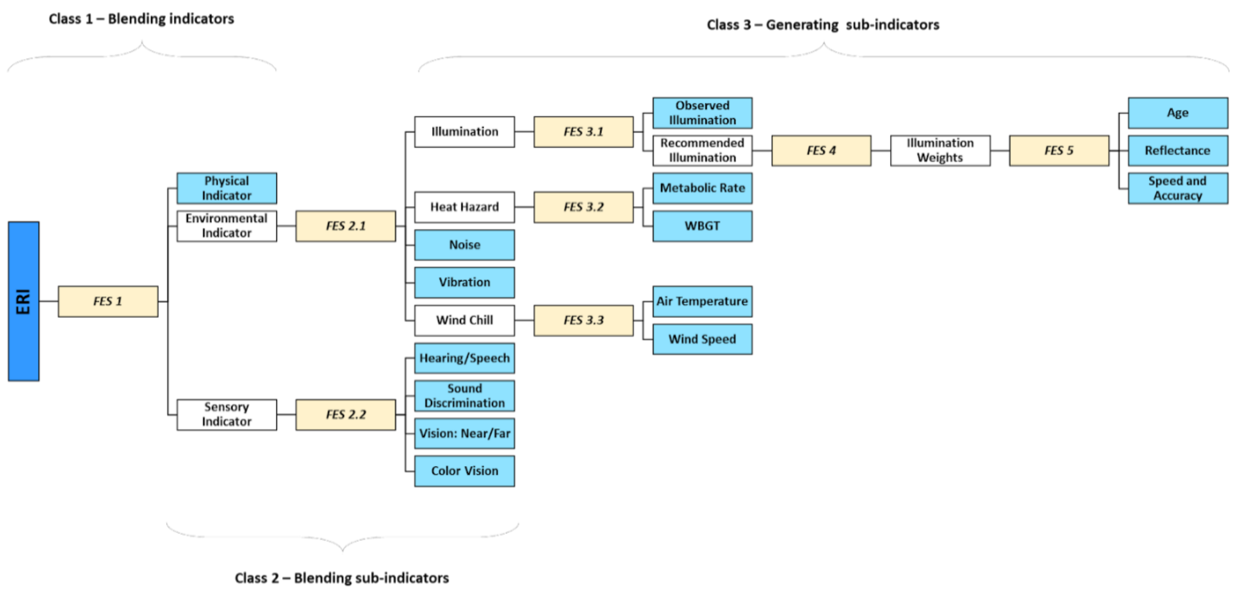

Figure 4-1 Architecture of the proposed DSS

Moreover, as depicted in Fig. 4-1, the proposed DSS's FESs can be grouped into three classes based on functionality: (1) FES_Class3—FESs that automate the risk estimation workflows for the purpose of generating the Illumination sub-indicator (Freivalds et al. 2013), Heat Hazard sub-indicator (OSHA 2020), and Wind Chill sub-indicator (Freivalds et al. 2013); (2) FES_Class2—FESs that act as a blended layer in the proposed DSS, combining sub-indicators produced by FES_Class3 to generate indicators; and (3) FES_Class1—FESs that act as the final blended layer in the proposed DSS, combining the indicators produced by FES_Class2 to generate the ERI.

4.3.2 Design of DSS

In order to fully comprehend the DSS's design and its constituent FESs, it is first necessary to comprehend the FES's general operation. All the FESs making up the proposed DSS are constructed specifically with the fuzzy logic toolbox available in MATLAB. These FESs are designed using the simple and widely accepted Mamdani-type inference method. Fig. 4-2 illustrates the block diagram for FES. As can be seen, the FES in general consists of four main components: fuzzification, inference engine, rule base, and defuzzification (Kayacan et al. 2016). The function of the FES can be described as the process of formulating the mapping of crisp inputs to crisp outputs using the theory of fuzzy sets (Wong et al. 2013). The inputs and outputs of the FESs, it should be noted, are referred to as crisp values, as they assume a distinct value as opposed to a fuzzy membership value. To elaborate, the inputs of the FES are crisp (non-fuzzy) numbers that are limited to a specific range. When the crisp inputs are passed to the FES, they are fuzzified by determining the degree to which they belong to each membership function. In this context, a fuzzy set is any set that permits its elements to have varying degrees of membership with linguistic variables within the interval [0,1]. After fuzzifying the inputs, the inference engine evaluates each fuzzy rule in the rule base to generate an output for each fuzzy rule. Consequently, fuzzy output sets are obtained. Following this, the output fuzzy sets obtained are aggregated into a single fuzzy set using the aggregation method. Finally, the aggregated output fuzzy set is defuzzified using defuzzification methods to produce a crisp number as an output. In this way, the FESs making up the proposed DSS use these four components—fuzzification, an inference engine, a rule base, and defuzzification—to formulate the mapping between a given input and output. In addition, it must be highlighted that there are many types of membership functions (triangle, trapezoid, gaussian, bell-shaped, sigmoid, etc.) that can be used in the Mamdani fuzzy systems for fuzzification and defuzzification. For the proposed DSS, only triangle and trapezoidal membership functions are employed owing to their simplistic nature.

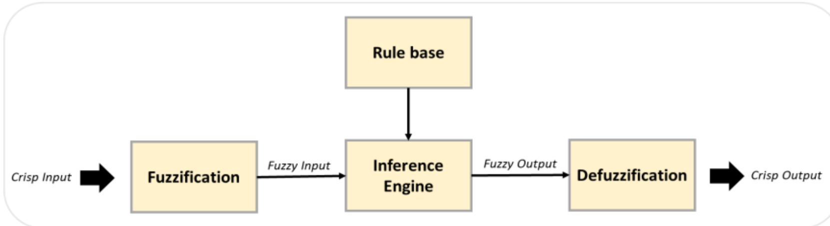

Figure 4-2 FES block diagram

At this juncture, it is important to underscore that, in the proposed DSS, eight FESs are used to generate the composite risk score (i.e., ERI). Moreover, on the basis of their functionality, these eight FESs are divided into three categories: FES_Class3, FES_Class2, and FES_Class1 as discussed above. The rule base underlying the FESs in each of the aforementioned FES classes is essential for the estimation of outputs based on the given inputs. The number of heuristic rules present in the rule base of each FES, meanwhile, is contingent upon the number of input/output variables and membership functions of the FES. While the number of input/output variables is a function of the ergonomics risk assessment tools chosen for the DSS's architecture, the number of membership functions for each FES is determined in such a manner as to strike a balance between design simplicity and performance. In general, the rule bases of FESs can be designed using a large numerical dataset from which rules can be extracted, while they can also be created using linguistic data, typically obtained from expert opinion. In the proposed fuzzy logic-based DSS, the rules are designed using both numerical and linguistic data.

4.3.2.1 Design of FES_Class3

The rule base underlying FES_Class3 is essential for determining the Environmental sub-indicators, and it is developed using numerical datasets derived from the tools themselves (Freivalds et al. 2013; OSHA 2020). The rule base for the FESs in FES_Class3 consists of 9 rules for FES 3.1, 45 rules for FES 3.2, 16 rules for FES 3.3, 7 rules for FES 4, 27 rules for FES 5, 7 rules for FES 4, and 27 rules for FES 5.

For instance, the rule base for FES 3.3, which estimates the Wind chill sub-indicator, its rule base is derived from the Wind chill index chart (Freivalds et al. 2013). This chart requires users to determine the Wind chill index based on the air temperature (at 5° F intervals) and wind speed (at 5 mi/h intervals). In other words, this chart provides a discrete index that is limited in its ability to provide continuous values in real case scenarios (i.e., due to the discrete nature of the input parameter). Thus, FES plays an important role here in providing continuous estimation of the Wind chill sub-indicator based on the rules extracted from the Wind chill index chart (Freivalds et al. 2013). To achieve this, the FES 3.3 is created, and the performance of the model is evaluated by contrasting the Wind chill indices determined by the chart with the estimated Wind chill sub-indicator determined by the FES 3.3 using the mean absolute error.

Furthermore, considering the inclusion of FES 3.2, which generates the Heat hazard sub-indicator, it is worth noting that its rule base is derived from the Threshold Limit Value or Action Limit chart as outlined by OSHA (2020). This chart requires users to determine whether the heat hazard is below or above the danger zone using the inputs of Metabolic Rate (watts) and WBGT (°C). This chart can be used to determine whether the heat hazard risk is below, above, or on the borderline, but it does not provide any index. Thus, the FES plays an important role here in providing continuous estimation of the Heat hazard sub-indicator based on the rules extracted from the Threshold limit value or Action limit chart (OSHA, 2020). To accomplish this, the FES 3.2 is developed, and the effectiveness of the model is evaluated by examining the accuracy of the FESs in classifying whether the heat hazard risk is below, above, or borderline when compared to the Threshold limit value or Action limit chart.

Additionally, the hierarchically connected FES 5, FES 4, and FES 3.1 can be taken into consideration as they collectively contribute to the generation of the Illumination sub-indicator. In this case the rule base is derived from the procedure proposed by Freivalds et al. (2013). However, this procedure does not provide an index per se; rather, it assists the user in determining the extent of deviation between the observed illumination (fc) in the work system and the recommended illumination (fc). Thus, FES plays an essential role here in illustrating not only the degree of deviation between observed illumination (fc) in the work system and the recommended illumination (fc) based on Freivalds et al. (2013), but also in quantifying the level of risk that is proportional to the deviation. To model such a procedure, however, a single FES is insufficient; consequently, this procedure is modeled using three hierarchically interconnected FESs. First, FES 5 is used to estimate the continuous illumination weights of a job task using inputs such as the average age of the workforce, the reflectance of the work system, and the required speed and accuracy category for the work system's job task. Second, FES 4 estimates the recommended illumination (fc) using the illumination weights obtained in FES 4. Finally, FES 3.1 uses the observed illumination (fc) of the work system and the recommended illumination range (fc) from FES 4 as inputs to illustrate the deviation of observed illumination (fc) from the recommended illumination (fc). Here, the effectiveness of FES 5 and FES 4 are assessed using the mean absolute error by comparing the estimated values to the actual values, in accordance with Freivalds et al. (2013). Meanwhile, FES 3.1, with the assistance of FES 5 and FES 4, is modeled not only to illustrate the degree of deviation between observed illumination (fc) in the work system and the recommended illumination (fc) based on Freivalds et al. (2013), but also to quantify the level of risk that is proportional to the deviation.

Finally, it should be noted that, in contrast to the Wind chill, Heat hazard, and Illumination sub-indicators, the Noise (dBA) and Vibration (m/s2) sub-indicators do not require any modeling because the collected ergonomic data for Noise (dBA) and Vibration (m/s2) can be directly used as sub-indicators to feed FES 2.1.

4.3.2.2 Design of FES_Class2

The rule base of the FES_Class2 is essential for determining of Environmental and Sensory indicators. The FESs of FES_Class2 consists of 216 rules for FES 2.1, and 625 rules for FES 2.2. The rule bases for FES_Class2 are developed using reasonable assumptions and trial-and-error with respect to the validation phase rather than engaging human experts to obtain linguistic data, as neither an expert nor a study in the literature is capable of speaking to the question of how to model blended layers such as those in FES_Class2. Therefore, FES_Class2's rule bases assume that input risk is proportional to output risk. For example, if FES 2.1 has multiple high-risk inputs for the Illumination, Heat hazard, Noise, Vibration, and Wind chill sub-indicators, then the Environmental indicator must be high. Similarly, if FES 2.1 has multiple low-risk inputs, the Environmental indicator must be low. However, it is challenging to establish Environmental indicators for mixed cases in which inputs vary across the risk spectrum. In these situations, the rule base of FES 2.1 is tuned using a trial-and-error approach with respect to the validation phase (discussed in Section 4). Similarly, the rule base of FES 2.2 is also designed to output the Sensory sub-indicator by combining reasonable assumptions and a trial-and-error approach. It should be noted, however, that, because FES_Class2 acts as a blended layer in the proposed DSS, it cannot be directly validated. Therefore, the dependability of the FESs in FES_Class2 is dependent on the evaluation of the entire DSS. By evaluating the final blended layer of the DSS, FES_Class1, the performance of the entire DSS can be determined.

4.3.2.3 Design of FES_Class1

Despite the fact that all eight FESs play crucial roles in generating the ERI, in the interest of brevity only FES_Class1 (FES 1) is discussed in detail in this study (due to its significance in evaluating the DSS as a whole). In terms of its inputs and outputs, the first input of FES 1, the Physical Indicator, requires that the average frequency of body positions and load handling at workstations be reported by workers in accordance with the PLI questionnaire. The responses are rated on a five-point scale from "never" to "very often." The 5-point rating scale is then used to calculate the PLI score for the workstation using the equation provided by Hollmann et al. (1999). Following this, the PLI of the workstation recorded for each employee is averaged to calculate the Physical indicator of the workstation. The second input of FES 1, the Environmental Indicator, necessitates that the practitioner collects environmental data using a variety of sensors, such as the illuminance meter, WBGT meter, Decibel meter, hand-arm vibration meter, Air temperature meter, and wind speed meter, on the workstation whose Environmental indicator is to be calculated. The collected environmental data is then relayed through the respective FESs across FES_Class3 and FES_Class2 to calculate the Environmental indicator. The third input of FES 1, the Sensory Indicator, requires the average frequency of visual and auditory demand at workstations be reported by workers in accordance with the questionnaire developed by Li et al. (2015). The responses are rated on a five-point scale ranging from “never” to “continuous.” Consequently, the average visual and auditory demands of all workers at the workstation are calculated in order to approximate the visual and auditory demands of the workstation. Following this, the averaged visual and auditory demands of the workstation are relayed through FES 2.2 to calculate the Sensory indicator. Moreover, according to the PLI established by Hollmann et al. (1999), the Physical Indicator is assigned a range of 0 to 56, whereas the Environmental Indicator, Sensory Indicator, and ERI are assigned a range of 0 to 1 because they are the result of blending sub-indicators. Overall, when the Physical Indicator, Environmental Indicator, and Sensory Indicator are passed into FES 1, the output ERI is generated.

To shed further light on the manner in which FES 1 determines the ERI, the membership functions and rule base of FES 1 also warrant discussion. The design of the input and output membership functions for FES 1 is illustrated in Fig. 4-3. The Physical Indicator is defined using linguistic variables such as Low Risk (LR), Medium Risk (MR), High Risk (HR), and Extremely Extreme Risk (EER) for input membership functions, whereas the Environmental Indicator and Sensory Indicator use linguistic variables such as LR, MR and HR for input membership functions. Moreover, the output membership function of the ERI is defined using linguistic variables such as LR and HR to indicate the overall ergonomic risk intrinsic in the work system. Fig. 4-3 also depicts the heuristics rules designed for the rule base of FES 1.

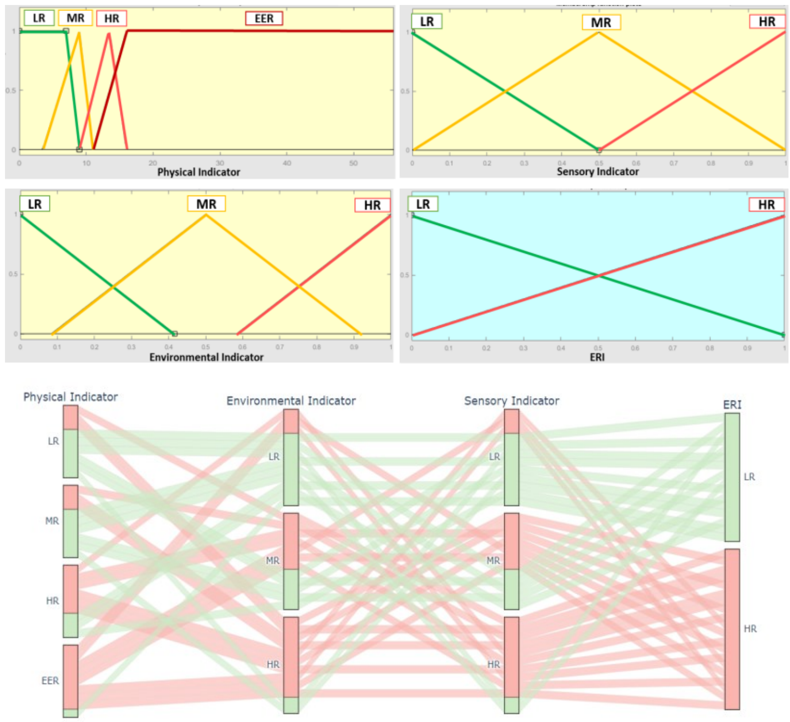

Figure 4-3 Visualization of membership functions and heuristics rules of FES 1

At this juncture, it is important to note that the rule base of FES 1 consists of 36 heuristic rules designed to blend the Physical, Environmental, and Sensory indicators to generate the composite risk score (i.e., ERI). Since the generated ERI is the blended result of the Physical, Environmental, and Sensory indicators, it cannot be compared to any actual ERI score. As a result, not only FES 1 but also the overall DSSs performance is evaluated using a proxy indicator such as the 'Count of total injuries' recorded in the plant, which is retrievable from the occupational injury reports as described in Section 4. The 36 heuristic rules of FES 1 are depicted in Fig. 4-3, which were developed by combining reasonable assumptions with a trial-and-error approach such that the input risk is proportional to output risk. In addition, Fig. 4-4 presents graphically the fuzzy inference process underlying FES 1.

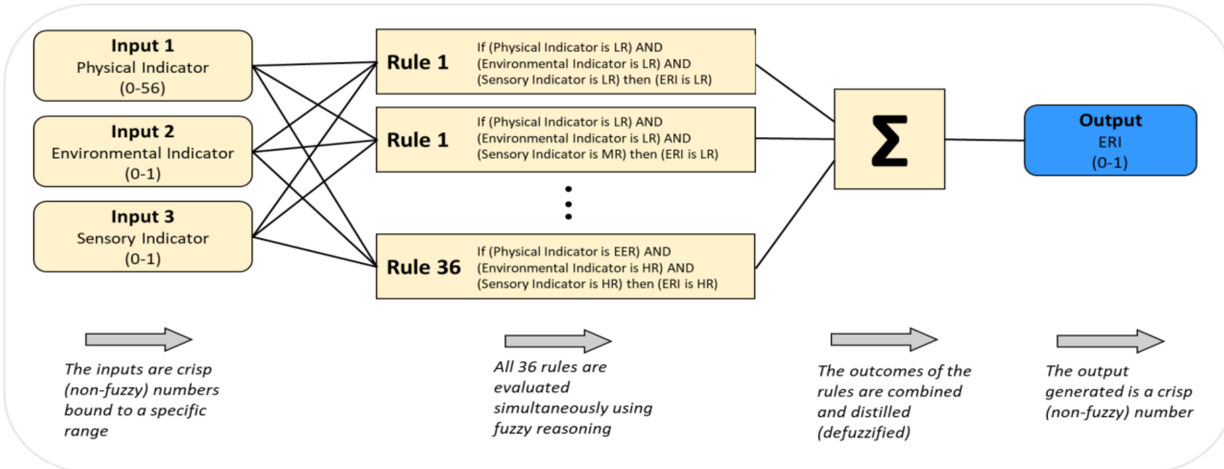

Figure 4-4 Fuzzy inference process of FES 1

Finally, it is important to note that the proposed DSS can be used to calculate the workstation ERI for any hypothetical work system. However, in order to evaluate the performance of the DSS, the workstation ERI obtained from FES 1 must be compared to a proxy indicator such as the 'Count of total injuries' recorded in the plant (since the workstation ERI cannot be compared to any actual ERI score). However, this proxy indicator may be recorded at the plant level by work area rather than at the level of the individual workstations comprising each work area. In such cases, it may be necessary to calculate the Area ERI from the Workstation ERI using workload-weighted averages, where metabolic rates of workers (OSHA 2020) can be used as the weights of the workstation. Equation 4-1 provides the formula for calculating the Area ERI of a work area through the use of weighted averages. This Area ERI can then be compared to the proxy indicator, such as "count of total injuries," that is recorded by plant area.

$$A = \sum_{i=1}^{n} \frac{wi\ Xi}{wi} \qquad \mathbf{(4-1)}$$

A = Area ERI

n = Number of terms to be averaged

wi = Metabolic rates applied to X values

Xi = Workstation ERI values to be averaged

4.4 Evaluating the performance of DSS

4.4.1 Application of DSS

Before evaluating the developed DSS, it is important to discuss the manner in which modular construction organizations can expect to make use of it. This section thus proposes the concept of the ergonomic risk management lifecycle for understanding the interactions between the practitioner and the developed DSS. The ergonomic risk management lifecycle, as illustrated in the block diagram in Fig. 4-5, is a cyclical process developed to detect, assess, and control ergonomic risks in an organization using the developed DSS. The ergonomic risk management lifecycle consists of six stages: (1) Data Collection—this phase entails the collection of ergonomics data from various workstations that are to be passed to the DSS; (2) Run DSS—at this juncture, the practitioner inputs the collected ergonomics data into the DSS in order to determine the composite risk score (i.e., ERI) for the workstation under review (bearing in mind that the DSS can only assess one workstation at a time); (3) Interpret DSS results—this stage represents the practitioner's interpretation of the DSS results, in which the practitioner interprets the risk level of the assessed workstation using the ERI score (0–1), where a high ERI score is indicative of high ergonomic risk, while a low score is indicative of low risk; (4) Prioritize work systems—at this stage, the practitioner must compare the ERI results for all of the workstations under investigation and prioritize the workstation with the highest ERI score; (5) Make a risk-control decision—at this stage, the practitioner must investigate and choose a specific risk-control strategy to reduce, mitigate, or eliminate the ergonomic risks associated with the prioritized workstation (this can be accomplished by retrieving the Physical, Environmental, and Sensory Indicator scores of the prioritized workstation—the retrieved risk profile of the prioritized workstation, in turn, can aid the practitioner in making tactical and strategic decisions to address certain risk factors over others based on their high indicator scores, thereby reducing the workstation's ERI); and (6) Risk control—this stage requires the practitioner to implement the selected risk control strategy to alleviate ergonomic risks in the selected workstation. It is imperative to note that risk management is a continuous process that must be performed periodically in order to continuously improve the organization's occupational health and safety.

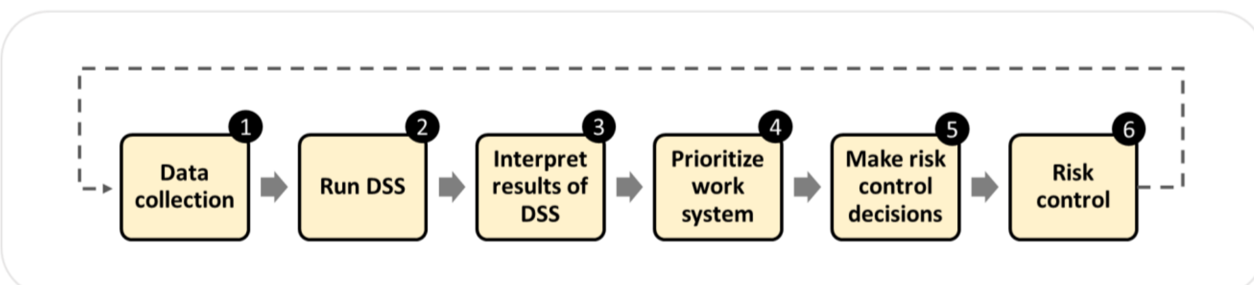

Figure 4-5 Ergonomic risk management lifecycle

4.4.2 Case Study

4.4.2.1 Description of the organization selected for case study

The organization selected for the case study is a modular construction plant. Modular construction involves fabricating modular components in a plant that are then transported and assembled on-site to form a building. The manufacturing plant chosen as the case study consists of five work areas: (1) Wall area—the wall frame assembly area involves precutting all materials with high accuracy using automated robotic machinery, inspecting these precut wall frames for defects and then passing them to the next position using conveyors, manually placing the wall panels and fitting them to the wall frame using power tools, then passing them to the Windows and Doors Area; (2) Windows & Doors area—this area involves workers moving and fitting windows and doors to the wall using vacuum lifts and power tools; (3) Manual area—this area involves workers building components using a combination of power tools and non-powered hand tools as per the requirements of the component being fabricated (the Manual Area is typically using for building auxiliary components such as stairs, decks, and verandas); (4) Floor area—floor assembly is predominantly conducted on computerized tables, although the floor panels are glued and the sheeting is mounted on the floor panel assembly manually by the workers prior to computerized robots screwing down the materials; and (5) Roof area—the roof area involves job tasks such as loading, sorting, and assembling the trusses to form the roof frame. With regard to this last work area, depending on the type of roof, the work may also include installing drywall and the addition of Tyvek home wrap in preparation for siding installation. Furthermore, the roof assembly also necessitates sheathing rooftops and installing shingles, siding, and waterproof paper, and cutting vents.

4.4.2.2 DSS Experiment

In this case study, the ergonomics data for the aforementioned five work areas are gathered and appropriately passed to the DSS, as illustrated in Fig. 4-1. It is crucial to note that some of these work areas comprise several workstations within them. Therefore, the DSS must be executed on each individual workstation. Table 4-1 shows the collected ergonomic data that are passed to the DSS, while Table 4-2 provides a summary of the DSS results

Table 4-1 Ergonomic input data collected for the case study

Workstation	Age	Reflectance	Speed and Accuracy	Observed Illumination (fc)	Metabolic Rate (watt)	WBGT (°C)	Noise (dBA)	Vibration (m/s²)	Air temperature (°F)	Wind Speed (mph)	Hearing/ Speech (%)	Sound Discrimination (%)	Vision: Near/Far (%)	Color Vision (%)	Physical Indicator
Wall Panel Sheeting	<40	30%–70%	Critical	25.20	300	15.80	85.92	2.80	74.90	0.33	1.00	0.50	1.00	0.50	15.25
Wall Line Transfer Area	<40	30%–70%	Critical	25.20	300	15.80	85.92	4.30	74.90	0.33	1.00	0.50	1.00	0.50	10.74
Windows and Doors Area	<40	30%–70%	Critical	22.79	300	15.40	82.33	3.60	74.20	0.20	0.28	0.05	0.75	0.50	5.47
Framing Stairs Area	<40	30%–70%	Critical	23.44	300	13.83	86.33	2.40	70.79	0.00	0.60	0.50	0.92	0.24	11.54
Finishing Area	<40	30%–70%	Critical	23.44	415	13.83	86.33	3.00	70.79	0.00	0.60	0.50	0.92	0.24	13.22
Floor Loading	<40	30%–70%	Critical	46.42	300	15.75	83.07	0.00	74.60	0.06	0.75	0.92	0.65	0.50	8.57
Floor Panel Framer	<40	30%–70%	Critical	46.42	300	15.75	83.07	2.00	74.60	0.06	0.75	0.92	0.65	0.50	12.87
Sheathing and Shingles	<40	30%–70%	Critical	48.46	415	15.77	82.00	5.20	74.03	0.26	0.78	0.80	1.00	0.20	20.73
Truss Assembly	<40	30%–70%	Critical	48.46	415	15.77	82.00	4.50	74.03	0.26	0.78	0.80	1.00	0.20	15.51

Table 4-2 Summarization of DSS results

Area	Workstation	Physical Indicator	Environmental Indicator	Sensory Indicator	Workstation ERI
Wall	Wall Panel Sheeting	13.511	0.285	0.837	0.62
Wall	Wall Line Transfer Area	10.744	0.452	0.837	0.59
Windows	Windows and Doors Area	5.469	0.496	0.500	0.29
Manuals	Framing Stairs Area	11.539	0.150	0.532	0.64
Manuals	Finishing Area	13.223	0.319	0.532	0.64
Floor	Floor Loading	8.567	0.380	0.817	0.61
Floor	Floor Panel Framer	12.871	0.380	0.817	0.66
Roof	Sheathing and Shingles	20.731	0.568	0.831	0.67
Roof	Truss Assembly	15.513	0.538	0.831	0.67

The Workstation ERI in Table 4-2 represents the overall ergonomic performance of a workstation; therefore, it can be used to interpret the DSS results. The results of Table 4-2 can be interpreted as follows: The ‘Windows and Doors Area’ has the lowest ergonomic risk, as indicated by the low Workstation ERI score of 0.29, whereas the ‘Sheathing and Shingles’ and ‘Truss Assembly’ workstations have the highest Workstation ERI score of 0.67, indicating that they have the highest ergonomic risk among the assessed workstations. Naturally, a reasonable approach for prioritizing a workstation is to select the workstation with the highest ERI score. In this case study, both the ‘Sheathing and Shingles’ and the ‘Truss Assembly’ workstations have the highest ERI score of 0.67. This indicates that both workstations present an equivalent level of ergonomic risk. Thus, either of these two workstations could be prioritized for workplace modification over other workstations. For illustration purposes in this discussion, the ‘Sheathing and Shingles’ workstation is given priority. Following the prioritization of the 'Sheathing and Shingles' workstation, risk control decisions must be made to reduce the Workstation ERI of the 'Sheathing and Shingles' workstation. In order to make the best risk control decision, a correlation analysis is performed, as shown in Table 4-3, to characterize the relationships between the Physical, Environmental, and Sensory indicators and the Workstation ERI score for the nine workstations presented in Table 4-2.

Table 4-3 Correlation matrix based on Workstation ERI

	Physical Indicator	Environmental Indicator	Sensory Indicator	Workstation ERI
Physical Indicator	1.00			
Environmental Indicator	0.46	1.00		
Sensory Indicator	0.29	0.44	1.00	
Workstation ERI	0.73	0.52	-0.21	1.00

Taylor (1990) proposes the following interpretation of the coefficient for correlation analysis purposes: $\rho \leq 0.35$ = weak correlation; $0.36 \leq \rho \leq 0.67$ = moderate correlation; $0.68 \leq \rho \leq 0.89$ = high correlation; and $\rho \geq 0.90$ = very high correlation. Based on Taylor's (1990) interpretation of the coefficient for correlation analysis, the Physical Indicator has a high correlation of 0.73 with the Workstation ERI, the Environmental Indicator has a high correlation of 0.52 with the Workstation ERI, while the Sensory Indicator has a low correlation of −0.21 with the Workstation ERI. Notably, the correlation analysis reveals which of the three indicators has the greatest influence on the Workstation ERI scores for the nine workstations analyzed in Table 4-2. This insight may enable the practitioner to prioritize the reduction of certain indicators over others during the 'Make a risk-control decision' stage in the ergonomic risk management lifecycle. For instance, Table 4-2 indicates that the 'Sheathing and Shingles' workstation poses a high physical and sensory risk. Therefore, for the 'Sheathing and Shingles' workstation, if either the physical or the sensory risks of the workstation must be treated, it may be effective if the practitioner prioritizes treating the physical risks over the sensory risks owing to the high correlation of 0.73

between the Physical Indicator and the Workstation ERI for the nine workstations analyzed in this study. Nevertheless, it is ideal that the practitioner aims to address both physical and sensory risks of the workstation. Finally, for any prioritized workstation, engineering controls are preferable to administrative controls because they eliminate ergonomic risk factors at the source (Centers for Disease Control and Prevention 2015). For instance, for the prioritized 'Sheathing and Shingles' workstation, the practitioner may redesign material handling systems associated with the workstation to alleviate the physical risks. However, when engineering controls are too cost-prohibitive or otherwise impractical, administrative controls can be used to temporarily reduce worker fatigue by limiting exposure to ergonomically hazardous job tasks. Examples of administrative controls that can be used are worker rotation, minimizing shift duration of workers, providing PPE, increasing staffing, and providing sufficient breaks. However, to reduce Workstation ERI for the prioritized workstation, engineering controls must be implemented at the workstation.

4.4.2.3 Validation and testing of DSS

This section describes the validation and testing of the DSS, where the case modular construction company's 2015–2022 injury reports are used to validate and test the developed DSS. Validation is especially useful for fine-tuning the DSS to select the best DSS configuration for the fuzzy rules and membership functions, while testing is used to achieve an unbiased final evaluation of the DSS. It would be ideal to compare the DSS's ERI with an actual ERI score to evaluate the DSS's performance; however, since there is no actual ERI score against which the DSS's ERI can be compared, the 'Count of total injuries' in each work area from the case modular construction company’s 2015–2022 injury reports is used as a proxy to evaluate the DSS's performance in estimating the risk level of work areas.

To validate the developed DSS, the Area ERI outputs of the DSS are compared to the ‘Count of total injuries’ for the wall, windows, manual, floor, and roof work areas. It is important to recall that the Area ERI (ERI per work area) is derived from the Workstation ERI in Table 4-1 using Equation (4-1). The results of the validation are displayed in Fig. 4-6. Overall, for the validation phase, a high correlation of 0.7 is observed between ‘Count of total injuries’ and ‘Area ERI’, demonstrating the extent to which the developed DSS is valid for assessing ergonomic risks in the workplace. The developed DSS is then tested by comparing the Area ERI outputs of the DSS to the ‘Count of total injuries’ extracted for the ‘Loading area’ that was not exposed during the fine-tuning of the DSS. The findings of the testing are also shown in Fig. 4-6 (i.e., in the same figure where the validation results are displayed, but appearing to the right of the dashed line). The findings indicate a low 'Area ERI' of '0.3' for the ‘Loading area’, which is consistent with the low ‘Count of total injuries’ for the area. The consistency between ‘Count of total injuries’ and the 'Area ERI' for the loading area demonstrates the degree of generalizability of the developed DSS for assessing ergonomic risks of any hypothetical work area. Overall, for both the validation and testing phases, a high correlation of 0.8 is observed between ‘Count of total injuries’ and ‘Area ERI’.

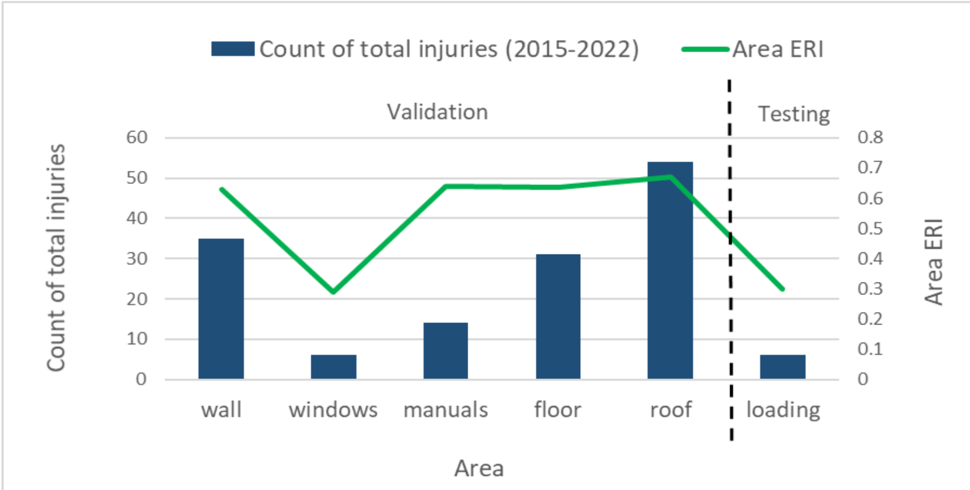

Figure 4-6 Validation–testing outcomes for the DSS

Examining the experimental results, the validation shows a correlation of 0.70 between the 'Count of total injuries' and the 'Area ERI,' and the validation and testing phase's together show a correlation of 0.80. Moreover, in testing the developed DSS, the consistency between 'Count of total injuries' and the 'Area ERI' for the 'Loading area' demonstrates the degree of generalizability of the developed DSS for assessing ergonomic risks for any hypothetical work area. Overall, in terms of classifying workstations as high-risk or low-risk, the DSS provides a reliable assessment of the risk posed by each work area. However, in its current form, the developed DSS is not perfect in differentiating the risk level between workstations. For example, the DSS generates a comparable ERI for the wall, manual, and floor area despite the difference in their 'Count of total injuries'. Nonetheless, it is able to determine that the roof workstation has the highest risk, in keeping with the 'Count of total injuries.' Thus, it can be concluded that the developed DSS in its current form can reliably distinguish between high-risk and low-risk workstations, notwithstanding the noted deficiency with respect to distinguishing the level of risk between workstations. To enhance the DSS's ability to differentiate the risk level between workstations, future work could be undertaken to modify the fuzzy rules and membership functions of the DSS's FESs.

4.5 Discussion and Conclusion

In this study, an integrated fuzzy logic-based DSS for ergonomics risk assessment that evaluates physical, environmental, and sensory aspects of work systems simultaneously is developed. The developed DSS generates a composite risk score, ERI, representing the combined physical, environmental, and sensory risk levels in work systems.

The key highlights of this study are:

- The developed DSS provides a reliable assessment of the risk posed by each work area and can serve as an automated, integrated ergonomics risk assessment tool to help practitioners improve occupational health and safety.
- The DSS can distinguish between high-risk and low-risk workstations but has a deficiency in differentiating the risk level between workstations.

The proposed DSS offers a significant contribution to the field of ergonomics risk assessment by evaluating the physical, environmental, and sensory aspects of work systems simultaneously. The developed DSS provides a reliable assessment of the risk posed by each work area and can be used as an automated, integrated tool to improve occupational health and safety. However, the DSS needs further modification to enhance its ability to differentiate the risk level between workstations. Moreover, the proposed DSS is fine-tuned, validated, and tested for only one modular construction plant, the developed DSS should be tested on other modular construction plants to confirm its generalizability. Overall, this study provides valuable insights for comprehensively understanding the ergonomic risk of work systems, thereby, facilitating the reduction of ergonomic discomfort and the enhancement of work system productivity.

Chapter 5: A DATA ANALYTICS FRAMEWORK FOR IDENTIFYING AND CHARACTERIZING INCIDENT CLUSTERS IN THE DIAGNOSIS OF RISK FACTORS IN MANUFACTURING

5.1 Introduction

Improving OSH is a key industrial concern, particularly in manufacturing. According to 2021 statistics from the Association of Workplace Safety and Insurance Boards of Canada (Abdi et al. 2010), the manufacturing industry has the second-highest rate of injuries/diseases in Canada. Effective management of OSH risks in manufacturing is essential because it helps to lower the risk of accidents, lower workers' compensation costs, and improve productivity and product quality (Pawłowska et al. 2011; Li et al. 2019; Lee et al. 2021). OSH researchers have traditionally used qualitative, quantitative, or quali-quantitative methods to minimize occupational risks (Fera et al. 2009). However, with recent developments in machine learning (ML), researchers have developed several ML-based quantitative methods for interpreting, classifying, and evaluating OSH performance (Sarkar et al. 2020; Lee et al. 2021; Chan et al. 2022) that have outperformed their traditional counterparts.

ML is a branch of artificial intelligence that is becoming more popular in many fields as a result of technological advances that have made it easier to collect and process large volumes of data. ML refers to the use of algorithms to optimize a performance criterion based on training data and/or historical data (Alpaydin et al. 2020). ML algorithms 'learn' from existing data and create models that reveal underlying structures (unsupervised learning) or forecast discrete or continuous output variable(s) in unseen data (supervised learning) while employing hyperparameters set by the researchers (Meena et al. 2020). Recent reviews on ML methods in OSH (Sarkar et al. 2020; Lee et al. 2021; Chan et al. 2022) reveal the effectiveness of ML methods in enhancing OSH and reducing occupational injuries.

In OSH, occupational risks are often implicit and ill defined. Therefore, it is vital for the manufacturing industry to have a risk classification system that can be used to better understand risk factors. In recent years, manufacturing OSH researchers have created numerous classification-based ML models for facilitating risk factor diagnosis. Despite the usefulness of numerous classification-based ML models in OSH research, to effectively mitigate OSH risk, it is crucial to understand the predictors of ML models for risk diagnosis (Sarkar et al 2020; Chan et al. 2022). Therefore, this study concentrates on a specific sub-theme of OSH research, namely, risk factor diagnosis in manufacturing.

Recognizing the significance of risk factor diagnosis, numerous researchers have developed classification-based ML models alongside model interpretation techniques to comprehend the models they had developed. However, these models are often accompanied by model interpretation techniques that may not be easily interpretable for non-technical personnel, such as business stakeholders and health and safety specialists. Therefore, it becomes challenging to persuade these non-technical personnel to implement safety intervention policies. In addition, existing studies have used pre-labeled datasets to develop and interpret classification-based ML models. However, pre-labeled datasets in some cases may not be readily available for model development. In such circumstances, substantial efforts must be put to labeling the datasets, a task that can be time-consuming and that may delay risk factor diagnosis. For these reasons, an interpretable ML-based data analytics framework is presented that does not require pre-labeled datasets for safety and ergonomics risk factor diagnosis using incident data.

5.2 Methodology

This section provides an overview of the proposed framework (as depicted in Figure 5-1), which comprises three modules: (a) data collection—the collecting of incident details that are then translated into structured data; (b) data preprocessing—the translation of unprocessed data into a format suitable for subsequent analysis; and (c) identification and characterization of incident clusters—labeling of unlabeled incident data utilizing clustering algorithms, followed by cluster interpretation for the diagnosis of risk factors

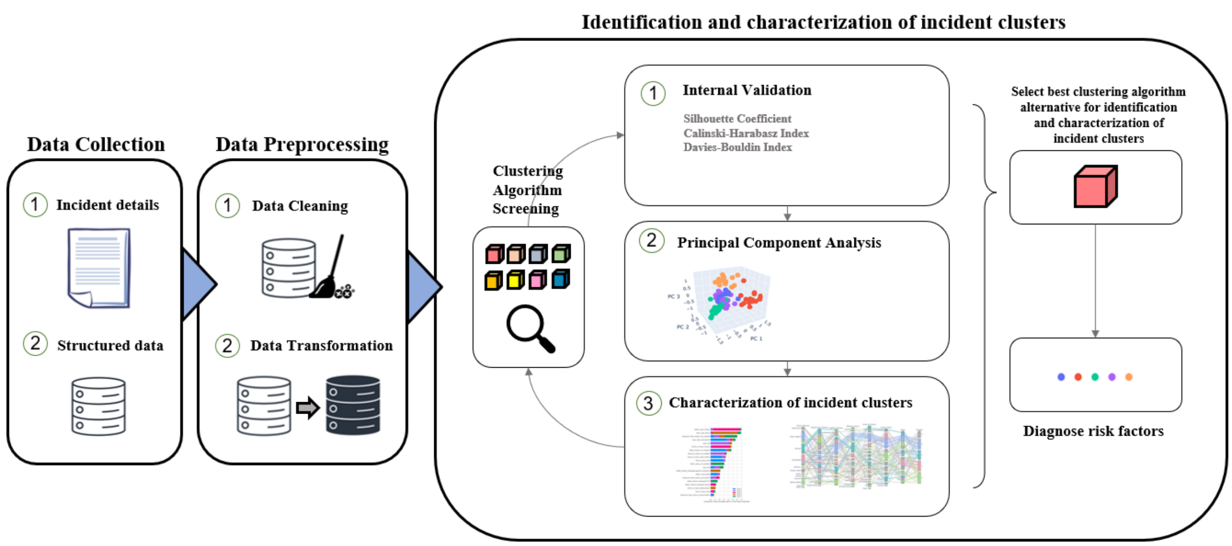

Figure 5-1 An overview of the proposed framework

5.2.1 Data collection

The data collection module involves the collection and translation of incident data into a structured format to create a dataset that can be used to identify and characterize clusters of incidents. As incidents occur in a given organization, the practitioner initially gathers incident reports or 'incident details' in the form of comments from injured workers. The practitioner then manually converts the comments provided by the injured workers into a structured format. Converting injured workers' comments into a structured format entails translating incident details into a tabulated format to extract meaningful insights. Specifically, the dataset can be translated into a structured format using the specifications demonstrated in Table 5-1. (In addition, an e.g., of a translated dataset is shown in Figure 5-2) It is important to note that the categorical values extracted from the comments of each incident detail are designed to be compatible with the modular building manufacturing facility investigated in the case study. If the proposed framework were to be applied to a different industry, the categorical values listed under each Feature in Table 5-1 could be tailored to meet the needs of that industry. It should also be noted that, when the practitioner sets multiple categorical values, each feature in the dataset must have sufficient variance to help the subsequent modules discover meaningful patterns from the incident reports.

Table 5-1 Overview of dataset specifications for case study dataset

Feature	Categorical data
Injury source	*heavy objects, nail gun, falling objects, metal items, trailer, ladder, hammer, vehicle, machine, foreign object, crane*

Ergonomic risk factor	*poor posture, forceful exertion, vibration, repetition, contact stress, force exertions/ poor posture (F/P), repetition/ poor posture (R/P), working from height*
Safety factor	*inadequate guards or protection, inadequate clearances, inadequate PPE, working from height, inadequate maintenance, inadequate equipment and tool, inadequate training, weather condition*
Motion injury	*nailing, slipping, lifting, falling, carrying, walking/ moving, pulling, pushing, swinging, driving/craning, exiting*
Area of injury	*back, finger, hand, knee, face, shoulder, ankle, arm, wrist, foot, head, neck, elbow, leg, hip, chest*
Injury type	*strain/sprain, cut/laceration, bruise, foreign object, fracture*
Area	*wall, windows and doors, manual, floor, roof*

Table 5-1 contains two columns — 'features' and 'categorical data':

1. 'Features' are the variables that will be used in the dataset. The particular features listed in Table 5-1 are selected due to their ability to effectively identify meaningful clusters of incidents. The structured dataset may contain features such as 'Date' and 'Incident details,' which would simply be the date the incident occurred and incident-related comments for reference.
2. 'Categorical data' refers to the vast array of industry-specific categorical values extracted from 'incident detail' comments for each feature listed in Table 5-1. It should be noted that practitioners may leave some cells blank if there is some uncertainty with respect to the 'incident details' comments or if the incident does not fall within the predetermined categories. However, if there are many empty cells, the proposed framework may not be able to extract meaningful insights from the incident reports.

5.2.2 Data Preprocessing

In this module, the proposed framework must transform unprocessed data into a format suitable for identifying and characterizing clusters with high risk. Before this dataset is passed to the subsequent modules, it must be cleaned in order to avoid incorrect or misleading results. In addition, the proposed framework uses only categorical features, so the categorical features must be transformed to accommodate Unsupervised ML algorithms.

5.2.3 Identification and characterization of high-risk clusters

This module uses Unsupervised ML, specifically clustering algorithms, to group and label injury instances based on the features in Table 5-1. Selecting the most suitable clustering algorithm is one of the key issues that must be addressed before identifying and characterizing incident clusters. In this study, the k-Means Clustering, Agglomerative Hierarchical Clustering, Birch Clustering, and Optics Clustering algorithms are evaluated for illustrative purposes to determine the best clustering algorithm. As per the proposed framework, the task of screening clustering algorithms is an iterative process that requires the practitioner to iterate between three stages before the best clustering algorithm can be identified: (1) internal validation—computing internal validation indices for various clustering algorithms to guide the selection of the best clustering algorithm (i.e., the one with the optimal number of clusters, k); (2) principal component analysis (PCA)—visualizing the results of clustering analysis using a dimensionally reduced plot; and (3) characterization of incident clusters—interpreting the results of PCA using interpretable ML and clustering visualization techniques. Overall, this iterative process simply entails subjecting different clustering algorithms with different k-values to internal validation, PCA, and characterization of incident clusters stages, and annotating the results to evaluate and determine the best clustering algorithm (i.e., the one with the optimal k-value). Once the best clustering algorithm has been identified, it can be used to identify and characterize incident clusters from incident reports.

5.2.3.1 Internal validation

There are two methods for validating the performance of clustering algorithms for a given dataset: (1) external validation—determines if clustering results correspond to an a priori expected cluster (when the 'true cluster labels' are known, the clustering output is compared to a given 'correct' clustering), and (2) internal validation—examines the clustering outcomes using internal validation indices that do not require prior knowledge from the dataset. The latter method is employed when the 'true cluster labels' are unknown (Rendón et al. 2011; Pedregosa et al. 2011). Since the unlabeled incident report dataset is used in the present study, the proposed framework employs internal validation to guide the selection of the best algorithm (i.e., optimal k-value) among the algorithms screened.

Popular internal validation indices such as the 'Silhouette Coefficient', 'Caliński-Harabasz Index', and 'Davies-Bouldin Index' (Rousseeuw et al. 1987; Caliński et al. 1974; Davies et al. 1979) are used, where a greater Silhouette coefficient is indicative of a model with more coherent clusters. The score ranges from −1 (clustering errors) to +1 (dense clustering), where a score close to 0 indicative of cluster overlap (Rousseeuw et al. 1987; Pedregosa et al. 2011). A greater Caliński-Harabasz Index, meanwhile, indicates dense clusters that are well-separated (Caliński et al. 1974; Pedregosa et al. 2011), and a lower Davies-Bouldin Index corresponds to a model with superior cluster separation. Zero is the lowest possible Davies-Bouldin Index, and values closer to 0 indicate better partitioning between clusters (Davies et al. 1979; Pedregosa et al. 2011).

Von Luxburg et al. (2012) argue that the available internal cluster validation indices are unsuitable for objective evaluation of clustering algorithms, asserting that these indices reveal relatively little about a clustering's usefulness across algorithms. They suggest that, for every index favoring one clustering over another, one can invent the opposite, and therefore, in essence, no global, objective clustering score exists (Von Luxburg et al. 2012). To overcome the deficiency of individual indices, then, three internal validation indices (i.e., the 'Silhouette Coefficient,' 'Calińki-Harabasz Index,' and 'Davies-Bouldin Index,') are employed in combination to select the best clustering algorithm (i.e., the one with the optimal k-value) rather than using just a single index. The rationale for using these three clustering indices in particular is that they are compatible with the widely-used scikit-learn package, created by Pedregosa et al. (2011), that is employed in this research.

5.2.3.2 Principal component analysis

Visualization plays a crucial role in determining the performance of the selected clustering algorithm and its corresponding k-value in a manner that facilitates the discovery of meaningful clusters within a dataset (Von Luxburg et al. 2012). Von Luxburg et al. (2012) also argued that clustering and visualization need to be examined together in order to find meaningful clusters in data. In other words, it is reasonable to sacrifice some accuracy in the clustering algorithm in exchange for improved visualization performance (Von Luxburg et al. 2012). In light of the importance of visualizing the clustering results, the proposed framework uses an Unsupervised ML algorithm called PCA (Abdi et al. 2010). PCA reduces the dimensionality of clustering results so that they can be more easily visualized by practitioners. Dimensionality reduction, it should be noted, refers to the transformation of high-dimensional datasets to low-dimensional datasets (Bruce et al. 2020). In this regard, Nguyen & Holmes (2019) asserted that conventional PCA cannot be applied to categorical variables but applies to numerical variables. Consequently, categorical features are handled in the present research by converting them to dummy binary features (one-hot encoding) to make them suitable for PCA. However, other suitable transformations can also be applied to the categorical features in order to make the dataset adaptable to PCA. Thus, using PCA, the incomprehensible results of high-dimensional clustering become comprehensible. Nevertheless, the characterization of incident clusters, as discussed in the following section, is critical in any effort to make sense of the PCA results.

5.2.3.3 Characterization of high-risk clusters

Clustering algorithms can identify clusters, but they cannot descriptively label (characterize) them. Typically, a domain expert is required to characterize each cluster through manual analysis of the clustering results, which is a laborious task. Consequently, a simplified method using the latest advances in the field of interpretable ML in conjunction with intuitive visualization charts to effortlessly characterize incident clusters is incorporated.

The risk cluster characterization process suggested in this module can be used in conjunction with PCA results in order to better understand meaningful structures in the clustered data. Specifically, the SHAP value, an important technique in interpretable ML that was originally developed in the context of game theory (Lundberg et al. 2017; Strumbelj et al. 2010) is selected for the proposed framework owing to its strong theoretical underpinnings. In this regard, Liu & Udell (2020) explored how a model's predictive accuracy affects interpretation quality and concluded that the use of the extreme gradient-boosting algorithm (XGBoost) with SHAP provides the most reliable model interpretation. Accordingly, in the present research, an XGBoost classifier model is trained on the clustered incident report dataset to predict cluster membership over n-folds. SHAP values are then applied to the developed XGBoost classifier model for intuitive model interpretation. In other words, the proposed framework uses the XGBoost classifier in conjunction with SHAP on the clustered incident report dataset to simplify the process of cluster characterization.

In addition, Hinneburg (2009) recommends the use of a parallel coordinates plot for visualizing the overall clustering results on the dataset, and this can be done without any dimensionality reduction. However, since plotting of parallel coordinates is for numerical data, the parallel categories plot is used instead. The parallel categories plot, it should be noted, is a type of flowchart that illustrates data patterns and trends using flow streams, which are assigned to parallel vertical axes. The blocks on these vertical axes represent the distribution of categorical data for all the features in the incident report dataset. Each block is different in size, and flow streams pass through each in a different manner. Essentially, the user can identify the extensiveness of incident patterns and trends in each risk cluster using the parallel categories plot.

5.3 Case Study

To evaluate the performance of the proposed framework, a case study in a modular building manufacturing facility is examined. Modular building manufacturing is popular in North America due to its efficiency. This construction approach involves fabricating modular components in an offsite facility and then transporting them to the site for assembly. The manufacturing plant chosen for the case study consists of five work areas:

1. Wall Area—In the wall frame assembly area, automated robotic machinery is used to precut all materials with high accuracy. These precut wall frames are inspected for defects and then passed on to the next position using conveyors. Wall panels are then manually placed and fixed to the wall frame using power tools, and finally passed on to the Windows and Doors Area.
2. Windows and Doors Area—This area involves workers moving and fixing windows and doors to the wall using vacuum lifts and power tools.
3. Manual Area—In this area, workers fabricate various wood building components (e.g., stairs, deck, veranda) using power tools and non-powered hand tools.
4. Floor Area—Floor assembly is conducted primarily on computerized tables. However, floor panels are glued and sheeting is mounted on the floor panel assembly manually by the workers prior to the computerized robots fastening the materials.
5. Roof Area—The roof area involves job tasks such as loading, sorting, and assembling the trusses into a roof frame. Depending on the type of roof, drywall boarding and Tyvek home wrap may also be installed at this juncture. The roof assembly also necessitates installing sheathing, shingles, siding, and waterproof paper and cutting vents.

The descriptions above clearly show that the plant is only partially automated in its operational processes and involves several manual tasks that pose occupational risks.

5.3.1 Data Collection

In the first module, a structured and unlabeled incident report dataset containing 102 manufacturing facility incident reports from the period, 2019 to 2021, is collected. A sample of the structured and unlabeled incident report dataset used for the case study is provided in Figure 5-2.

	Date	Injury_source	Ergonomic_risk_factor	Safety_factor	Motion_injury	Area_of_injury	Injury_type	Area	Incident_details
0	2019-01-15	metal items	NaN	inadequate PPE	pushing	hand	Cut/Laceration	wall	I was loading a party wall onto the trailer wh...
1	2019-01-17	heavy objects	repetition	NaN	lifting	back	strain/sprain	wall	Reptitive heaving lifting and pulled lower back.
2	2019-01-31	nail gun	vibration	NaN	nailing	hand	Cut/Laceration	manual	Nail hit hand ricochet in manual station
3	2019-02-21	heavy objects	F/P	NaN	lifting	back	strain/sprain	wall	Was lifitng up a lift point, from my jig to in...
4	2019-03-05	NaN	working from height	working from height	falling	knee	strain/sprain	roof	stepped off alittle roof, the drop was about t...

Figure 5-2 A sample of the incident report dataset

5.3.2 Data Preprocessing

In this module, the dataset is inspected for any errors and cleaned in order to prevent erroneous and misleading results in the subsequent modules. The original dataset comprises 102 rows with 9 features. The 'Date' and 'Incident details' features are then removed, owing to their irrelevance to clustering analysis. Moreover, data is missing across some features of the dataset. These values are missing because they are left blank either when they do not match the categorical values in Table 5-1 or when they are unknown. In general, it is typical to replace missing values with the most common class. However, in this study, the missing data have been replaced with the constant 'Unavailable' value because missing values can provide meaningful results during cluster characterization. Subsequently, the categorical features of the incident report dataset are transformed to be PCA-adaptable by applying one-hot encoding to all of the categorical features. Finally, the transformed dataset that is used for the identification of incident clusters entails consists of 102 rows with 68 features.

5.3.3 Identification and characterization of high-risk clusters

This module involves the labeling of injury instances using clustering algorithms based on similarity of worker incidents. k-Means Clustering, Agglomerative Hierarchical Clustering, Birch Clustering, and Optics Clustering are screened to identify the best clustering algorithm (i.e., the one with the optimal k-value) for identifying incident clusters. As noted above, screening of clustering algorithms is an iterative process that requires the practitioner to iterate between three stages—internal validation, PCA, and characterization of incident clusters—in order to identify the best clustering algorithm. This iterative process simply entails selecting an algorithm with a particular k-value and running it through the three stages, after which the best clustering algorithm can be identified. Once the best clustering algorithm (i.e., the one with the optimal k-value) has been identified, it can be used to identify and characterize incident clusters from incident reports.

5.3.3.1 Internal validation

As noted above, it is essential to select the best clustering algorithm for the identification of risk clusters. The internal validation indices, ‘Silhouette Coefficient’, ‘Caliński-Harabasz Index’, and ‘Davies-Bouldin Index’, are used to investigate the performance of the clustering algorithms. The results of the ‘Silhouette Coefficient’, ‘Caliński-Harabasz Index’, and ‘Davies-Bouldin Index’ validation indices for running k-Means Clustering, Agglomerative Hierarchical Clustering, Birch

Clustering, and Optics Clustering algorithms for k-values between 2 and 10 are displayed in Tables 5-2, 5-3, and 5-4, respectively.

Table 5-2 Results of Silhouette Coefficient

	k								
Algorithm	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
k-Means	0.116	0.127	0.140	**0.150**	0.138	0.128	0.144	0.138	0.123
Agglomerative Hierarchical	0.102	0.118	0.132	0.137	0.127	0.128	0.138	0.146	**0.151**
Birch	0.102	0.118	0.134	0.141	0.129	0.130	0.132	**0.141**	0.141
Optics	n/a	**0.087**	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: *k* = number of clusters; n/a = not applicable

Table 5-3 Results of Calinski-Harabasz Index

	k								
Algorithm	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
k-Means	**14.580**	13.096	11.935	11.028	9.886	8.845	8.328	8.061	7.477
Agglomerative Hierarchical	**13.477**	12.473	11.447	10.410	9.442	8.760	8.320	7.995	7.627
Birch	**13.477**	12.473	11.581	10.451	9.478	8.758	8.281	7.901	7.538
Optics	n/a	**10.616**	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: *k* = number of clusters; n/a = not applicable

Table 5-4 Results of Davies Bouldin Index

	k								
Algorithm	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
k-Means	2.316	2.247	2.447	2.217	2.135	2.168	2.072	**2.004**	2.055
Agglomerative Hierarchical	**1.866**	2.274	2.444	2.315	2.200	2.119	2.228	2.099	1.946

Birch	**1.866**	2.274	2.442	2.296	2.192	2.178	1.984	1.879	2.002
Optics	n/a	**2.143**	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: *k* = number of clusters; n/a = not applicable

The highlighted k-values in Tables 5-2, 5-3, and 5-4 represent the 'optimal k-value' for k-Means Clustering, Agglomerative Hierarchical Clustering, Birch Clustering, and Optics Clustering algorithms based on the internal cluster validation indices employed. Although only four algorithms are used in the screening procedure, there are numerous alternatives (based on k-values) to evaluate. To determine the most suitable clustering algorithm, specifically the one with the optimal k-value, for the case study, a comprehensive evaluation is conducted. This evaluation involves the consideration of four clustering algorithms and three internal validation indices, resulting in a total of 28 distinct alternatives. For the k-Means Clustering, Agglomerative Hierarchical Clustering, and Birch Clustering algorithms, the k-value ranges from 2 to 10 (27 alternatives), whereas, for Optics Clustering algorithms, the k-value is determined by the algorithm to be 3 (i.e., 1 alternative). Consequently, there are a total of 28 alternatives from which one clustering algorithm (i.e., the one with the optimal k-value) is selected. However, evaluating all 28 clustering algorithm alternatives can be a lengthy procedure.

Therefore, to simplify the procedure, simply the highlighted potential 'optimal k-values' in Tables 5-2, 5-3, and 5-4, can be evaluated and eliminate the remaining alternatives from further consideration. Consequently, k-Means (k = 5, 2, 9), Agglomerative hierarchical (k = 10, 2), Birch (k = 9, 2), and Optics (k = 3), a total of eight different alternatives are selected for evaluation. These eight alternatives are evaluated using PCA (Section 4.3.2) and characterization of incident clusters (Section 4.3.3) to filter out the best clustering algorithm (i.e., the one with the optimal k-value).

5.3.3.2 Principal Component Analysis

As noted above, the proposed framework evaluates clustering and visualization together. Thus, the results in Tables 5-2, 5-3, and 5-4 are examined using PCA to determine the best algorithm (i.e., the one with the optimal k-value) that provides useful clustering results. Although the details of such an investigation are not elaborated on in detail in this paper due to space limitations, qualitative descriptors such as (1) convoluted clusters (the clusters are not meaningful and/or are difficult to interpret), (2) moderately meaningful clusters (the clusters are somewhat ambiguous but can be interpreted to a satisfactory degree), and (3) meaningful clusters (the clusters are meaningful and easy to interpret) are used to summarize of the quality of the clustering results.

With respect to the Silhouette Coefficient results (Table 5-2), it is found that both k-Means and Optics Clustering algorithms achieve meaningful clusters. However, the results of the Agglomerative Hierarchical Clustering and Birch Clustering are reflective of convoluted clusters. With respect to the Caliński-Harabasz results (Table 5-3), meanwhile, the Optics Clustering algorithm is found to achieve meaningful clusters, the k-Means Clustering algorithm revealed moderately meaningful clusters, and the Agglomerative Hierarchical Clustering and Birch Clustering convoluted clusters. With respect to the Davies-Bouldin results (Table 5-4), finally, the Optics Clustering algorithm is found to achieve meaningful clusters, the Agglomerative Hierarchical Clustering and Birch Clustering moderately meaningful clusters, and the k-Means Clustering algorithm convoluted clusters.

In summary, having a relatively small number of clusters (i.e., small k-values) is found to be helpful in identifying clusters that are simple to characterize, whereas having a larger number of clusters (i.e., large k-values) makes cluster characterization more difficult. Overall, examining the results of the respective indices (Tables 5-2, 5-3, and 5-4) jointly with the PCA results (i.e., in tandem with characterization of risk clusters—Section 4.3.3) reveals that the k-Means clustering algorithm (k = 5), and optics clustering algorithm (k = 3) both achieve meaningful clusters useful for the intended purpose of the case study. Figure 5-3a illustrates the PCA visualization for the Optics clustering algorithm (k = 3), while Figure 5-3b illustrates the PCA visualization for the k-Means clustering algorithm (k = 5). To aid understanding of Figures 5-3a and 5-3b, the cluster characterization results (as per Section 3.3.3) are discussed as follows.

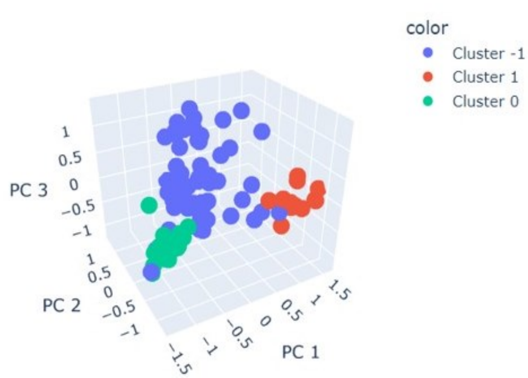

Figure 5-3a PCA plot

Optics clustering algorithm.

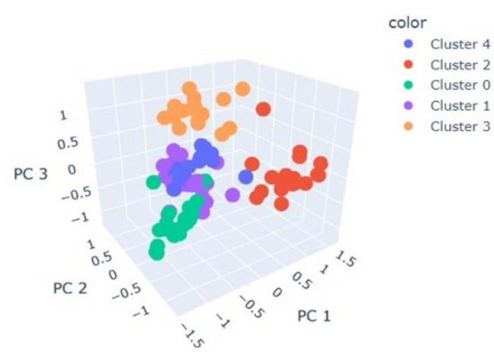

Figure 5-3b PCA plot for *k*-

Means clustering algorithm. (*k* =

Figure 5-3 PCA plot for the selected algorithms

Figure 5-3a depicts the Optics clustering algorithm (k = 3). The defining characteristics of the incident clusters generated by the Optics clustering algorithm (k = 3) are as follows: (1) Cluster 1—arbitrary injuries (blue cluster—here, ‘hybrid injuries’ refers to injuries caused by a combination of ergonomic and safety hazards); (2) Cluster 0—nailing injuries (green cluster); and (3) Cluster 1—heavy lifting injuries (red cluster).

Figure 5-3b, meanwhile, depicts the k-Means clustering algorithm (k = 5). The defining characteristics of the incident clusters of the k-Means clustering algorithm (k = 5) are as follows: (1) Cluster 0—injuries related to inadequate training and nailing (green cluster); (2) Cluster 1—injuries from ergonomic and safety hazards, particularly in the Roof area (purple cluster); (3) Cluster 2—injuries caused by heavy lifting, back injuries, and strain/sprain injuries, especially in the Wall area (red cluster); (4) Cluster 3—injuries caused by inadequate machine guards and bruising-related injuries (orange cluster); and (5) Cluster 4—arbitrary injuries (blue cluster).

Overall, both the Optics clustering algorithm (k = 3) and the k-Means clustering algorithm (k = 5) are found to achieve meaningful clusters. In the present study, however, k-Means clustering (k = 5) is selected due to it having identified a small but significant difference between the incident clusters that the Optics clustering algorithm (k = 3) was not able to identify.

5.3.3.3 Characterization of incident clusters

This subsection discusses the characterization of incident clusters for cluster analysis results. For demonstration purposes but in the interest of brevity, only the results of the selected k-Means clustering algorithm (k = 5) are shown. Figure 5-4 shows the results of applying the k-Means clustering algorithm (k = 5) to the unlabeled incident report dataset.

	Date	Injury_source	Ergonomic_risk_factor	Safety_factor	Motion_injury	Area_of_injury	Injury_type	Area	Incident_details	Cluster
0	2019-01-15	metal items	NaN	inadequate PPE	pushing	hand	Cut/Laceration	wall	I was loading a party wall onto the trailer wh...	Cluster 4
1	2019-01-17	heavy objects	repetition	NaN	lifting	back	strain/sprain	wall	Reptitive heaving lifting and pulled lower back.	Cluster 2
2	2019-01-31	nail gun	vibration	NaN	nailing	hand	Cut/Laceration	manual	Nail hit hand ricochet in manual station	Cluster 0
3	2019-02-21	heavy objects	F/P	NaN	lifting	back	strain/sprain	wall	Was lifitng up a lift point, from my jig to in...	Cluster 2
4	2019-03-05	NaN	working from height	working from height	falling	knee	strain/sprain	roof	stepped off alittle roof, the drop was about t...	Cluster 1

Figure 5-4 Sample of the labeled incident report dataset via k-Means clustering algorithm (k = 5)

The XGBoost classifier model is trained on the results of the labeled incident report dataset to predict cluster membership over 5-folds (using an 80/20 training/testing split). The F1 score is reported as the performance metric to account for any potential class imbalances. The developed XGBoost model is found to predict cluster membership with 92% performance on the test set. The confusion matrix of the XGBoost model's test set is also displayed in Figure 5-5. SHAP values are then applied to the developed XGBoost classifier model to reveal the significance of each feature for each cluster identified. The significant characteristics of each of the incident clusters are displayed as a SHAP summary plot in Figure 5-6.

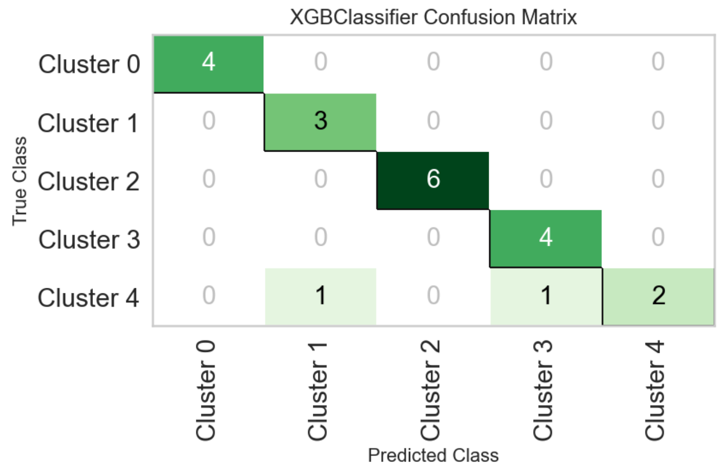

Figure 5-5 Confusion Matrix

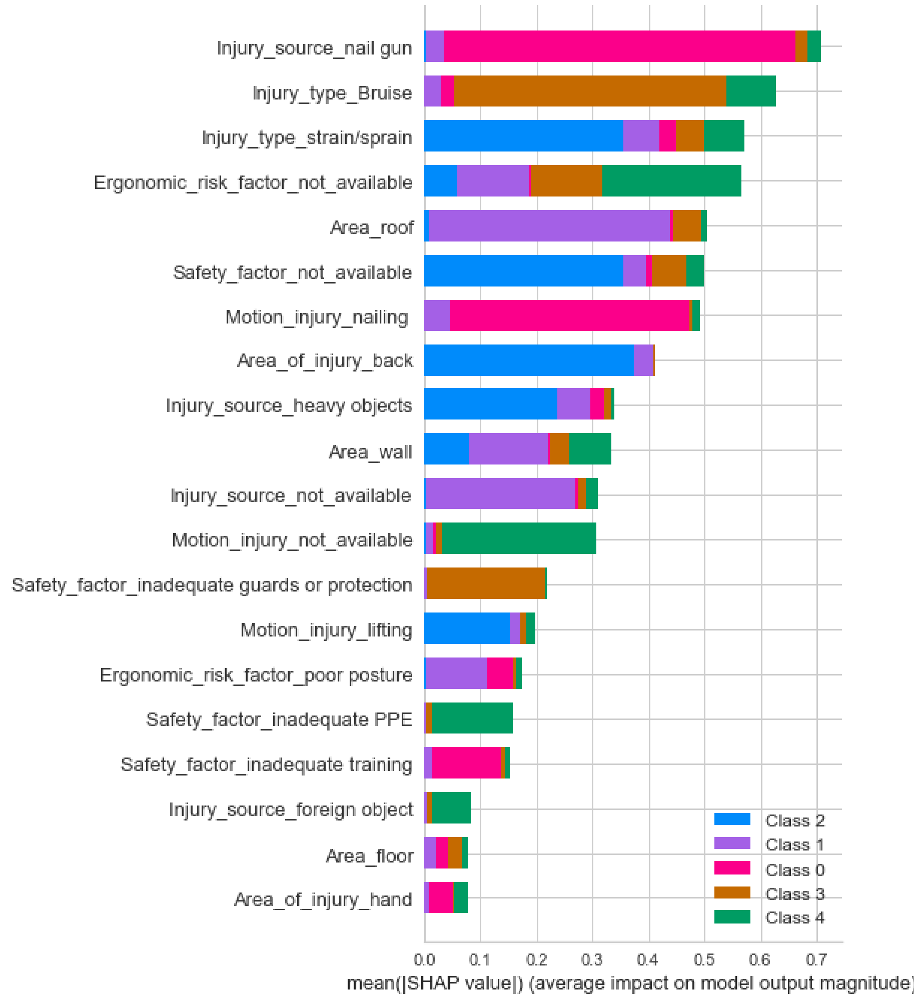

Figure 5-6 SHAP summary plot

Unlike the confusion matrix, the SHAP values do not shed light on the XGBoost model's performance, but instead facilitate the interpretation of the characteristics of cluster membership. In Figure 5-6, the y-axis represents all of the important features of the model, whereas the x-axis represents the mean absolute SHAP values of the associated features. Here, the greater the SHAP value is, the greater the significance of the specific features will be. In this way, by understanding the significant features of each class, it is possible to characterize the incident clusters. For example, Class 0 or Cluster 0 (magenta color) is easily interpretable by observing the four most dominant magenta-colored portions of the horizontal bars in Figure 5-6. Evidently, 'Injury_source_nail gun,' 'Motion_injury_nailing,' 'Safety_factor_inadequate training,' and 'Area_of_injury_hand' are some of the key characteristics of Cluster 0. These descriptors, provided by the y-axis of the SHAP summary plot, clearly indicate that Cluster 0 has injuries resulting from insufficient training and nailing activities. Other incident clusters of the k-Means clustering (k = 5) can be characterized in a similar manner. Meanwhile, to gain further insights into the characteristics of incident clusters, the SHAP summary plot can be used in conjunction with the parallel coordinates plot. In this regard, Figure 5-7 depicts a parallel categories plot for the clustering analysis results. It can be seen in the figure that Cluster 0 includes the 'Puncture' and 'Cut/Laceration' injury types as other critical cluster characteristics for the e.g., discussed with regard to Figure 5-6.

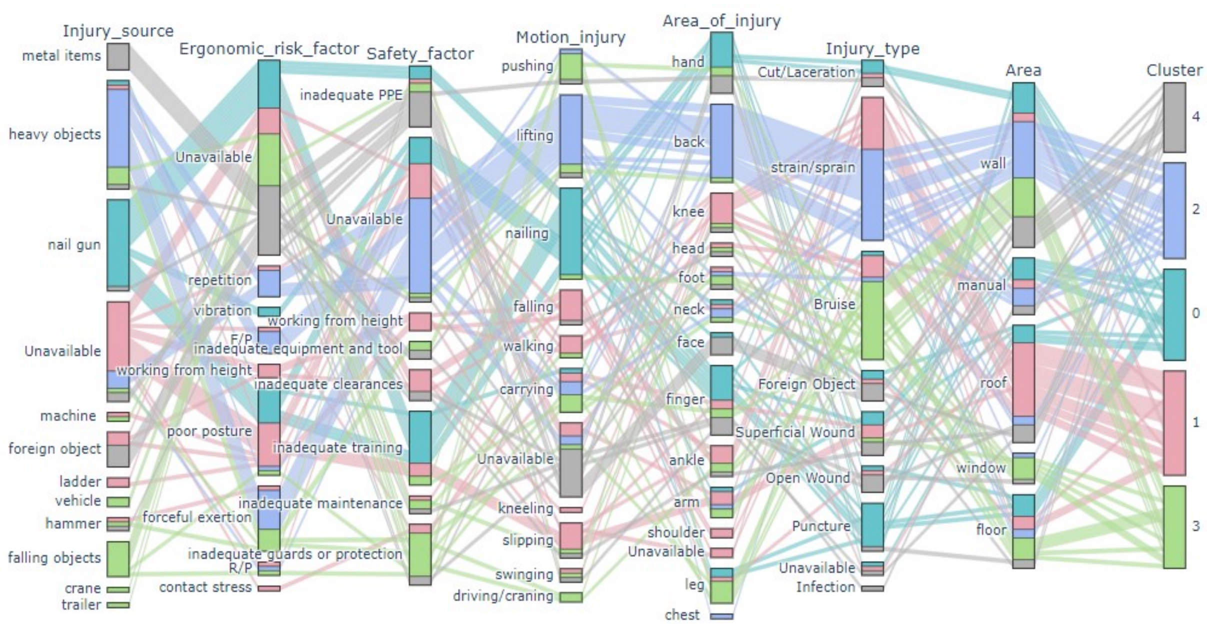

Figure 5-7 Parallel categories plot

In addition, the modular building manufacturing facility's health and safety expert is interviewed to explore implicit expert knowledge concerning workplace injuries. The health and safety expert is asked to explain the most prominent risk factors in the plant. The expert's comments reveal four groups of injuries: (A) nailing accidents; (B) strain/sprain and back injuries from manual materials handling; (C) injuries from working on uneven surfaces with awkward body postures, especially in the roof area; and (D) arbitrary high-risk factor injuries (ergonomic and safety injuries). The health and safety expert's insights are found to be comparable to the results of the proposed framework (i.e., Group A injuries correspond to Cluster 0 injuries, Group B to Cluster 2, Group C to Cluster 1, and Group D to Cluster 4). However, the proposed framework identifies another group of injury instance, Cluster 3, which includes injuries caused by inadequate machine guards and bruising-related injuries.

Overall, the proposed framework achieved a high F1 score of 92% with the developed XGBoost classifier model, and worker incident clusters identified by the framework were comparable to an expert's injury groupings, indicating its reliability for enhancing safety intervention efforts. Thus, the presented framework simplifies the process of diagnosing risk factors by effectively identifying and characterizing incident clusters in a meaningful manner.

5.4 Discussion and Conclusion

In this study, an interpretable ML-based data analytics framework for identifying and characterizing worker incident clusters is developed. This frameworks effectiveness is validated by assessing the performance of the XGBoost classifier model, and also by comparing the results to expert’s opinion. Proposed framework is effective for diagnosing risk factors and has a low barrier to entry for implementation in manufacturing, simplifying the process of enhancing safety intervention efforts.

The key highlights of this study are:

- The proposed framework does not require pre-labeled datasets for identifying and characterizing incident clusters, making it a useful tool for safety and ergonomics risk factor diagnosis.
- The proposed framework demonstrated effectiveness in the case study, achieving a 92% F1 score with the developed XGBoost classifier model and providing worker incident clusters comparable to an expert's injury groupings.

The proposed framework effectively identifies and characterizes incident clusters using worker incident data, simplifying the process of diagnosing safety and ergonomics risk factors in the manufacturing industries.

Chapter 6: STRATEGIC VISIONS FOR IMPROVING ML-BASED PHYSICAL ERGONOMIC RISK ASSESSMENT TOOLS: PRIORITIZING HUMAN CONVENIENCE IN TOOL DESIGN AND UTILIZATION

6.1 Introduction

The manufacturing sector in Canada has the second-highest injury/disease rate, according to 2013 figures from the Association of Workplace Safety and Insurance Boards of Canada (AWCBC, 2013). Improving the ergonomic performance of work systems is a key industrial concern, particularly for manufacturing industries. Workers often experience musculoskeletal issues due to physical demands like repetitive tasks and awkward positions (Li et al., 2019). Addressing ergonomic performance is vital to minimize these risks and enhance productivity (Lee et al., 2021). Moreover, optimizing the interactions between human-system elements also has positive effects on organizations in regards to financial, technical, legal, social, organizational, political, and professional contexts (Resnick, 1997; Wilson, 2000; Shikdar, 2002; Shikdar, 2003). Trained ergonomists, according to Pascual et al. (2008), recommend the NIOSH Lifting Equation (Waters et al., 1993), RULA (Lynn et al., 1993), and REBA (McAtamney et al., 2004) for evaluating physical ergonomic risks. However, there also exist several other physical ergonomic risk assessment tools (Karhu et al., 1977; Moore et al., 1995; Hollman et al., 1999; Health and Safety Executive 2006) that can facilitate work system improvement. While these tools offer advantages, they frequently demand significant time and labor for risk assessments. This can be particularly challenging for small and medium-sized enterprises lacking ergonomic expertise and resources. In such cases, ML systems emerge as a viable solution to automate assessments (Drury et al., 2021).

Hence, the implementation of ergonomic risk assessment tools, including advanced ML-powered methods, offers a pivotal pathway to enhance safety and productivity in manufacturing industries. However, considerations about integration and practicality remain important. The focus on manufacturing ergonomics in the paper is driven by the sector's high injury rates, the need to improve worker safety and productivity, and the potential of ML-driven automation to address these challenges.

ML is increasingly influential, benefiting from technological progress that enables automated data collection and processing (Alpaydin, 2020). This capacity for automated data handling proves invaluable for the partial or complete automation of ergonomics risk assessments. Numerous researchers have crafted ML-based solutions to automate ergonomic risk assessments (Parsa et al., 2020; Arora et al., 2021; Ciccarelli et al., 2022; Arora et al., 2022; Lee et al., 2022; Kwon et al., 2022; Fernandes et al., 2022; Generosi et al., 2022; Kunz et al., 2022). ML involves algorithms that maximize performance using training or historical data, learning from known information to create models for structure revelation or outcome prediction (Meena et al., 2020). Supervised learning, a subset of ML, includes regression for continuous prediction and classification for discrete variable prediction (Meena et al., 2020), underscoring data's importance for ML-powered ergonomic risk assessment tools. It must be noted here that, the field of ergonomics offers a range of data collection methods to collect ergonomic data: self-reports, where exposure data is gathered through interviews and questionnaires; observational methods, including both simple techniques involving manual recording and advanced methods using computer vision algorithms; and direct measurements using sensors or markers attached to individuals (David 2005).

Initially, ergonomic risk assessment tools primarily leaned on self-reports and basic observational methods (Wang et al., 2015). Nevertheless, the field has since evolved, embracing advanced observational methods and direct measurements (David 2005; Wang et al., 2015) often in tandem with ML to streamline the ergonomic risk assessment process. However, legitimate concern arises about whether humans will still be needed in the process of ergonomic risk assessment given these advancements. The definite response is that humans will continue to hold a crucial position in the near future. This is grounded in the reality that fully autonomous artificial general intelligence (AGI) is still a distant prospect (Sawyer et al. 2021). Thus, human-ML collaboration is crucial to limit worker exposure to ergonomic risks in the near future. Human-ML teams can identify areas needing improvement while allocating tasks effectively between repetitive tasks for ML systems and non-repetitive tasks for humans (Daughtery et al., 2018). This collaboration operates in cycles, as the end-user observes the machine's state, and vice versa, driving an ongoing process that helps improve work systems (Sawyer et al., 2021; Flemisch et al., 2008). The cyclical nature of human-machine collaboration is presented in Figure 1. In conclusion, the evolution of ergonomic risk assessment tools incorporates advanced methods and ML, underscoring the ongoing importance of human-ML collaboration in ensuring effective risk management. Given the collaborative nature of human-ML interactions for robust risk management, it is crucial to prioritize human convenience when designing and utilizing ML-powered ergonomic risk assessment tools. This emphasis ensures a smooth integration of ML within the manufacturing sector.

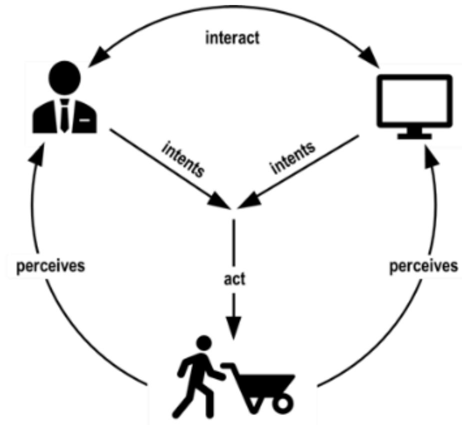

Figure 6-1 Ergonomic risk management framework

Xu (2019) highlights that the success of ML-powered applications hinges on incorporating human factors into their design, recognizing that intelligence lies in creating advanced ML systems with human convenience in focus, rather than solely in the capabilities of computers. With this understanding in mind regarding the cyclical nature of practical ML systems within manufacturing ergonomics, the discussion turns to the design of these ML systems. Before introducing an ML system for improving work systems, it is essential to define how it aims to achieve this. Hence, developers need to translate a business problem into an ML problem (Huyen, 2022). Throughout this process, involving human stakeholders and end-users is critical to ensure the viability of the ML system (Huyen, 2022). It is important to note that maintaining engagement with end-users is a gradual process, rather than a one-time leap (Endsley & Kiris, 1995). Following ML model design, the deployment and monitoring of the model come into play (Sawyer et al., 2021; Sheridan & Parasuraman). Furthermore, since ML systems differ from rule-based expert systems, the availability of relevant data is paramount in their design. However, the data requirements can vary across different ML applications (Huyen, 2022).

Up to this point, existing literature, including studies by Joshi et al. (2019), has explored comparative analyses of ergonomic risk assessment techniques. Some research has highlighted the significance of wearable technologies in this domain (Lim and D'Souza, 2020; Stefana et al., 2021). Chan et al. (2022) have delved into the latest advancements in ML applications for preventing Work-Related Musculoskeletal Disorders (WMSD), utilizing the framework provided by Van Der Beek et al. (2017). Additionally, Lee et al. (2021) have examined the current progress of ML in manufacturing ergonomics, considering the perspectives of ML, ergonomics, and manufacturing systems. In summary, existing literature has explored various aspects of ergonomic risk assessment techniques, including wearable technologies and ML applications. However, a significant gap exists in comprehensively reviewing ML's application in ergonomic risk assessments within manufacturing, emphasizing human convenience in tool design for enhanced integration. Therefore, this chapter pinpoints challenges and opportunities in the state-of-the-art literature, to present strategic visions that enhance future ergonomic risk assessment tools.

6.2 Research Method

This section outlines the research methodology employed to systematically examine the contemporary landscape of machine learning (ML)-powered ergonomic risk assessment tools within the manufacturing sector. The methodological framework is illustrated in Figure 2. The review of relevant articles encompassed a comprehensive search across multiple databases, notably Google Scholar and Scopus. The search strategy was meticulously crafted, employing the search terms "manufacturing" AND "ergonomics" AND ("risk" OR "posture") AND ("machine learning" OR "deep learning"), while systematically excluding papers related to nursing and construction (-nursing, -construction). The temporal scope spanned from January 1, 2000, to the present, concentrating on research articles that resonate with the manufacturing domain. To ensure comprehensiveness and eliminate redundancy, duplicate papers were carefully removed.

The subsequent filtration process was informed by a set of predefined review criteria, consisting of the following components:

1. Language Criterion: Only papers published in English were considered for inclusion.
2. Exclusion of Literature Review Papers: Papers primarily focused on literature reviews were excluded from the review process.
3. Source Type Exclusion: Non-journal and non-conference papers were excluded to ensure the reliability and rigor of the selected studies.
4. Citation-based Filtering: Papers with citations below a threshold of three were excluded to ensure the inclusion of impactful contributions.
5. Relevance to ML/Deep Learning: Inclusion was limited to papers where machine learning or deep learning played a pivotal role in the presented ergonomic assessment tools.

Emphasis on Worker Safety Enhancement: Included papers were those that explicitly demonstrated efforts to enhance worker comfort and safety.

Papers failing to meet the specified criteria were purposefully excluded from the review process. The procedural integrity of this process is detailed in Figure 2 through a comprehensive flowchart depicting the literature screening trajectory, adhering meticulously to the established review criteria. It is important to underscore that after thorough title and abstract scrutiny, a total of 121 full-text papers were subject to rigorous eligibility assessment, culminating in the eventual inclusion of 32 full-text papers for comprehensive review and synthesis in this study.

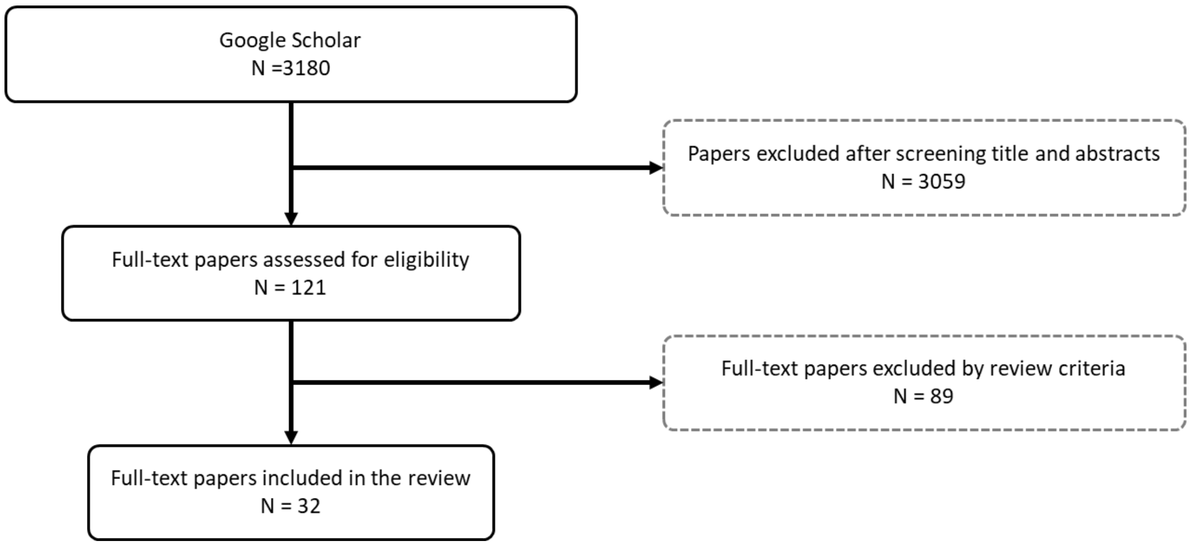

Figure 6-2 Overview of research method

6.3 Insights from Literature Review

The following are the key insights drawn from the reviewed literature in section 2.5:

1. The most employed ML technique was Binary Classification (44%). Binary classification was followed by Multiclass classification (28%), Regression (22%), a combination of Binary classification and Multiclass classification (3%), and a combination of Binary classification and Regression (3%). In addition, it is essential to note that manufacturing ergonomics researchers do not currently use Unsupervised ML for the development of ergonomics risk assessment tools. Moreover, an examination of the dominant of Binary classification ML applications revealed that majority (57%) of Binary classification models proposed by researchers use Marras et al's., (1993) dataset as a benchmark dataset to improve the occupational lower-back disorder risk classification task.
2. The most common data source for designing ML tools was pre-established datasets (41%). Subsequently, Advanced Observational Method (28%), Direct Measurement (25%), Self-

report (3%), and Simple Observational Method (3%) were also used by researchers to build datasets. The predominant usage of pre-established datasets in the proposed tools may indicate that researchers face challenges in collecting their own datasets.

3. The most employed ML application was Risk classification (53%). Risk classification was followed by Posture identification (31%), Identification of risk factors (12%), and Risk quantification (3%). This evidently reveals that manufacturing ergonomics researchers favor the development of Risk classification applications over other applications.

Overall, manufacturing ergonomics risk assessment research has revealed several exciting technical ML applications that can improve the ergonomic performance of manufacturing work systems. Furthermore, a thorough examination of the literature revealed in Table 6-1, uncovers that ML research in manufacturing ergonomics is now of an academic nature. Academic ML research is defined by Huyen (2022) as research that marginally outperforms state-of-the-art results on benchmark datasets and research that disregards human factors in the design of ML applications. Based on the literature reviewed in Table 6-1, 25% of the investigated papers utilize the same benchmark dataset presented by Marras et al., (1993). In addition, after assessing each publication separately, it was discovered that the ML tools offered by researchers addressed just the technical aspects of ML tool design and lack a human-centered design approach. Although model performance outcomes that outperform state-of-the-art results are significant, it is vital in practical applications to incorporate the needs of end users and broader users who use the ML applications. In light of this, it is determined that present ML research in manufacturing ergonomics is largely academic in nature. Therefore, due to the prevalence of research-focused ML tools in manufacturing ergonomics research, researchers must bridge the gap between research-focused ML tools (which encompass only the technical aspect of an ML application) and practical ML systems (which encompass both the technical and human factors of a practical ML application) because the primary objective of designing ML applications is to employ them in the real world to solve real-world issues. For future ML applications of manufacturing ergonomics research to be trusted and adopted by real-world manufacturing industries, researchers must jointly consider both the technical and human factors of ML applications and bridge the gap between research-focused ML tools and practical ML systems.

6.4 Research opportunities and challenges

This section proposes four strategic visions to close the gap between research-focused ML tools and practical ML systems in manufacturing ergonomics considering technical and human challenges.

6.4.1 Improving data availability

The following technological limitations are found to influence the advancement of current automated ergonomic risk assessment tools: 1) high costs of the technologies behind data sources, such as motion capture data, data from cameras and sensors; and 2) the difficulty of conducting experiments in real-world settings due to technical and ethical issues, both of which lead to data availability (Wang et al., 2015; Li et al., 2018; Lee et al., 2021). These are significant issues because data is one of the most valuable ingredients for designing ML systems. The unavailability or difficult access to ergonomic data due to technology limitations makes it challenging to design ML systems for automating ergonomic risk assessments, and design both practical and prototype applications. In addition, the cumbersome nature of the available technology for collecting ergonomic data restricts researchers to develop practical applications that are effective in the real world. This may explain why majority (25%) of the ML applications presented by manufacturing researchers use pre-established datasets. To solve the problem of data availability, reducing the cost and enhancing the performance of the data collection technologies through technological improvements can alleviate experimental challenges and lead to practical applications. Alternately, research efforts can be made to construct and share datasets, as done by Marras et al., (1993), and Maurice et al., (2019), which can be useful for the design of practical ML systems. However, excessive use of the same benchmark datasets can also impede the advancement of manufacturing ergonomics research by preventing the emergence of new research. In addition, the literature review revealed that researchers occasionally incorporate open-source ML models such as OpenPose (Cao et al., 2017), VIBE (Kocabas et al., 2020), and DeepFace (Taigman et al., 2014), and tf-pose (TF-Pose, 2021) into the automated ergonomic risk assessment tools they present. Therefore, we also propose that researchers develop useful open-source ML models, so that these models can be easily incorporated by future researchers without requiring them to reinvent the wheel. Crafting open-source models can indirectly provide a solution to the challenges linked with data collection complexities. In summary, it is believed that technological advances, the creation of public datasets, and the development of open-source ML models may help alleviate the data availability problem and lessen the burden for future researchers working to develop ML-powered ergonomic risk assessment tools.

6.4.2 Aligning business and ML objectives

Manufacturing ergonomics researchers must create ML-powered ergonomic risk assessment tools to move business metrics for real-world success. Technology boosts organizational effectiveness but complicates management, requiring new methods, procedures, and worker skills (Reiman et al., 2021; Karwowski et al., 2012; Siemeniuch et al., 2015; Neumann et al., 2021). Without organizational and social elements, new technologies are more likely to fail (Clegg et al., 2007). Therefore, it is suggested that technology must be adapted to the people and processes of an organization to be beneficial (Kennedy, 2004). Despite tremendous breakthroughs in ML technology, it is difficult for enterprises to incorporate ML technology. Every ML system must be justified, and manufacturing ergonomics ML systems are no exception. Therefore, this study proposes that manufacturing ergonomics research must consult the broad users of the ML-powered ergonomic risk assessment tools to identify business objectives and convert them into ML objectives. Moreover, it is observed from the literature review that manufacturing ergonomics researchers have dedicated lots of effort to improving ML metrics, whereas in the real-world business stakeholders are more concerned with how ML systems affect business metrics. Subsequently, after ML objectives are identified and the ML systems are designed, it may crucial for researchers to understand how the proposed ML system works in the real world. For this purpose, researchers can seek to validate ML-powered ergonomic risk assessment tools in terms of business metrics in addition to ML metrics. For example, a hypothetical ML-powered ergonomic risk assessment tool may be needed in manufacturing companies to reduce ergonomic discomfort and increase worker productivity, or to reduce ergonomic injuries and lower worker compensation costs. In these cases, the productivity of workers and the compensation costs are business metrics. Therefore, these business metrics must be used to validate the designed hypothetical ML-powered ergonomic risk assessment application. As a result, when formulating ML objectives, researchers designing ML applications must consider business requirements and also attempt to verify if their ML applications influence business metrics as intended by businesses through case studies. Moving business metrics is required for ML applications intended for ergonomic risk reduction, such as Risk classification, Risk quantification, and Risk factor identification, but may not be required for supporting applications such as Posture identification.

6.4.3 Cooperative development of intelligent ML systems

Designing sophisticated ML systems for human convenience is where intelligence rests, not in computers themselves. Introducing ML systems to collaborate with people is fascinating, but such systems must meet human needs. Human activities are growing more complex, and digitization allows highly capable individuals to take on additional responsibilities. In such cases, technological advances may boost people's adaptability (Ras et al., 2017). Farr et al., (2003) show that intrinsic motivation is crucial for cutting-edge technologies. Blocking unnecessary information can improve human-computer interaction, according to Peifer et al., (2020). More importantly, Kennedy (2004) contends that technology should be designed to complement an organization's people and processes rather than the other way around. As a result, it is required to maximize end-user motivation and flow states, as well as to develop ML-powered ergonomic risk assessment tools for people associated with the ML system. To ensure ML-powered ergonomic risk assessment tools are beneficial, they must be created with input from end-users (such as health and safety specialists) and broader users (such as business stakeholders). According to Ren et al., (2020) and Xu et al., (2019), people desire computers to deliver more direct and natural services. End-users seek for sophisticated, easy-to-use services. User experience (UX) determines the effectiveness of ML-powered solutions (Huyen, 2022). Moreover, it is observed from the literature review that manufacturing ergonomics researchers have not considered UX till now and have confined themselves to the technical domain. However, ML system design cannot be limited to the technical domain despite being technical. ML systems are created by humans, utilized by humans, and may even leave a lasting impression on society (Huyen, 2022). The studies listed in Table 1 did not create intelligent ML systems collaboratively; rather, they proposed ML systems based on gaps in the literature. This approach is justifiable, but we suggest that ML systems that incorporate the needs of potential end-users and broader users can be significantly more valuable to solve real-world issues. To this end, researchers can seek to cooperatively develop intelligent ML systems. To accomplish this, the design thinking framework proposed by Gibbons (2016) for creating usable, safe, and pleasurable ML systems can be utilized. Figure 3 depicts a graphical representation of the human-centered design thinking process for enhancing user experience. The six steps for a Human-centered design thinking framework proposed by Gibbons (2016) are as follows:

1. Empathize: Entail comprehending the user needs involved.
2. Define: Reframe and define the problem from a human perspective.
3. Ideate: Create numerous ideas in ideation sessions.
4. Prototype: Adopt a hands-on approach in prototyping.
5. Test: Develop a prototype/tool to the problem.
6. Implement: Put the idea into action.

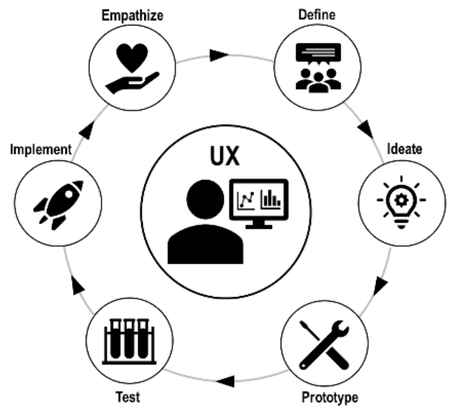

Figure 6-3 Human-centered design framework (Gibbons, 2016, Xu et al., 2019)

6.4.4 Optimization of task allocation in ML systems

Optimization of task allocation in ML systems is a sub-problem of cooperative development of intelligent ML systems. However, due to its importance in ML system design, this article examines it separately. ML-powered ergonomic risk assessment systems can only be successful if they have optimal human-ML task allocation. To elaborate, until recently, automated ergonomic risk assessment tools were created solely to automate the ergonomic risk assessment process. However, researchers in manufacturing ergonomics have not justified whether the ML systems they have developed allocate tasks optimally between the human agent and the ML agent. Therefore, is essential for manufacturing ergonomics researchers to justify task allocation between humans and ML agents for their ML tools. After all, empowering health and safety specialists is one of the primary purposes of designing ML-powered ergonomic risk assessment systems. Hendrick (2007) identifies a "leftover" approach to assigning human jobs as a reason for technology failure. This means that before assigning work to a computer or human, it should be assessed if a person is needed (Kleiner, 2006). This rationale is reasonable, considering that human energy should be conserved for the hardest problems. Moreover, Korteling et al., (2021) highlight the importance of hybrid intelligence systems that blend human and machine intelligence. As a result, there has recently been a great deal of interest in human-machine teams that consider both their cognitive strengths and weaknesses (Sawyer et al., 2021; Korteling et al., 2021). Consequently, future ergonomic researchers must analyze which tasks are appropriate for humans, machines, and mixed activities. For example, it is best if repetitive tasks such as data collection can be done by machines. While complex tasks such as risk control can be done by humans. However, activities such as identification of risk factors may involve human-AI collaboration. Nevertheless, the preceding examples are illustrative and not conclusive, because allocating tasks between humans and ML may be problem specific. Nevertheless, it can be conceived that optimal task allocation in ML-powered ergonomic risk assessment systems can be challenging. In addition, even though this study says ML systems should be created with human requirements in mind, not all ML technologies are resilient. ML has functional constraints, like humans. In trade-off scenarios, where ML systems cannot be adapted to human needs, it is unclear what developers should do. Consequently, independent research is required to determine the optimal ways to divide tasks between humans and machines in ML-powered ergonomics risk assessment systems, particularly in trade-off scenarios.

6.5 Discussion and Conclusion

In this study, the current status, challenges, and opportunities in the application of ML for the improvement of physical ergonomics in manufacturing industries has been investigated. Although, researchers demonstrated the viability of several ML-powered ergonomics risk assessment tools, the dominance of research-focused ML tools is indicative of challenges in developing human-centered ML systems. Therefore, strategic visions are proposed for future research to bridge the gap between research-focused ML tools and practical ML systems.

The key highlights of this study are:

- This study found that existing ML tools in manufacturing ergonomics primarily focused on technical aspects and lacked a human-centered design approach.
- Four strategic visions are proposed to advance the design of practical ML systems for manufacturing ergonomics with a human-centered design approach, including improving data availability, aligning business and ML objectives, cooperative development of intelligent ML systems, and optimizing task allocation in ML systems.

In summary, the challenges, and opportunities for developing human-centered ML-based Physical Ergonomic Risk Assessment Tools are discussed, with a focus on the human aspects of designing human-ML systems. More complex challenges, such as computational priority of ML systems, fairness of ML systems, and interpretability of ML systems, are not covered. Overall, the presented strategic visions are anticipated to contribute to the advancement of manufacturing ergonomics research towards the design of human-centered ML systems.

Chapter 7: CONCLUSIONS

7.1 Research Summary

The field of ergonomics focuses on optimizing work system interactions through theory, concepts, data, and design (International Ergonomics Association, 2003). Manufacturing industries involve humans interacting with system elements to produce finished goods, and ergonomic discomfort can result in unproductive worker activities that affect production and product quality. Despite the benefits of prioritizing health and safety in manufacturing, many businesses ignore ergonomic performance assessments due to a lack of convenient tools. This study endeavors to overcome four key challenges that make ergonomics risk assessment less convenient for health and safety specialists: (1) lack of versatile physical-ergonomics risk assessment tools, (2) fragmented ergonomics risk assessment tools, (3) challenge of developing intuitive occupational risk diagnosis framework with ML, and (4) an inability to develop practical ML-powered ergonomics risk assessment tools.

First, a versatile physical-ergonomics risk assessment tool called the Revamped PLI is developed to address the limitations of existing tools that are only compatible with specific data collection methods. This tool simplifies tool selection and aids health and safety specialists in improving work systems. Its implementation in real cases and comparison against the widely-used REBA tool validate its effectiveness, offering potential benefits in enhancing workplace safety and preventing injuries.

Second, a fuzzy logic-based Decision Support System (DSS) that comprehensively evaluates the ergonomic performance of work systems by considering the physical, environmental, and sensory factors together. The proposed DSS offers the potential benefit of providing a holistic approach to ergonomics risk assessment, enabling organizations to assess and improve the overall performance of their work systems more effectively.

Third, an interpretable ML-based data analytic framework is developed to diagnose risk factors for enhanced occupational injury management. The framework combines unsupervised and supervised ML techniques, along with Explainable AI, to diagnose occupational risk factors. Validation in a prefabricated construction facility demonstrates its utility in accurately identifying and characterizing worker incident clusters, offering potential benefits in improving occupational injury management and targeted risk mitigation.

Lastly, a literature review on ML research is conducted in the field of manufacturing ergonomics. The review highlights challenges caused by research-focused ML tools dominating the field. To bridge this gap, the study proposes four strategic visions: improving data availability, aligning business and ML objectives, fostering cooperative development of intelligent ML systems, and optimizing task allocation in ML systems. These visions aim to enhance the integration of ML in manufacturing ergonomics, aligning research with human convenience in mind.

7.2 Research Contributions

This research found four significant challenges that make ergonomics risk assessment less convenient for health and safety specialists, therefore it pursues four objectives, with each identified challenge addressed in a distinct chapter. The primary contributions of this research, corresponding to chapters 3, 4, 5, and 6, are summarized as follows:

1. The development of Revamped PLI, a near comprehensive and versatile physical-ergonomics risk assessment tool, is presented. Unlike traditional tools, Revamped PLI can be used with all data collection methods and has no narrow specializations, allowing for a near comprehensive assessment of any work system's physical ergonomic performance. This makes it a potential sole tool for assessing industrial job tasks, regardless of time and budget constraints.
2. A new approach to assess the ergonomic performance of work systems by integrating physical, environmental, and sensory risk factors using a fuzzy logic-based DSS is presented. This approach overcomes the fragmented nature of existing tools, which enables health and safety specialists to obtain a more complete and accurate evaluation of industrial work systems. By integrating physical, environmental, and sensory risk factors, the proposed DSS offers a holistic view of ergonomic performance, which addresses the limitations of existing tools that only assess these aspects separately.
3. An effective and interpretable ML-based data analytic framework to identify and characterize worker incident clusters, facilitating improved occupational injury management is presented. The framework combines unsupervised and supervised ML techniques along with Explainable AI occupational risk diagnosis. The framework has a low barrier to entry for implementation in manufacturing industries and simplifies the process of diagnosing safety and ergonomics risk factors using worker incident data.
4. The current state of ML in manufacturing ergonomics is reviewed. The challenges in developing human-centered ML systems is addressed. Subsequently, the study proposes four strategic visions, including improving data availability, aligning business and ML

objectives, cooperative development of intelligent ML systems, and optimizing task allocation in ML systems, all with the ultimate goal of enhancing human convenience.

7.3 Limitations and Future Research

Notwithstanding these contributions, there are opportunities for further work in this area as summarized below:

1. The computational methodology of Revamped PLI is validated against REBA. However, further testing is required for PLI II (advanced observational methods) and PLI III (direct measurements). Future research can compare the performance of Revamped PLI with other widely used tools, like RULA and the NIOSH Lifting Equation. It is also worth noting that the risk categories established for Revamped PLI are provisional and may require amendment with a larger dataset containing a variety of job tasks.
2. A fuzzy logic-based DSS for ergonomics risk assessments is evaluated using a real-life case study. The results showed promising performance for the DSS in classifying work systems as high or low risk. However, there is room for improvement in distinguishing risk levels between work systems. The developed DSS was fine-tuned, validated, and tested using data from a prefabricated construction company, and further testing on other companies is necessary to confirm its generalizability.
3. A promising framework for occupational risk factor diagnosis is developed and validated. However, the framework is only suitable for categorical datasets, which may not be applicable in datasets that have both numerical and categorical variables. In addition, the clustering algorithms and internal validation indices are not exhaustively considered.

Although the conducted case study identifies an optimal algorithm, future research can address these limitations to further improve the framework.

4. The challenges and opportunities in developing practical ML-powered ergonomics risk assessment systems are discussed with a focus on human-centered design. However, it does not cover more complex challenges such as computational priority, fairness, and interpretability. Moreover, the scope is limited to only the human aspects of designing ML systems.

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APPENDIX

The template used in MS Excel for calculating the PLI II score of a specific job task is portrayed in the Figure below.

STEP (1)

Posture Code	Activities	Start time	Stop time	Time (s)	%	total %
A1	Both arms below shoulder height	02:52:28	02:54:21	00:01:53	70.62	100.00
	Both arms below shoulder height	02:52:03	02:52:50	00:00:47	29.38	
L2	Standing	02:52:28	02:52:41	00:00:13	7.26	7.26
L4	Kneeling with one knee or with both	02:52:03	02:52:50	00:00:47	26.26	59.22
	Kneeling with one knee or with both	02:52:50	02:53:27	00:00:37	20.67	
	Kneeling with one knee or with both	02:53:59	02:54:21	00:00:22	12.29	
L5	Walking, Moving	02:53:22	02:53:52	00:00:30	16.76	33.52
	Walking, Moving	02:53:28	02:53:52	00:00:24	13.41	
	Walking, Moving	02:52:44	02:52:50	00:00:06	3.35	
T1	straight, upright	02:53:28	02:53:52	00:00:24	17.91	25.37
	straight, upright	02:52:50	02:52:58	00:00:08	5.97	
	straight, upright	02:52:28	02:52:30	00:00:02	1.49	
T2	slightly inclined	02:52:03	02:52:50	00:00:47	35.07	55.97
	slightly inclined	02:53:59	02:54:21	00:00:22	16.42	
	slightly inclined	02:53:21	02:53:27	00:00:06	4.48	
T3	strongly inclined	02:52:59	02:53:20	00:00:21	15.67	18.66
	strongly inclined	02:52:31	02:52:35	00:00:04	2.99	

STEP (2)

Posture Code	Weight	Linguistic Categories	NEVER	SELDOM	SOMETIMES	OFTEN	VERY OFTEN	SUM OF SCORES
		Frequency %	0%	1-5%	6-33%	34-66%	67-100%	
T1	0	straight, upright			25.37			25.37
T2	0.974	slightly inclined				55.97		55.97
T3	1.104	strongly inclined			18.66			18.66
T4	0.068	twisted						0
T5	0.173	laterally bent						0
A1	0	Both arms below shoulder height					100	100
A2	0.157	One arm above shoulder height						0
A3	0.314	Both arms above shoulder height						0
L1	0	Sitting						0
L2	0	Standing			7.26			7.26
L3	0.405	Squatting						0
L4	0.152	Kneeling with one knee or with both				59.22		59.22
L5	0.152	Walking, Moving			33.52			33.52
Wu1	0.549	Light (up to 10kg)						0
Wu2	1.098	Medium (10-20 kg)						0
Wu3	1.647	Heavy Weight (more than 20 kg)						0
Wi1	1.777	Light (up to 10kg)						0
Wi2	2.416	Medium (10-20 kg)						0
Wi3	3.056	Heavy (more than 20 kg)						0

STEP (3)

Posture Code	Weight	Linguistic Categories	NEVER	SELDOM	SOMETIMES	OFTEN	VERY OFTEN	SUM OF SCORES
		SCORES ASSIGNABLE	0	1	2	3	4	
T1	0	straight, upright			2			2
T2	0.974	slightly inclined				3		3
T3	1.104	strongly inclined			2			2
T4	0.068	twisted						0
T5	0.173	laterally bent						0
A1	0	Both arms below shoulder height					4	4
A2	0.157	One arm above shoulder height						0
A3	0.314	Both arms above shoulder height						0
L1	0	Sitting						0
L2	0	Standing			2			2
L3	0.405	Squatting						0
L4	0.152	Kneeling with one knee or with both				3		3
L5	0.152	Walking, Moving			2			2
Wu1	0.549	Light (up to 10kg)						0
Wu2	1.098	Medium (10-20 kg)						0
Wu3	1.647	Heavy Weight (more than 20 kg)						0
Wi1	1.777	Light (up to 10kg)						0
Wi2	2.416	Medium (10-20 kg)						0
Wi3	3.056	Heavy (more than 20 kg)						0

STEP (4)

	Score
PLI	6

Template for calculating PLI II score