Assessment Methods for Advanced Masonry Work Systems

by

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This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.
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STATEMENT OF CONTRIBUTIONS

Parts of this thesis are based on the results of collaborative research and co-authored publications as detailed here:

Chapter 4:

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  This paper is co-authored with my supervisors, Drs. Carl Haas and Eihab Abdel-Rahman, and a former M.A.Sc. student, Mr. Moshen Direneyya. I developed the methodology and experimental design under the supervision of Drs. Haas and Abdel-Rahman. I carried out the experiments, collected and analyzed the experimental data, and drafted the paper. Mr. Mireneyya developed algorithms and code for joint angle estimation for the automated rule-based assessment system. Drs. Haas and Abdel-Rahman revised the paper.

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Chapter 6:

- **<u>Ryu, J.,</u>** McFarland, T., Haas, C., and Abdel-Rahman, E. (2020) "Automatic Clustering of Proper Working Posture". *27th International Workshop on Intelligent Computing in Engineering*, DOI: 10.14279/depositonce-9977

  This paper is co-authored with my supervisors, Drs. Carl Haas and Eihab Abdel-Rahman, and a M.A.Sc. student, Ms. Tasha McFarland. I developed the methodology and experimental design under the supervision of Drs. Haas and Abdel-Rahman. I carried out the experiments, collected and analyzed the experimental data, and drafted the paper. Ms. McFarland assisted in writing the paper. Drs. Haas and Abdel-Rahman revised the paper.

Chapter 7:

- **<u>Ryu, J.,</u>** McFarland, T., Banting, B., Haas, C., and Abdel-Rahman, E. (2020) "Health and Productivity Impact of Semi-Automated Work Systems in Construction". *Automation in Construction*, DOI: 10.1016/j.autcon.2020.10339

  This paper is co-authored with my supervisors, Drs. Carl Haas and Eihab Abdel-Rahman, a M.A.Sc. student, Tasha McFarland, and Dr. Bennet Banting. I developed the methodology and experimental design with supervision from Drs. Haas and Abdel-Rahman and advice from Dr. Banting. I carried out the experiments, collected and analyzed the experimental data, and wrote most of the paper. Ms. McFarland contributed in developing a methodology to evaluate the health and productivity impacts of semi-automation described in this thesis and assisted in writing the paper.

ABSTRACT

The physically strenuous and demanding nature of construction tasks exposes workers to injury risks, can reduce productivity, and contributes to undesirable early retirement. In spite of these risks, human performance in the workplace is often managed by over-simplified standards. Complex construction sites require continuous manual labor intervention. Site complexity also preclude objective and reliable quantification of labor exposure to ergonomic risk factors. It also impedes the introduction of automation and robotics in construction industry despite recent advancements in other construction technologies.

The overarching goal of this dissertation is to identify opportunities for human-centric advanced work assessment systems that can

1) objectively and simultaneously evaluate ergonomic risk levels and productivity in construction tasks involving heavy material handling,
2) effectively identify safe and productive working postures and techniques that workers develop as they gain experience, and
3) evaluate the impact of introducing new, semi-automated work systems on health and productivity in a construction context.

To achieve these goals, this research adopts wearable inertial measurement unit (IMU) based motion capture systems as means of data collection in construction worksites. It analyzes the resultant whole-body kinematic data using analytical tools including combined biomechanical-productivity analysis, rule-based postural ergonomic risk assessment, statistical analysis, and data clustering algorithms. This research specifically focuses its efforts on the masonry field, one of the most labor-intensive trades in construction. Over the span of four years, 45 masons at various levels of experience participated in field experiments within the framework of this study.

The acquired data was used to develop automated ergonomic assessment systems to evaluate risk levels via various rule-based assessment tools as well as biomechanical analysis. This approach enabled us to objectively evaluate ergonomic risk level in construction tasks, then analyze the relationships among body loads, experience, and work methods to quantitatively investigate differences in joint loads between experts and apprentices. Furthermore, motion data-driven identification of expert work technique was proposed as a guide to proper working methods and apprentice training. These approaches allowed us to identify proper work techniques adopted by experts and suggested the utilization of expert' techniques in apprentice training to reduce the prevalence of occupational injuries and to improve productivity.

Leveraging these insights, this study proposed a systematic and objective methodology to assess the value of a semi-automated work system in a construction context. The proposed methodology fills an important technology gap by representing a proactive approach for the evaluation of semi-automated work systems in terms of reduction in exposure to health risks and improvements of productivity. Ultimately, the present research seeks to maximize occupational performance by minimizing the level of human efforts in construction.

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DEDICATION

To my parents,

ChiHo Ryu and SeoYeong Lee

And to my sister,

DaHyeon Ryu

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

3DSSPP	3D Static Strength Prediction Program.
BVH	Biovision Hierarchy
CMU	Concrete Masonry Unit
DOF	Degree freedom
IMU	Inertial measurement unit
ISB	International Society of Biomechanics
NIOSH	National Institute for Occupational Safety and Health.
OWAS	Ovako Working posture Analysing System
REBA	Rapid Entire Body Assessment
RULA	Rapid Upper Limb Assessment
WMSD	Work-related musculoskeletal disorders

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND

Due to the physically strenuous and demanding nature of construction tasks, work-related musculoskeletal disorders (WMSDs) present a considerable challenge in the construction industry (Boschman et al., 2012; Fung et al., 2008; Holmstrom & Engholm, 2003; Merlino et al., 2003; Rosecrance et al., 2001; Schneider, 2001). In 2017, the Bureau of Labor Statistics reported that the incidence rate of work-related musculoskeletal disorders (WMSDs) was 28.6 for every 10,000 full-time workers for all industries in the U.S., with construction leading at 9% higher than average rate (CPWR, 2019).

Canada experiences a proportional impact. Over the past ten years in Canada, sprains/strains and overexertion were reported as the leading injuries and injury events, accounting for 44% and 18%, respectively, of allowed lost time claims in 2019 (WSIB, 2020). WMSDs also impose significant economic burden to workers, society, and health insurance systems (Sultan-Taieb et al., 2017). Given the reports from both the United States and Canada, risks of WMSDs are clearly a significant issue in North America.

A consensus has been established that working postures and motions are associated with WMSD risks (Kivi & Mattila, 1991; NIOSH, 2014; Punnett & Wegman, 2004). As a result, research efforts have attempted to address WMSD by identifying risk factors in workers' postures and motions. Researchers and practitioners utilized body posture and motion patterns as the primary input to evaluate workers' ergonomic risks. However, the current practice—heavily reliant on manual assessment of workers' tasks—suffers from several limitations. Specifically, obtaining accurate working postures and motions through manual observation is time-consuming, expensive, and error-prone due to the subjective judgment of observers (Golparvar-Fard et al., 2013; Taneja et al., 2011). Therefore, reliable ergonomic assessment based on comprehensive kinematic (motion) data is essential not only to identify any potential issues in health and safety but also to evaluate and improve productivity.

Recently, advanced sensing, whether computer-vision or wearable-sensor based, technologies have enabled the acquisition of accurate and sufficient motion data. Although several studies have successfully assessed workers' ergonomic risks using these sensing technologies, these studies consist of limited investigations of lightweight material-handling tasks (e.g., using a screwdriver (Vignais et al., 2013), a brick (Valero et al., 2016)) in well-controlled experimental conditions (e.g., laboratory and warehouse (Battini et al., 2014)). These limitations have impeded implementation of those technologies in complex construction sites and in relation to physically demanding tasks. In fact, discussion of consistent and quantitative risk assessment is also sparse. Hence, the first motivation of this research is to address the need to develop objective work assessment methods for construction workers that do not require sophisticated measurement and processing systems.

Furthermore, it has been reported that more experienced workers adopted superior work techniques, in terms of safety and productivity, as opposed to less experienced workers (Alwasel et al., 2017a; Authier et al., 1995; Authier et al., 1996; Patterson et al., 1987). However, few studies have quantitatively investigated the relationships between body loads and work techniques, on one hand, and working postures and movements, on the other hand, in both experts and less experienced workers. Therefore, the second motivation of this research is to carry out a quantitative analysis of these relationships using the objective work assessment methods.

The use of advanced sensing technologies and analytical tools has enabled us to identify and monitor risk factors in construction tasks. However, an objective definition of proper work techniques has not been forthcoming. With the findings that more experienced workers adopt safer and more productive work techniques, identification of proper working postures and techniques from expert workers motions has a great potential in defining proper work techniques. The third motivation is to identify those work techniques and use them as a basis for construction workers' apprenticeship training in order to improve their safety and health.

Lastly, the variability of construction worksites has made their automation prohibitively complex. The flexibility of semi-automated work systems, where operators work in conjunction with machines and robots, presents an attractive alternative. However, it is critical to estimate the anticipated effectiveness of these interventions before integrating them into current work processes. This research proposes a systematic and objective methodology to assess the value of semi-automated work systems in a construction context, as it pertains to productivity improvements and reduced exposure to WMSDs. This methodology presents a proactive approach to the evaluation of health and productivity impacts of semi-automated work systems, filling an existing technical gap.

1.2 PROBLEM STATEMENT

Different ergonomic risk evaluation methods for the worksite have been proposed to proactively prevent WMSDs (Li and Buckle, 1999; Punnett & Wegman, 2004). However, the employment of such methods in an occupational setting, particularly in construction, is limited because it is difficult to collect data on working postures and motions with the reliability levels required for effective evaluation. For instance, postural ergonomic assessment methods have been widely used to evaluate risk exposures and provide ergonomic intervention using detailed guidelines of rule-based practical assessment tools (Golabchi et al., 2016) such as Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett, 1993), Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), and Ovako Working posture Analysing System (OWAS) (Karhu et al., 1977). The use of these methods, however, relies heavily on an ergonomic experts' manual observation to measure posture and body movement, which can lead to subjective and imprecise results due to human error and missing information (Li and Buckle, 1999; Valero et al., 2016). Although video recording may relax these limitations, the extra cost, the additional effort required to setup equipment and eliminate occlusions and the limited accuracy of the resulting motion data (due to the limited viewpoints of the cameras) remain as shortcomings. Lastly, both manual observation and video recording cannot provide continuous and simultaneous data on multiple body segments and joints.

Motion capture systems present a possible replacement for manual observation, providing automatic, continuous, whole body motion data acquisition. They enable accurate measurement of workers' postures and motions, which is essential not only for automated rule-based ergonomic assessment (Li and Buckle, 1999) but also for in-depth analysis of physical demands and loads on body segments via biomechanical models (Radwin et al., 2001). In construction, there are two main methods for motion capture: optical (camera or video-based) systems and inertial measurement unit (IMU) systems. In laboratory studies, marker-based optoelectronic motion capture systems are considered the ‘gold standard’ for kinematic data collection (Kim & Nussbaum, 2013). However, these systems are often impractical for use in field studies due to their illumination requirements, which can be sensitive to outdoor conditions, and their need for a clear line of sight to the individual, restricting data collection to a bounded area (van der Kruk & Reijne, 2018).

Another type of camera-based systems uses remote-sensing or computer vision algorithms to detect 2D and 3D kinematics without markers (van der Kruk & Reijne, 2018). These systems have already been tested in construction settings for posture recognition and ergonomic analysis of workers (Ray & Teizer, 2012; Yan et al., 2017). While these systems have the advantage of marker-less tracking, they still rely on cameras. They are, thereby, limited by line-of-sight requirements and can be adversely affected by light conditions and occlusions (Seo et al., 2015). Compared to optical systems, motion capture systems based on IMUs are more advantageous for use in working environments because they are portable, lightweight, low-cost, adept in various illumination conditions, and do not require a line of sight (Alwasel et al., 2017a; Bolink et al., 2016; Morrow et al., 2017; Robert-Lachaine et al., 2017; van der Kruk & Reijne, 2018) They have demonstrated ab acceptable level of accuracy and validity in measuring kinematics (Bolink et al., 2016; Morrow et al., 2017; Robert-Lachaine et al., 2017).

Additionally, the research efforts to clarify desirable and undesirable working postures and motions on a practical basis are still insufficient. Since construction is one of the most labor-intensive industries, it is extremely important to maximize workers' productivity without compromising health and safety (e.g., WMSDs), which is directly related to success in construction projects (Seo et al., 2016). However, most of the current worker-related studies mainly focus on monitoring work performance regarding productivity (e.g., work sampling) or identifying health and safety issues (e.g., risk factors of WMSDs). A lack of understanding of proper and improper working postures, motions, and techniques hinders the mitigation of ergonomic issues and the improvement of productivity on worksites.

Lastly, to alleviate workers' physical demands, the formation of flexible semi-automated work systems has been promoted in the industry, such as robotics arms supporting external weight (Li and Ng, 2017). The integration of automation into a conventional work system could reduce industrial injury risks, and further, have economic values through both reductions of the injuries and increase productivity (Shan et al., 2016). To effectively implement semi-automated work systems into conventional work processes, quantitative and objective assessment of its value, especially in terms of health and productivity, is critical. However, no systematic and objective methodology to assess their value is introduced in a construction context.

1.3 RESEARCH OBJECTIVES

With this background, the overarching goal of this research is to identify opportunities for human-centric advanced work systems that can 1) objectively evaluate ergonomic risk levels and productivity in construction tasks involving heavy material handling, 2) effectively identify safe and productive working postures and techniques that workers develop as they gain experience, and 3) evaluate the impact of introducing new, semi-automated work systems on health and productivity in a construction context. Specific objectives in this research are listed below.

1. **To investigate comprehensive methods for WMSD assessment that can objectively evaluate risk levels in construction tasks including heavy material handling:** Over the past few decades, various rule-based postural assessment systems have been developed and widely used to facilitate the measurement and evaluation of risks related to WMSDs in many industries. However, the applicability of rule-based assessment to tasks involving heavy material handling has not yet been examined. Through inter-methods reliability and comparison with ground truth (biomechanical analysis), we can investigate the applicability of the rule-based assessments, which can contribute to the development of interventions to effectively manage ergonomic risks for workers.

2. **To analyze the relationship between body loads, experience, and work methods:** Continued exposure to the physically demanding tasks can contribute workers' undesirable early retirement, resulting in a shortage of skilled craft workers. On the contrary, expert workers gain distinctive techniques, which adventitious regarding safety and productivity. Therefore, a systematic and comprehensive understanding of the relationship between body loads, work experience, and work methods can greatly contribute to workers' safety, health, and productivity, especially to apprentice-training methods and applied to high musculoskeletal-disorders-risk trades.

3. **To identify the proper working postures and techniques that workers develop as they gain experience to increase safety and productivity:** Skilled experts are often unable to articulate or convey their ‘physical wisdom’ to apprentices. Experts tend to underestimate how difficult a task can be for apprentices; also, they are often unaware of all knowledge behind their superior performance resulting in omitting information that apprentice may find valuable. Therefore, by analyzing experts' work techniques and identifying their distinctive working postures differed from less-experienced workers, we can investigate the experts' knowledge of work methods as well as the improvement of work systems for safer and more productive.

4. **To develop a systematic and objective methodology to assess the value of semi-automated work systems in a construction context:** Combined biomechanical-productivity analysis using the kinematic data provide an accurate estimation of physical demands and work performance from construction operations. When integrating a semi-automated work system into current work processes, it is critical to objectively estimate the anticipated effectiveness of the interventions. A systematic and objective methodology to assess the value of semi-automated work systems based on the combined biomechanical-productivity analysis can evaluate not only the productivity increments incurred from the implementation of a semi-automated work system, but also the impact on workers' physical exposures as an equally important component.

To achieve these research objectives, an inter-disciplinary approach is used in this research. The first approach taken in this research is wearable motion capture system-based ergonomic assessment that enables an automated assessment of postural load by automatically evaluating workers' postures. The automated rule-based assessment enables us to investigate applicability of industrial standard rule-based assessments without inter- and intra- rater misinterpretations (Research Objective #1). The central hypothesis of this approach is that accurate and objective human motion allows in-depth analysis which is not possible with human observation alone.

The novelty of the proposed research lies in automatic estimation of joint angles and continued evaluation of postural load based on a rule-based assessment guideline using massive whole-body motion datasets collected from wearable motion capture system. Manual observation-based working posture evaluation can lead to unreliable results due to different raters and viewpoints. Furthermore, the human observation cannot provide decimal-level joint angle estimates as well as continuous whole-body angle measure. Therefore, automated rule-based postural load assessment using a whole-body motion capture system overcomes the shortcomings from the human observation.

Another approach used in this research is motion data-driven a combined biomechanical-productivity analysis for ergonomics (Research Objective #2 and #3) and for human-machine interactions (Research Objective #4). Accurate motion data collection without interfering with on-going works in construction sites is one of the main technical challenges for the implementation of on-site biomechanical analysis. The main advantage of the wearable motion capture system is that it provides information rich and direct whole-body motion data without interrupting workers' on-going tasks. Furthermore, kinematic measurement directly from workers will open door toward analyzing diverse in-depth analysis of physical demand based on workers' postures and motions; furthering configure the relationships of their work techniques and experiences as well as the incorporated with machine and automations.

The final approach taken in this research is whole-body-posture-based proper working posture identification using a clustering algorithm (Research Objective #3). For proper posture identification, the proposed framework distinguishes frequent working postures according to the workers' level of experiences. Specifically, experienced workers' strategies to mitigate body loads and increase productivity are represented in the clustering algorithm. One limitation of the clustering algorithm is that postures dominated by experts and apprentices occur concurrently, which indicated common to human locomotion and the given tasks rather than those related to experience. As will be introduced in Chapter 6, a process to identify postures distinctive to each experience group (i.e., expert and apprentice) by assessing the proportion of expert and apprentice population for the postures assigned by both expert and apprentice is proposed to address the co-existence issue.

1.4 STRUCTURE OF THE DISSERTATION

This dissertation is a compilation of the studies used to achieve the proposed research objectives. This dissertation is composed of 8 chapters, and Chapter 4 – 7 introduce each of the studies that corresponds to a research objective. Following is the list of the Chapters.

CHAPTER 1: INTRODUCTION. This chapter covers the background, problem statements, and objectives and approaches of the proposed research.

CHAPTER 2: LITERATURE REVIEW. This chapter provides a critical appraisal of the previous studies related to the dissertation in order to contextualize the research objective and eventual contribution of this research.

CHAPTER 3: RESEARCH METHODS. This chapter introduces the main research methods used in common for the completion of this thesis.

CHAPTER 4: APPLICABILITY OF RULE-BASED ERGONOMIC ASSESSMENT OF BRICKLAYING. This chapter introduces automated rule-based assessments developed using wearable motion capture system. The automation rule-based assessment is used to investigate the applicability of industry standard postural stress assessment to the heavy material handling tasks.

CHAPTER 5: ANALYSIS OF THE RELATIONSHIPS BETWEEN BODY LOAD AND TRAINING, WORK METHODS, AND WORK RATE. This chapter presents an analysis relationship between body-loads experiences, and work methods using motion-data-driven biomechanical-productivity analysis on masonry tasks.

CHAPTER 6: ERGONOMIC EVALUATION OF EXPERT MASONS WORK TECHNIQUES. This chapter extends biomechanical analysis to investigate the expert masons' work techniques regarding safety of different masonry activities to determine the associated risks. Furthermore, this chapter introduces an automated posture clustering technique to identify proper working postures adopted by experts.

CHAPTER 7: A METHODOLOGY TO EVALUATE THE IMPACT OF SEMI-AUTOMATED WORK SYSTEMS IN CONSTRUCTION. This chapter introduces a systematic and objective methodology to assess the value of a semi-automated work system in a construction context, as it pertains to reduced exposure to musculoskeletal disorder risks and productivity improvements.

CHAPTER 8: CONCLUSIONS. This chapter provides a summary of the conclusions that can be drawn from the research. Several recommendations for future streaming from the research are also provided.

CHAPTER 2
LITERATURE REVIEW

The objective of this chapter is to identify the research gap and opportunities for human-centric advanced work systems and their assessment methods. The chapter reviews: (1) the prevalence of occupational injuries in construction and their impact on the industry, (2) the methods of ergonomic risk assessment and the state-of-the-science of the sensing technologies they use, and (3) previous research on adoption of automation into construction work systems. This review is meant to justify and contextualize the research objectives and eventual contributions.

2.1 ERGONOMICS OF CONSTRUCTION

Construction workers perform a multitude of diverse physically demanding tasks, which have varying degrees of ergonomic risks. Work-related musculoskeletal disorders (WMSDs)—defined as a "*group of painful disorders of muscles, tendons, and nerves*" (CCOHS, 2014)—are widely exhibited by construction workers due to task characteristics, such as overexertion, repetitive motion, and awkward postures. Continued exposure to the risks of WMSDs is associated with workplace injuries and loss of workdays, which can lead to a decline in well-being and other undesirable social and financial burdens (Cheng et al., 2013; Gatti et al., 2014).

2.1.1 Prevalence of WMSDs in Construction

The U.S. Center for Construction Research and Training (CPWR, 2018) reported that the number of WMSDs in construction have continuously dropped in the past decades. However, in 2015, the rate of WMSDs in construction was still 16% higher than the combined all industry rate at 29.8 per 10,000 full-time workers. Even worse, the overall reported numbers may be underestimated due to the likelihood of injuries going underreported and the difficulty of estimating work-relatedness of musculoskeletal disorders (CPWR, 2018).

Exposure to risk factors for WMSDs, including overexertion (excessive physical effort), repetitive motion, and awkward postures, increases a worker's injury risk (CDC, 2020). Particularly, overexertion is a major risk factor in WMSDs resulting in days away from work in construction. It is also a leading cause of other nonfatal injuries nationally (CPWR, 2018). In 2015, overexertion during lifting and lowering accounted for 29.9% of the total 20,490 WMSDs in construction; the highest rate for a single risk factor (Figure 2-1). Furthermore, other types of overexertion—including pushing, pulling, carrying, and holding—accounted for an additional 37% of WMSDs. These risk factors are typical in common construction activities, and as a result, the rate of injuries stemming from both overexertion in lifting and other forms of overexertion was higher than all other industry averages (CPWR, 2018).

Between 2003 and 2017 (CPWR, 2013, 2018, 2019), the body part most affected by WMSDs in construction is the back. Specifically, back injuries accounted for 41.7% of WMSDs in construction in 2017, which was even higher than all other industries combined (CPWR, 2019).

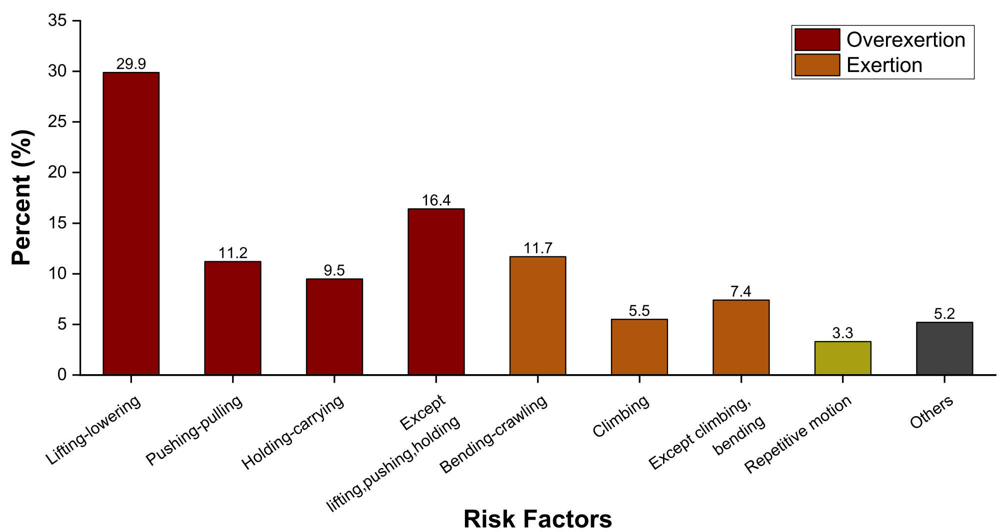


Figure 2-1: Distribution of risk factors for WMSDs resulting in days away from work in construction, total of 20,490 cases (CPWR, 2018)

2.1.1.1 Prevalence of WMSDs in Masonry

Among construction trades, masonry had the highest rate of overexertion injuries resulting in days away from work (66.5 per 10,000 full-time equivalent worker) in 2010, Figure 2-2,which was more than double the overall rate for the construction field at 28.5 per 10,000 full-time equivalent worker (CPWR, 2013). Although the rate of overexertion injuries decreased to 33.4 per 10,000 full-time equivalent worker in 2015, the combined rate for cement and brick masons was still the third highest between 2015 and 2017 (CPWR, 2019).

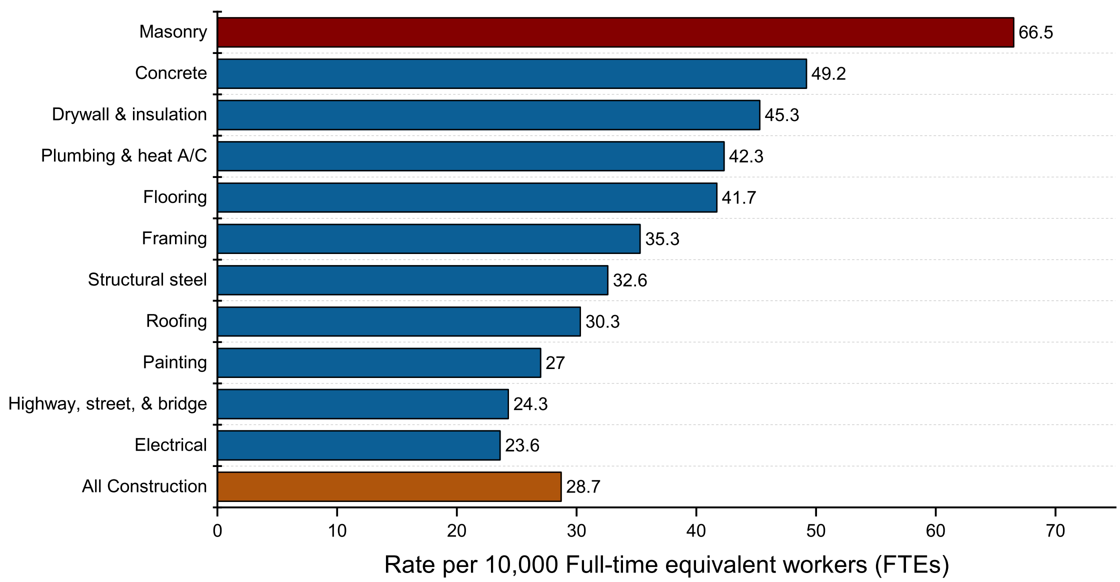


Figure 2-2: Rate of overexertion injuries resulting in days away from work for selected construction subsectors in 2010 (CPWR, 2013)

Masons' high injury rates are closely related to their physically demanding tasks. Particularly, manual block and brick lifting, which is an integral part of masonry work, requires masons to perform frequent deep bending of trunk, hips, and knees to lift and laydown heavy loads, such as concrete masonry units (CMU) (Hess et al., 2010; van der Molen et al., 2004). Hess et al. (2010) estimate that block masons manually lift at least 200 CMUs per day. Considering the standard CMU size (0.19 x 0.19 x 0.38m) and weight (16.6 kg) (CCMPA, 2013), masons manually lift over 3,300 kg per workday. Figure 2-3 shows a complete sequence of a typical CMU lift. Masons also spend up to 53% of their working time in a bending posture to pick up materials at or below knee level and 38% of their working time in awkward postures (Boschman et al., 2012). As such, the frequent handling of heavy materials in bent postures exposes masons to severe lower back injuries, which translates to masons recording the second-highest back-injury rate across construction subsectors (CPWR, 2013).

Figure 2-3: A complete CMU lift sequence from pick up to lay down

2.1.2 Losses from Occupational Injuries

Musculoskeletal injuries drastically impact the economy. For example, the estimated cost of aggregated musculoskeletal disease, including direct healthcare cost, deceased or lost wages, in the U.S. was $980.1 billion in 2014 alone (USBJI, 2018). As a share of Gross Domestic Product (GDP), the cost of musculoskeletal conditions accounted for 5.8% of GDP and exceeded the defense spending for that year. In Canada, the economic burden of musculoskeletal disorders is estimated to amount to $22 billion (CAD) annually, with a significant number of these disorders related to workplace hazards (IMHA, 2019).

The costs of occupational injuries can be categorized into three groups: (1) direct costs, (2) indirect costs, and (3) quality of life costs (Waehrer et al., 2007). Direct costs are associated with the treatment of injuries and worker compensation as a result of injury; those expenses are easily identified. Specifically, data on workers' compensation is an important source for evaluating costs associated with work-related injuries (Everett & Thompson, 1995; Hinze et al., 1995; Morantz et al., 2016). In 2015, the National Academy of Social Insurance (NASI) estimated that workers' compensation programs paid $61.9 billion in worker benefits across all industries in the U.S. (CPWR, 2018). Construction workers received significantly more compensation benefits compared to workers in other industries; the total compensation costs as a percentage of employer spending is in construction nearly three times the average cost for all other industries (3.6% vs. 1.4%) (CPWR, 2018). The direct costs of workers' compensation for non-fatal claims with more than five days away from work in construction was about $10.4 billion in 2017 (LMRIS, 2020b). It is worth noting that overexertion injuries involving outside sources, such as lifting, holding, and carrying objects, amounted to $1.48 billion in direct costs and accounted for 14.2% of the total compensation cost in construction. Overexertion was also ranked the first among the leading causes of disabling injuries for all workplaces in the U.S. in 2017, accounting for $13.98 billion which is 23.5% of the overall national burden (LMRIS, 2020a).

Indirect costs include long-term and short-term wage losses and household production losses as well as administrative costs (Waehrer et al., 2007). Although those costs are considerably more difficult to estimate due to incomplete or inaccurate evaluation, indirect costs have generally been found to exceed direct costs (Pillay & Haupt, 2008). For example, the ratio between direct and indirect costs of injuries in construction varies from a high of 1:30 to a low of 1:1 (Manuele, 2011). Furthermore, quality of life costs—the value of the pain and suffering that the victims and their families experience as a result of such injuries—were estimated at $1.9 million per workplace fatality for the average worker (Waehrer et al., 2007).

2.1.3 Relationship between Injury Rate and Experience

With more experience, workers earn essential skills and knowledge about safe working procedures that enhance their performance (Gyekye & Salminen, 2010). Many researchers have found that more experienced workers encounter fewer work-related injuries than their less experienced counterparts (Keyserling et al., 1993; Oh & Shin, 2003; Siskind, 1982). For instance, Authier et al. (1995, 1996) found that the strategies of experts differed from those of novices' during manual handling (e.g., straightening their back, orienting their pelvis, and taking short steps). Therefore, it can be concluded that a comparison of work methods between experts and novices may identify appropriate work practices that promote safety and productivity.

These practices can and should be used as means for injury prevention and practical training of apprentices (Plamondon et al., 2010). One tool to confirm or explain these findings is to carry out biomechanical analysis in order to estimate loads on the body segments using 2D or 3D biomechanical models (Radwin et al., 2001). Joint loads can provide a quantitative evaluation of safer working methods. However, only a few studies have used biomechanical analysis to examine the relationship between experience and load levels. Further, experimentally validated studies were limited to laboratory environments under restrictive conditions (Gagnon, 2005; Plamondon et al., 2010, 2012). To date, there are no quantitative investigations of the relationship between body loads and levels of experience, work methods, and productivity under realistic work conditions.

2.2 ERGONOMIC RISK ASSESSMENT

Appropriate work postures have long been also considered an essential factor in improving productivity on the job (Gilbreth and Gilbreth 1917). Awkward body-postures and forceful motions are also considered important risk factors for WMSDs because they tend to create excessive musculoskeletal stresses beyond the internal tolerance of tissues (Kumar, 2001). Identifying risk factors associated with WMSDs is essential to develop effective ergonomic interventions that can prevent WMSDs in construction workers. Different postural assessment approaches have been developed and utilized for that purpose. These approaches can be divided into three groups according to their measurement technique: self-reporting, observation-based methods, and direct measurement (Li & Buckle, 1999). Self-reporting assesses workers' physical loads, body discomfort, and work stress through checklists, rating scales, diaries, interviews, and questionnaires. Due to its simplicity and its ease of use, self-reporting is widely used in most worksites; however, its results can vary due to subjective assessments leading to unreliable results and misleading interpretations (Plantard et al., 2015; Spielholz et al., 2001).

2.2.1 Observation-based WMSDs Assessment

Observation-based methods are based on direct observation of workers' postures and tasks by ergonomic experts (Li and Buckle, 1999). The observational methods evaluate risk exposure by using rule-based practical assessment tools, which include Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), and Ovako Working posture Analysing System (OWAS) (Karhu et al., 1977). These tools are among the most cited and widely used observational assessment methods in industry (Andreoni et al., 2009; Kee & Karwowski, 2007; Kong et al., 2018a; Lee & Han, 2013; Roman-Liu, 2014).

Generally, these tools evaluate whole-body postures by combining scores for specific body segments to provide grand scores that indicate the degree of risk for each posture (David, 2005). For example, RULA and REBA divide the human body into two sections (i.e., Section 1 is the arms and wrists and Section 2 is the neck, trunk, and legs) whereas OWAS divides it into three sections (i.e., back, arms, and legs). These sections are scored according to pre-defined tables as shown in Figure 2-4. An assessment grid assigns a score for each body section called a "local score". Combinations of local scores are then classified into "grand scores" or action categories, which represent an overall evaluation of the posture and recommended actions accordingly.

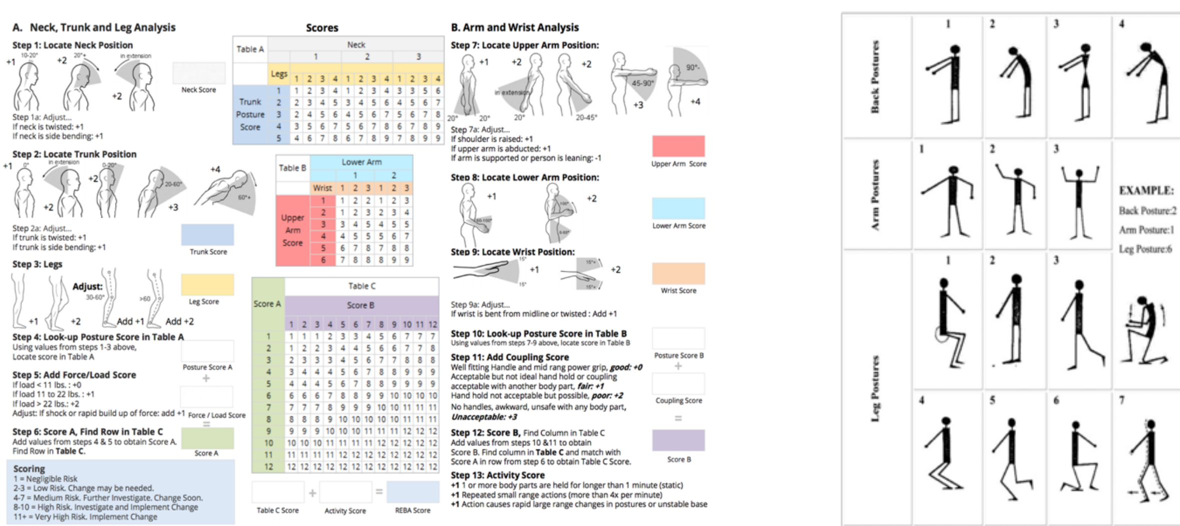


Figure 2-4: Pre-defined postural classification in REBA (left) and OWAS (right)

RULA, REBA, and OWAS have been tested in construction tasks. McGorry and Lin (2007) used RULA to demonstrate the utility of a proposed methodology that evaluates arm posture and grip strength in tool handling. Kim et al. (2011) used REBA to estimate the risk of

WMSDs in panel erection. Finally, OWAS was used to identify risky postures during hammering tasks at building construction sites (Mattila et al., 1993). From these studies, it appears that practical assessment tools have proven well-suited for working posture analysis at construction, identification of awkward or problematic postures, and post-intervention assessment of improved working postures.

These methods are traditionally based on manual observation of joint angles by ergonomic experts. Although manual observation is easily implemented, the evaluation results are prone to inaccuracies and inconsistencies due to human error (Valero et al., 2016). Furthermore, assessment tools typically assign risk levels using discrete bins determined by body angle ranges. However, it is challenging for observers to clearly distinguish the angle around the boundary between bins. Therefore, evaluation results are usually non-repeatable and subjective across different observers (Golabchi et al., 2016, 2017).

2.2.2 Direct Measurement

In order to replace manual human observation, automated worker activity data collection approaches have been devised using advanced sensing technologies. The use of these sensors allows for the collection of accurate and precise measurements, enhances assessment accuracy, and improves results reliability. As a result, direct measurement methods have been widely applied to monitor workers' status and the physical demands of diverse construction tasks.

2.2.2.1 Computer vision systems

In recent years, automated vision-based construction worker activity monitoring has drawn attention because it provides continuous data collection and an understanding of current activities. Computer vision technologies, which identify and categorize actions by using pictures and videos from single or multiple cameras, have been widely used to analyze the productivity of construction workers and to monitor their safety and health (Brilakis et al., 2011; Escorcia et al., 2012; Han et al., 2013; Weerasinghe & Ruwanpura, 2009). Peddi et al. (2009) proposed a human pose-analysis algorithm using a video camera for construction-productivity estimation, while Han and Lee (2013) suggested a motion-capture approach with

2-D images obtained from multiple cameras for behavior-based safety management. Computer vision-based approaches have also been applied to identify potential ergonomic risks by detecting awkward postures using range depth cameras (Ray & Teizer, 2012) and video images (Seo et al., 2015).

Computer vision also enables automated ergonomic evaluation systems that integrate motion capture with rule-based assessment tools. An early study, Li and Buckle (1999) created the Quick Exposure Check tools using a vision-based motion tracking system to assess the movement of workers. Recently, Plantard et al. (2015) presented a validation of RULA-grand scores automatically obtained from Microsoft Kinect v2 data. Furthermore, Dzeng et al. (2017) developed an automatic method of assessing WMSD risks in construction tasks (e.g., handling/moving materials and hammering) based on OWAS using motion data from Microsoft Kinect. Despite their contributions to automatic posture assessment, the occurrence of large errors in certain postures remains an important limitation of these systems. For example, Plantard et al. (Plantard et al., 2015) found that the mend and standard deviation of the shoulder and elbow flexion angles were 4.5° ± 8.9° and 12.6° ± 17.2°, respectively, and the peak error was larger than 40°.

Previous computer vision-based activity monitoring and ergonomic assessment studies have shown their advantages, such as providing a less intrusive method to collect a rich set of kinematic information. However, this method is adversely affected by lighting conditions and occlusions that require installation of multiple cameras, which is a limitation to its deployment in worksites (Seo et al., 2015).

2.2.2.2 Inertial measurement systems

The use of body-worn inertial measurement units (IMU), a sensor platform integrating 3D accelerometers, gyroscopes, and magnetometers, for construction activity monitoring has proven an effective method for ergonomic assessment. Specifically, single or multiple IMUs enable continuous tracking of workers' motion via measurement of segment accelerations and angular rates (Chen et al., 2017; Seel et al., 2012). In addition, wearable IMU-based motion capture suits, featuring a set of IMUs firmly attached to the worker's body, allows for direct motion data collection without interfering with ongoing worksite tasks. Indeed, wearable IMU-based motion capture systems have been used in industrial environments for various applications including ergonomic assessments, activity monitoring and productivity analysis.

2.2.2.2.1 Rule-based postural risk assessment using IMUs

In the section above, providing accurate input postural data to postural assessment systems (e.g., RULA, REBA, and OWAS) is crucial for reliable and objective risk assessment. Wearable IMU-based motion capture systems enable accurate joint kinematics measurement. Their accuracy was found to be comparable to the current gold standard, optical motion capture systems (Cuesta-Vargas et al., 2010; Robert-Lachaine et al., 2017, 2020; Schall Jr et al., 2016). The advantages of accurate kinematics estimation without interfering with motion, suggest integrating IMU-based motion capture systems into rule-based postural risk assessment systems.

Vignais et al. (2013) combined seven IMUs attached to the upper-body with RULA to compute the risk-level in real-time. In the experiment, participants were provided with visual and auditory feedback during light manual tasks, such as screwing and unscrewing. Battini et al. (2014) also introduced a visual feedback-based real-time ergonomic evaluation system using 17 IMUs integrated with different assessment tools (including RULA and OWAS) for manual material handling tasks in a warehouse environment. Furthermore, Vignais et al. (2017) conducted a continuous RULA evaluation on cleaning medical materials using a wearable IMU sensor network. By calculating the right and left side's RULA scores continuously, the evaluation provided ergonomic recommendations for a workplace redesign. Moreover, Valero et al. (2016) developed a system to detect basic unsafe postures of construction workers (e.g., stooping and squatting with back bending) using a wearable IMU suit. In a following study, Valero et al. (2017) assessed inadequate working postures in bricklaying integrating the IMU-based system into standardized ergonomic assessment rules defined by the International Organization for Standardization (ISO).

2.2.2.2.2 Motion data-driven biomechanical analysis

Chaffin et al. (2006) define occupational biomechanics as "*the study of the physical interaction of workers with their tools, mechanics, and materials so as to enhance the workers' performance while minimizing the risk of musculoskeletal disorders.*" To achieve these objectives, quantitative biomechanical models are required to estimate forces and moments on a human body while it conducts manual tasks, take different postures and movements, or is exposed to various external forces (Chaffin et al., 2006).

Due to the extensive effort required to estimate the internal loads in 3D whole-body biomechanical models, software packages, such as 3D Static Strength Prediction Program (3DSSPP) (Chaffin et al., 2006), AnyBody (Damsgaard et al., 2006), and OpenSim (Delp et al., 2007), have been developed to carry out biomechanical analysis (Seo et al., 2015). The software package 3DSSPP was adopted in this research as a tool to estimate the physical demands (e.g., spinal compression force and joint moments) under static loading conditions. Figure 2-5 shows an example of the input posture into 3DSSPP and the results of its biomechanical analysis. The stick figures shown are generated based on input posture data. The results shown on the right side include the net spinal compression force and the percent capability (i.e., the percentage of the population with a strength capability in excess of the resulting moment). 3DSSPP use body segment parameters, stature, body weight, link lengths, link weights, link centers of gravity, and strength, determined based on values for U.S. industrial population by The Center for Ergonomics at the University of Michigan .

It calculates compression forces in the lumbar joint at L4/L5 disc level, and the joint moments in the elbow, shoulder, L5/S1 disc, hip, and knee joints, using a top-down approach that starts from the forces and moments applied to the hands and ends with the forces and moments applied to the floor by the feet. Further, it uses ten L4/L5 level torso muscles, 5 each on the left and right side, to compute the compression force at the L4/L5 lumbar level (The Center for Ergonomics at the University of Michigan).

Integrating accurately collected motion data, from IMU motion capture systems, with biomechanical analysis tools enables automation of biomechanical analysis. For example, Alwasel et al. (2017a) assessed the loads acting on 21 masons' major body joints (lower back, shoulders, elbows, hips, and knees) using 3DSSPP driven by posture data obtained on-site by IMU-based motion capture. On-site biomechanical analysis can, thus, provide explicit and quantitative assessment of joint loads, which is an improvement over traditional ergonomic assessment methods, such as observation and self-reporting.

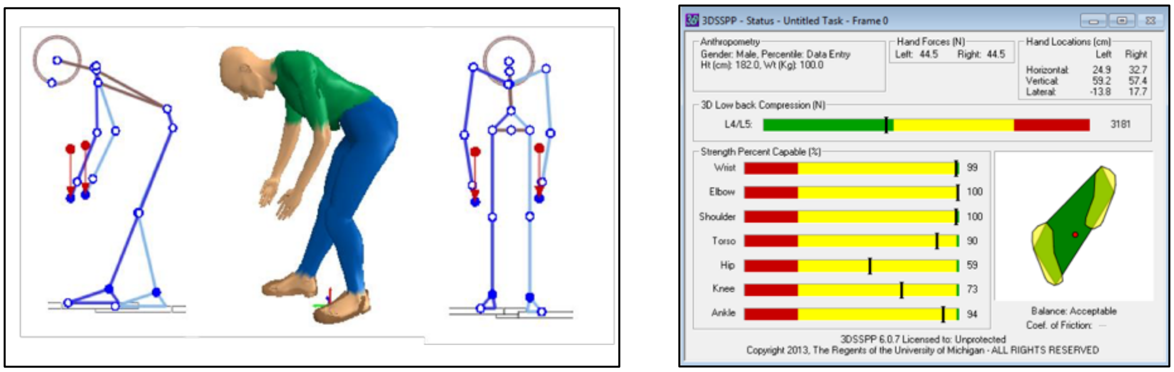


Figure 2-5: Graphical representations of the input posture (left) and biomechanical analysis results (right) in 3DSSPP

Wearable IMUs can also enable automated and objective investigation of various worker-related issues. For example, integration of IMUs with activity recognition has enabled identification of assembly tasks in manufacturing (Koskimaki et al., 2009), classification of automotive workers activities (e.g. sawing, drilling, and hammering) (Zappi et al., 2007) and tracking the productivity of masons (Joshua & Varghese, 2014; Ryu et al., 2016, 2019). Zhang et al. (2019a, 2019b) assessed the level of physical exertion and fatigue by analyzing the jerk, the time derivative of acceleration, obtained from wearable accelerometers. Ankle-located IMUs were able to assess fall-risk in construction workers (Jebelli et al., 2016a, 2016b; Yang et al., 2016, 2017).

2.3 SEMI-AUTOMATED FORCE-ASSIST SYSTEM

Howe (2000) classifies automation of manual labor in building processes into: (a) independent work cells that can be integrated into traditional building methods; (b) stationary on-site factories; and (c) dynamic on-site factories that move as the building is completed. Modern research promotes full automation of building processes—such as the Shimizu Manufacturing System by Advanced Robotics Technology (SMART) (Maeda, 1994), autonomous mobile robots (Ardiny et al., 2015), contour crafting (Khoshnevis, 2004), and other 3D printing techniques (Perkins & Skitmore, 2015). However, full automation is not yet feasible based considering available technologies and the current challenges in the industry (Ardiny et al., 2015; Howe, 2000; Perkins & Skitmore, 2015). These limitations have led to the emergence of semi-automated work systems in construction where human operators work in conjunction with automation and robotics (Balaguer & Abderrahim, 2008; Bock et al., 2012; Cai et al., 2019; Han, 2011; Kim et al., 2019).

In particular, semi-automated force-assist systems have the potential to mitigate exposure to WMSD risks from physically demanding tasks by directly reducing task demands. For example, robotic arms that externally support the weight and maneuver tools at construction sites offload physical demands from the operator to the mounting system, thereby reducing the associated risk (Li & Ng, 2017). Warszawski and Navon (1998) suggested that robotics can generate economic value by performing the most physically demanding tasks (e.g., heavy lifting, reaching to the ceiling and/or floors) to reduce the costs of injuries and time loss, leaving the more complex finishing tasks to humans. These robots can also enhance the well-being of workers and improve workers' skills, alleviating skilled labour shortage problems (Bock & Linner, 2016; Linner & Bock, 2012; Pan et al., 2018). As such, several streams of semi-automation research in construction have targeted improving the safety of operators with respect to WMSDs (Balaguer & Abderrahim, 2008; Pan et al., 2018; Paulson Jr, 1985; Warszawski & Navon, 1998).

The primary goal and driving factor for automation in construction has been its productivity and economic value (Balaguer & Abderrahim, 2008; Paulson Jr, 1985; Warszawski & Navon, 1998). A market research questionnaire about the importance of various attributes when implementing automation into construction revealed that the number one priority was increased productivity, followed by improved quality control and reliability, with safety being listed as the third most important attribute (Cobb, 2001; Kamaruddin et al., 2016; Son et al., 2010). Nevertheless, well-designed and implemented ergonomic interventions often have economic value as well, through the reduction of injuries, worker compensation, lost days, and other associated indirect and direct costs of WMSDs, or through increased productivity (Bevan, 2015; Oxenburgh et al., 2004; Rinder et al., 2008; Shan et al., 2016). According to the National Safety Council (NSC) (National Safety Council, 2017), the estimated cost of industrial work injuries were $161.5 billion in 2017, including wage and productivity losses, medical expenses, and administrative expenses. Therefore, integrating automation into the work system can reduce exposure to injury risks and, consequently, save billions of dollars annually.

2.4 CONCLUSION

This chapter reviewed the prevalence of ergonomic problems and their impact on the construction industry. Then, it described the current state-of-the-art on sensing technologies for ergonomic risk assessment and worker-related issues. Finally, the chapter reviewed the adoption of automation in construction. Findings suggest a growing body of knowledge pertaining to deployment of wearable motion capture systems for health, safety, and productivity purposes. Specifically, the use of these sensing technologies is promising, not only to overcome the limitations of manual observation, but also to develop continuous and automated worker activity-related data collection and analysis.

Wearable IMU-based motion capture systems have a greater potential for used in work assessment in construction because it enables the collection of realistic worker motion data. They are not interrupted by construction site conditions due to the sensors being firmly attached to the workers' bodies. They do not hinder the workers from performing their tasks. Hence, in the present study, accurate whole-body motion data collected using wearable IMU-based motion capture system suits are analyzed to assess the ergonomics of construction workers. The following chapter on the research methods utilized in this study describes in detail how body motion data are derived from the raw measurements of IMU's and how they are utilized in the ergonomic assessment.

CHAPTER 3
RESEARCH METHODS

This chapter introduces the research methods common to this thesis. As discussed earlier, one of the key challenges of current ergonomic assessments is the lack of an on-site automated evaluation method based on accurate whole-body motion data. Therefore, the basis of the proposed approaches in this thesis is to utilization of whole-body motion data from wearable IMU suits to derive body posture including 3D positions of body joints and joint angles. More details on analysis methods are directed to the experimental methods section included in each of the following chapters.

3.1 DATA COLLECTION

3.1.1 Participants

In Ontario, Canada, the 3-year masonry apprenticeship program consists of on-site and in-school training. Upon completion, the apprentice can apply to become certified as a journeyman (Ontario Masonry Training Centre). For the entire research project, sixty-six (66) healthy masons with different work experiences were recruited to collect motion data at two institutions: the Ontario Masonry Training Centre in Waterloo and the Canada Masonry Design Centre in Mississauga, Ontario. The participants were grouped into four cohorts based on their experience: (1) novice with no experience, (2) 1-year of experience, (3) 3-years of experience, and (4) journeyman with twenty or more years of experience. The number of participants and their demographics are shown in Table 3-1. With an estimation of motion data's sampling frequency of 125 Hz per joint, per mason, the overall data collected totals approximately 2 terabytes.

As participants were only requested to report their work experience categorically, their average age was estimated by taking a weighted measure of their years of work experience and distributing it by the proportion of the number of participants in each group. The estimated average age of each group is (1) 22.63 ± 6.35 years in novice, (2) 25.84 ± 4.79 years in 1-year apprentice, (3) 28.56 ± 3.59 years in 3-year apprentice, and (4) 40.93 ± 3.12 years in journeyman. This study and its protocols were approved by the Institutional Review Board (IRB) of both the University of Waterloo[1] and Conestoga College[2], Appendix A.

In this thesis, each chapter utilizes the entire dataset or a subset. Specifically, the masons' dataset size (n) for each chapter is as follows: (a) forty-three (43) for Chapter 4, (b) sixty-six (66, entire) for Chapter 5, (c) eight (8) and forty-five (45) for Chapter 6, and thirteen (13) for Chapter 7. Details of demographics for each subset of data are described in each chapter.

Table 3-1: Demographics of the entire participants

Experience group	Number of participants			Height (cm)		Weight (kg)	
	Conestoga College	CMDC	**Total**	Average	Std.	Average	Std.
Novice	5	12	**17**	182.9	7.1	86.1	14.3
1-year	4	15	**19**	180.8	5.4	89.3	15.5
3-years	7	9	**16**	181.3	4.6	90.7	15.2
Journeymen	5	9	**14**	178.1	6.4	87.3	10.7
Total	**21**	**45**	**66**	180.8	5.9	88.3	13.9

[1] University of Waterloo Research Ethics Committee (#30382)
[2] Conestoga College Research Ethics Board (#141)

3.1.2 Experimental Setup

Each participant completed a pre-built lead wall using 45 CMUs. Before initiating the experiment, the participants put on their personal protective equipment, namely a hard hat and a safety boot, and performed warm-up activities. Installing the motion capture suit, was comprised of fitting elastic bands carrying the IMUs around the participants' limbs and torso. It did not involve the use of a safety harness or other implements that may interfere with their motions. Figure 3-1 shows the participants equipped with the motion suit as well as the experimental setup at different stages of the experiments. Figure 3-2 shows the configuration of the lead wall. The pre-built lead wall consisted of 27 CMUs with 6-course height. The participants laid down CMUs from the 2nd course to the 6th course. The CMUs are CSA - Type "A", weighting 16.6 kg with dimensions of 0.39 x 0.19 x 0.19 m (CCMPA, 2013). The CMUs were stacked in three piles approximately one meter away from the pre-built lead wall, and each pile of CMUs consisted of 16 CMUs, which were stacked with 4 layers of 4 CMUs each. Mixed mortar was provided by helpers in two mortar boards placed between the stacked blocks. The participants were continuously supplied with mixed-mortar to avoid work-delays due to a lack of mortar. Furthermore, the Ontario Masonry Training Centre mortar mixers were used to maintain the same mortar fluidity. Participants were not instructed to take breaks or complete the experiment within a fixed time frame.

Figure 3-1: Experiment setup: placing a CMU at the 2nd course (Left), and 6th course (Right)

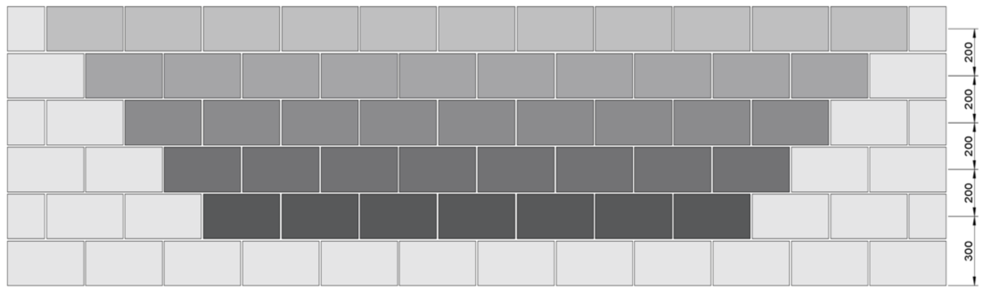


Figure 3-2: Pre-built lead wall configuration

3.1.3 Sensor Network

Two sets of wireless motion capture suits, namely MVN Awinda (Xsens, 2016) and Perception Neuron (Noitom Ltd, 2017) (Figure 3-3), were utilized to acquire whole-body motion data during the experiment. Each suit consists of 17-IMUs, with each unit is composed of a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer. Specifically, the IMUs were firmly attached using elastic straps to the head, back, each of the shoulders, the upper and lower arms, hands, the upper and lower legs, and the feet. Figure 3-4 shows a mason wearing the motion capture suit and highlights the IMU locations with blue dots. All participants reported that the motion capture suit was comfortable and did not interrupt their work.

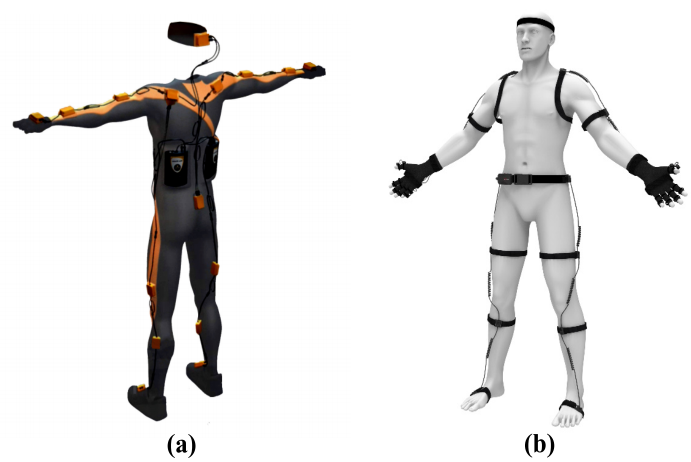


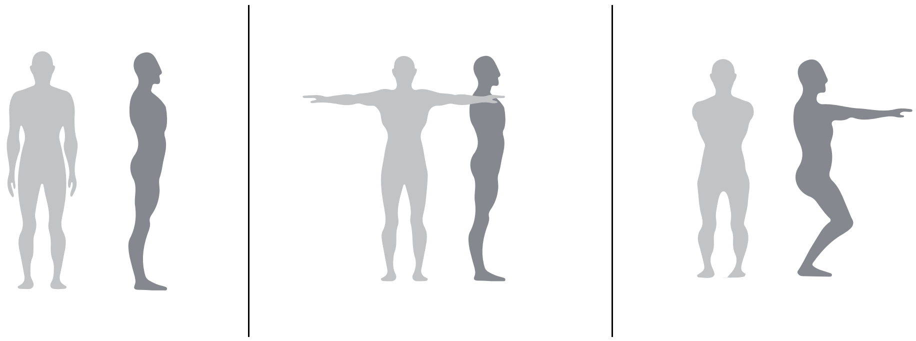
Figure 3-3: Wearable motion capture suits: (a) MVN Awinda (Xsens, 2016) and (b) Perception neuron (Noitom Ltd, 2017)

Figure 3-4: Photo of a mason wearing Axis Neuron (Noitom Ltd, 2017) motion capture. IMU locations are marked with blue dots

Each motion capture suit pairs and communicates with its in-house software, MVN Studio (Xsens, 2016) and Axis Neuron (Noitom Ltd, 2017), respectively. The software manages and calibrates the motion capture suits. Prompted by the software (Noitom Ltd, 2017; Xsens, 2016), each participant performed a calibration procedure (A-pose, T-pose, and S-pose, Figure 3-5) to determine the sensor-to-body alignment and body segment lengths at the beginning of the experiment.

Each IMU measures samples the segment motion at the rate of 125 Hz. Specifically, the accelerometer estimates acceleration due to the gravitational field and segment motions in the sensor frame, the gyroscope and magnetometer estimate the sensor's attitude. Then, a fusion algorithm combines this data to predict the segment kinematics using the calibrated sensor-to-body alignment in successive time steps based on preceding time step estimation and current time step measurements (Filippeschi et al., 2017; Roetenberg et al., 2009). Finally, the software reconstructs the 3D human skeletal model based on the estimated 3D spherical adjustment and Euler angles in the global reference frame (Filippeschi et al., 2017; Robert-Lachaine et al., 2020; Roetenberg et al., 2009; Sers et al., 2020). In addition, to counteract sensor drift, both software implemented a Kalman filter and a measurement proprietary algorithm, respectively

(Noitom Ltd, 2017; Xsens, 2016). Finally, the entire experiment was recorded using camcorders in order to label and segment data during the processing phase. As a part of the experiment consent form, the participants were asked for their consent to video recording prior to the beginning of the experiment.



(a) A-pose (b) T-pose (c) S-pose

Figure 3-5: Calibration postures (Noitom Ltd, 2021)

3.2 DATA PROCESSING

3.2.1 Data Segmentation

Manual block lifting is an essential part of masonry tasks. Masons are exposed to cumulative musculoskeletal injuries by performing frequent heavy block lifting (Alwasel et al., 2017a, 2017b). To investigate the levels of risks in block lifting, the acquired motion data was segmented into 45 single CMU lifting motion files for each participant. Based on the recorded video, each 'lift' was defined from the moment the participant picked up the CMU to the moment the CMU was entirely placed on the lead wall. Thus, the interval of spreading mortar on the CMU was not part of this analysis.

3.2.2 Joint Location Extraction

The obtained motion data was extracted as Biovision Hierarchy (BVH) files that define hierarchical body segments as local rotation and translation information from a root body joint, namely the hip (Meredith & Maddock, 2001). Then, the global position (3D coordinates) of body joints in the BVH file were repeatedly computed from local transformation matrices based on the hierarchical kinematic structure of humans. In this study, a “BVHViewer” software, which enables the export of 3D joint information from a BVH file to *.txt* files, was used. Finally, 28 body joint positions in three axes (i.e., X, Y, and Z) were obtained from the processed motion data. As the motion data was segmented into 45 single lifts, the 3D joint center information was also stored as 45 individual files. The data processing flow chart is shown in Appendix B.

3.3 BIOMECHANICAL ANALYSIS

To run the biomechanical analysis in 3DSSPP, the 3D joint center positions (*.txt*) exported from BVH motion files are converted to ‘joint location files (*.loc*)’, formatted following a hierarchical description of body joint center location (X, Y, and Z coordinates) using a MATLAB code. Combining the participants' anthropometric parameters (height and weight) with the joint location files corresponding to their lifts, along with the external forces (CMU weight) they experience, 3DSSPP calculates compression forces in the lumbar joint at the L4/L5 disc level, and the joint moments in the elbow, shoulder, L5/S1 disc, hip, and knee joints. Figure 3-6 compares the lumbar compression forces experienced by a journeyman to a novice mason during a CMU lift. It also demonstrates two loading thresholds recommended by the National Institute for Occupational Safety and Health (NIOSH, 1981), namely the action limit set to 3433 N (dashed green line) and the maximum permissible limit set to 6376 N (dashed red line).

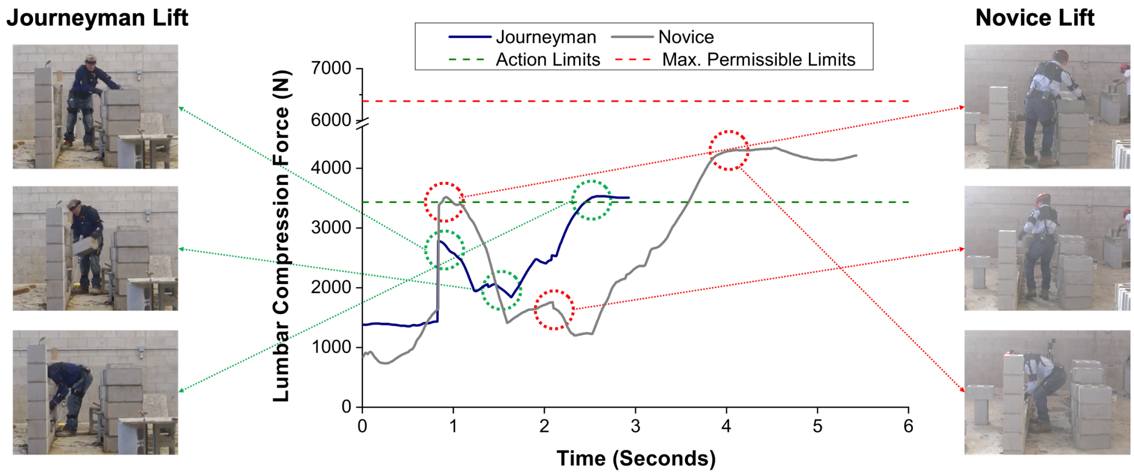


Figure 3-6: Comparison of lumbar compression force between a journeyman and a novice during a CMU lift by

This study does not account for dynamic loads generated by body segment and CMU accelerations. Instead, it treats the motion sequence as a set of static postures, which is a standard practice in ergonomic analysis. The analysis finds the 'most critical posture', defined as that where peak force or moment is registered, per lift. The peak joint loads were averaged and compared according to the experience level and course height. Therefore, the averages of the peak joint loads (i.e., most critical working postures) were investigated for each category. The steps of this analysis are shown in Appendix C.

3.4 PRODUCTIVITY ANALYSIS

In the typical job environment, masons are expected to complete a predetermined number of CMUs per day. Thus, productivity is an essential part of a mason's career. In this analysis, productivity was measured for all participants by recording the average time taken by masons to lay a block. The analysis sheds light on whether work experience enhances productivity substantially more than safety, or whether experts gain both safety and productivity skills.

CHAPTER 4
APPLICABILITY OF RULE-BASED ERGONOMIC ASSESSMENT IN BRICKLAYING[3]

4.1 INTRODUCTION

Different postural assessment systems (OWAS (Karhu et al., 1977); RULA (McAtamney & Corlett, 1993); REBA (Hignett & McAtamney, 2000)) have been developed and utilized to evaluate risk exposure as early as the 1970s. They were designed as a practitioner's field tool to objectively assign overall scores or indices based on pre-determined rules (i.e., posture categories) (David, 2005; Golabchi et al., 2016; Schwartz et al., 2019). The overall scores and indices indicate prescribed acceptable risk exposure limits for workers, with associated levels of intervention required to reduce risk (David, 2005). The design of these rule-based assessments is based on the pen-and-paper based observational approach, which allows a simple and rapid evaluation onsite (Li & Buckle, 1999).

As primary input, the rule-based assessments require a quantitative description of working posture. Thus, the reliability of the assessment results directly depends on the input posture information collected (Andrews et al., 2008a; Fagarasanu & Kumar, 2002). However, the current practice to collect and estimate posture is heavily reliant on manual assessment (e.g., human observer and estimation of projected angle in recorded videos/photos), which is subjective and qualitative (Li & Buckle, 1999; Valero et al., 2016). Specifically, rule-based assessment reports risk levels in discrete categories for various body angle ranges (i.e., bins).

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[3] This chapter is adapted from **Ryu, J.**, Diraneyya, M., Haas, C., and Abdel-Rahman, E. (2020) "Analysis of the Limits of Automated Rule-based Ergonomic Assessment in Bricklaying". *Journal of Construction Engineering and Management*. 147(2), 04020163. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001978.

Therefore, it is challenging for observers to clearly distinguish between bins when the angle is close to the boundaries (Andrews et al., 2008a). As a result, manual assessment may lead to a decrease in reliability due to the high intra- and inter-observer variability (Plantard et al., 2017).

Andrews et al. (2008b) investigated misclassification errors of trunk posture images. They reported mean bin misclassifications of 32% for trunk flexion/extension and 22% for trunk lateral bend. In particular, the bin class was 50% wrong when participants examined flexion/extension bend images representing postures near bin boundaries. In a laboratory setting, the optimal position to obtain reliable posture images is a sagittal (side) view (Sutherland et al., 2007). However, placing a camera, or an observer, in that position is not always feasible due to constrained worksite layouts (Sutherland et al., 2007). Therefore, significant errors also occur due to variations in viewing angles. Sutherland et al. (2007) investigated the reliability of working posture assessment based on images taken for eleven joint postures by four cameras placed at 0, 45, 60, and 90 degrees with respect to the frontal plane. They calculated 20% disagreement in bin selections between pairs of camera viewing angles. Considerable disagreement was reported with large joint angles, reaching 43% for left shoulder flexion. Given the inconsistency and non-repeatability of manual assessment, the collection of accurate motion data is essential for reliable postural assessment.

Recently, technological advances in motion capture systems have unlocked the possibility of replacing manual assessment with automated tools. As these systems provide quantitative measurements of human motion, they enable quantitative assessment of working postures. Particularly, wearable IMUs are increasingly being used for motion data acquisition. IMU-based motion capture suits have been developed to continuously capture full-body motion using measured acceleration, angular rate, and magnetic field orientation (Ahn et al., 2019; Chen et al., 2017; Seel et al., 2012). In these suits, individual IMUs are firmly attached to major body segments to directly track user's motions without interfering with tasks or site limitations. Furthermore, accurate estimation of joint kinematics using an IMU-based motion capture system is comparable to use of an optical motion capture system, the current gold standard (optical motion capture system) (Cuesta-Vargas et al., 2010; Robert-Lachaine et al., 2017, 2020; Schall Jr et al., 2016). Therefore, IMU-based motion capture systems are widely used to investigate ergonomic risk by integrating with rule-based assessment systems (Battini et al., 2014; Valero et al., 2016, 2017; Vignais et al., 2013, 2017).

For motion data to provide a sound basis for ergonomic assessment, the method must be valid for the target task (Takala et al., 2010). A problem arises because the extant rule-based assessment systems were developed for different purposes within special workplace conditions, excluding specifications for certain jobs like bricklaying in masonry (Kivi & Mattila, 1991; Levanon et al., 2014). Without these specifications, the evaluation results (i.e., overall scores or indices) for a given posture may vary according to which assessment system is used (Kee & Karwowski, 2007). A number of studies (Ansari & Sheikh, 2014; Kee & Karwowski, 2007; Kee et al., 2020; Kong et al., 2010; Kong et al., 2018b; Manavakun, 2004) have compared and evaluated the results from different rule-based assessment systems (i.e., inter-methods reliability) including RULA, REBA, and OWAS. Such comparisons among the evaluation of the rule-based assessments for the same task can be used to test inter-method reliability and prove convergent validity (Schwartz et al., 2019).

Furthermore, while comparison with a "gold standard" is the ideal way to assess validity, there is no general "gold standard" for assessing biomechanical risk exposure (Takala et al., 2010). As an alternative, biomechanical analysis has been widely used as an objective means to assess musculoskeletal risks during occupational tasks by estimating quantitative joint loads (Chaffin et al., 2006). A recent study (Alwasel et al., 2017a; Ryu et al., 2020) conducted a biomechanical analysis of a bricklaying task and reported quantitative estimates of masons' joint loads grouped by different levels of experience. It found that experienced journeymen adopt ergonomically safer and more productive working methods than less experienced masons.

However, no work has analyzed the validity of rule-based assessments for tasks involving heavy material handling, such as bricklaying in construction. This study investigates the applicability of three rule-based assessment systems, namely RULA, REBA, and OWAS, in a bricklaying task by 1) inter-methods reliability and 2) comparison with ground truth. To achieve this, the study develops an automated ergonomic assessment tool implementing RULA, REBA, and OWAS systems on motion data captured by IMU motion suits. The automated rule-based assessment tool eliminates intra- and inter-observer variability due to manual assessment. Then, the study demonstrates the use of this tool to assess risk levels in a standard CMU bricklaying task. The dataset is expanded from a previous study (Alwasel et al., 2017a), increasing the number of participants from twenty-one to forty-three. The assessment results of RULA, REBA, and OWAS are compared for inter-methods reliability. Finally, rule-based assessment findings are compared to those obtained from full-body biomechanical analysis (i.e., ground truth) to examine the validity of implementing a rule-based assessment to CMU bricklaying.

4.2 JOINT ANGLE ESTIMATION

Joint angles were calculated based on the International Society of Biomechanics (ISB) standards (Wu et al., 2002, 2005). Once the local coordinate system was defined for each segment using the joint centers, then the joint angles between adjoining segments' coordinate systems were calculated. Figure 4-1 shows an example of knee angles as per Grood and Suntay (1983). It is noted that this study treats the knee and elbow joints as one-degree freedom (DOF) joints allowing only for the flexion angle.

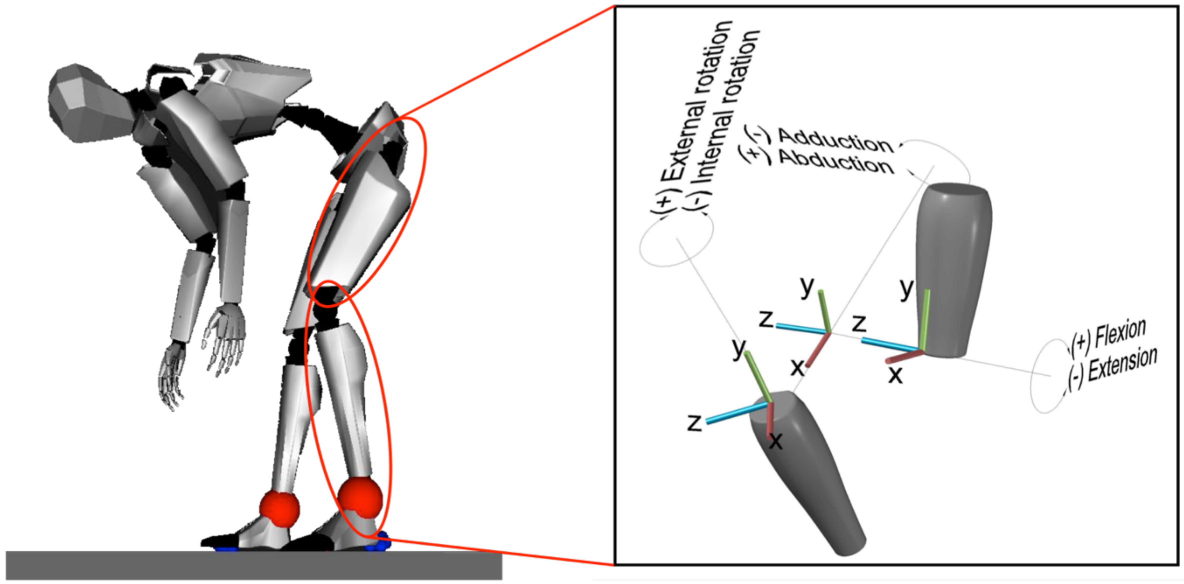

Figure 4-1: Knee angles as described by Grood and Suntay (1983)

The trunk angles were calculated between the trunk's local y-axis, extending from the center of the hip joints to the C7/T1 disc—interposed between the seventh cervical (neck) spine vertebrae and the first thoracic (chest) vertebrae—and the global y-axis that was defined by the direction of gravitational acceleration. From there, the trunk flexion was taken as the angle between those two vectors in the sagittal plane (vertical plane dividing the body into a left and right section), whereas trunk side bending was taken as the angle between them in the coronal plane (vertical plane dividing the body into a front and back section). Furthermore, the trunk twist was measured as the angle between the vector connecting the hip joints and the vector connecting the shoulder joints in the transverse plane (horizontal plane dividing the body into an upper and lower section). Figure 4-2 shows the joint angles of major body joints, namely the elbow, shoulder, knee, hip, neck, and trunk, as functions of the normalized time for a sample lift.

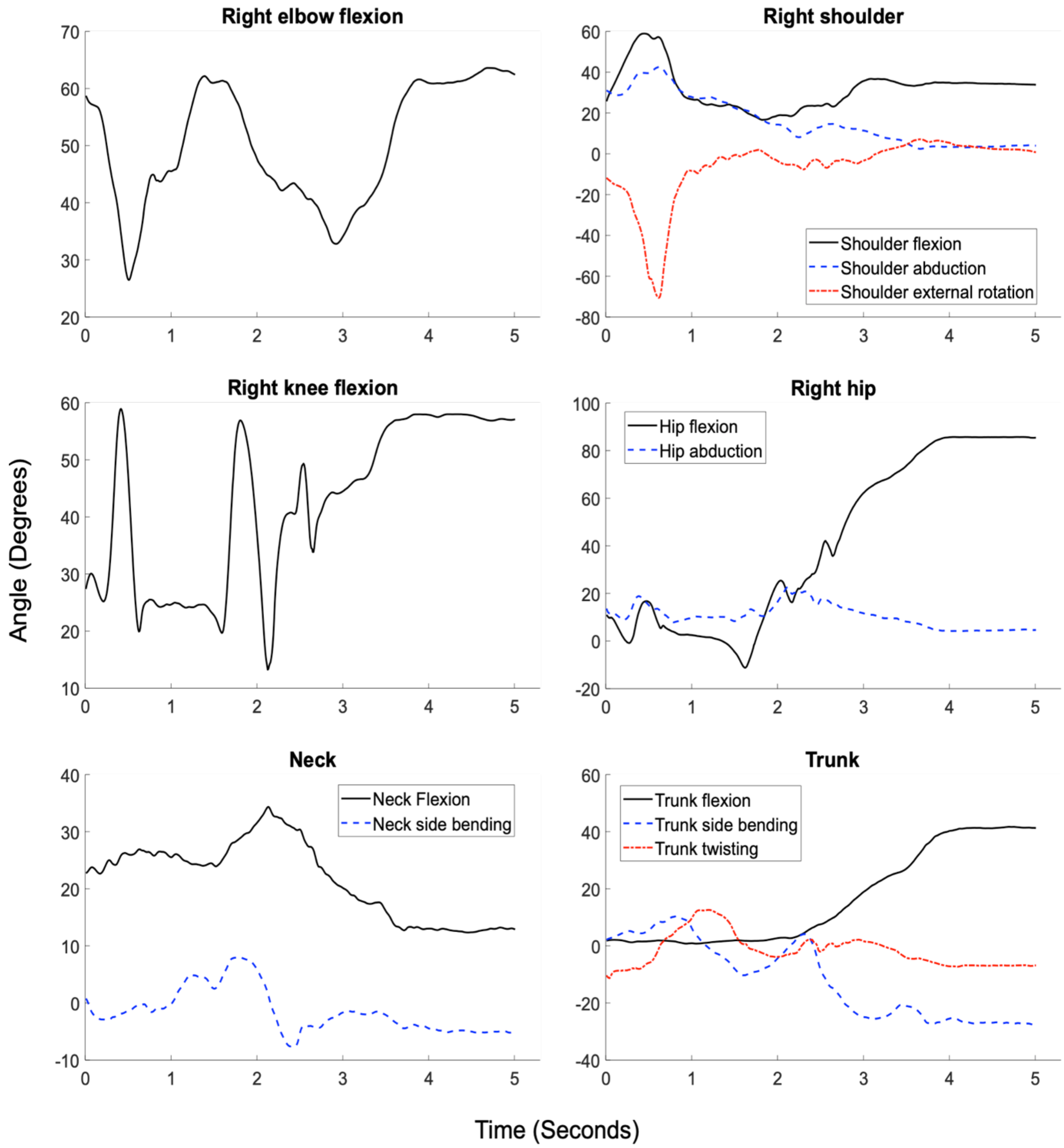

Figure 4-2: Joint angles for a sample lifting

4.3 AUTOMATED RULE-BASED ASSESSMENT

Worker postures, described by estimated joint angles, were ergonomically evaluated according to RULA, REBA, and OWAS assessment systems. These systems combine body section scores into a ‘grand score’ describing an overall risk index for a given posture. RULA and REBA divide the human body into two sections: namely, section 1, which is composed of the lower arms, upper arms, and wrists; and section 2, which is composed of the neck, trunk, and legs (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993). Section scores are assigned by combining individual joint scores according to an assessment grid with scores for external loads and repetitive exposure to loads. OWAS divides the body into three sections; back, arms, and legs (Karhu et al., 1977). Each section is assigned a local score which is then combined into various risk categories (OWAS). For example, RULA's grand score ranges from ‘1’ for minimum risk to ‘7’ for very high risk that requires change to be implemented.

The automated algorithm firstly calculates ‘joint scores’ from the estimated joint angles for the elbows, shoulders, knees, and hips as well as the neck (C7/T1 disc) and trunk (L5/S1 disc) joints. The joint scores are adjusted upward to account for awkward postures. Since those postures are defined qualitatively in rule-based assessments, quantitative thresholds were introduced to implement them in the automated algorithm as follows:

- RULA and REBA adjusted their joint scores by +1 when upper arm abduction, neck side bending, trunk side bending, and trunk twist “occur”. The criteria for this occurrence was interpreted as a joint angle in excess of 30% of the maximum joint range of motion, which was determined to be more than 20° of upper arm abduction, 10° of neck side bending, 20° of trunk side bending, and 10° of trunk twist.

- RULA's lower arm score was adjusted when the hand was positioned “across the midline” or “outside” the body frame. The corresponding quantitative threshold was defined as the relative position, in the transverse plane, of the wrist joint center concerning the body midline being negative or more than 35 cm.

- RULA and REBA wrist scores did not include adjustments for hand deviation from the midline (radial/ulnar deviation) since that motion is minimal in handling CMUs.
- REBA adjusted the leg score when one leg was not supported. As a quantitative threshold, it considered legs to be supported when both feet were standing still. However, when one foot was moving, the other foot was considered supported. Similarly, OWAS adjusted the grand score upward when a subject was walking; defined when one-foot speed was more than 0.5 m/s to filter out signal noise.

Section scores were also added to account for the external forces required to handle CMUs in all assessment systems. RULA section scores for the upper limbs and the rest of the body, as well as REBA score for the rest of the body, were adjusted by +3 to account for the CMU weight. Conversely, a score of 0 was assigned for the muscles use because the CMU handling period was less than the static load threshold (1 minute) and repetitive load patterns were below the exposure limit (4 times/minute). OWAS' fourth code, which accounts for external forces, was set to 2—corresponding to a load between 10 and 20 kg. Then, Table 4-1 shows the MSD risk levels corresponding grand score and action category ranges.

Table 4-1: Range of grand scores (RULA and REBA) and action categories (OWAS)

Assessment	Score/ Category	Levels of MSD Risks
RULA	1-2	Acceptable posture
	3-4	Further investigation, change may be needed
	5-6	Further investigation, change soon
	7	Investigate and implement change
REBA	1	Negligible risk, no action required
	2-3	Low risk, change may be needed
	4-7	Medium risk, further investigation, change soon
	8-10	High risk, investigate and implement change
	11+	Very high risk, implement change
OWAS	1	No action required
	2	Corrective action required in the near future
	3	Corrective actions should be done as soon as possible
	4	Corrective actions for improvement required immediately

Figure 4-3 demonstrates a sample of the RULA scoring process over a lift lasting 5 seconds. It starts with assigning joint scores based on the joint angles shown in Figure 4-3 (a) and (b), combined with load scores from the upper limbs and rest of the body as shown in Figure 4-3 (c) and (d), respectively. Lastly, a lookup table to combine section scores revealed the grand score shown in Figure 4-3 (e).

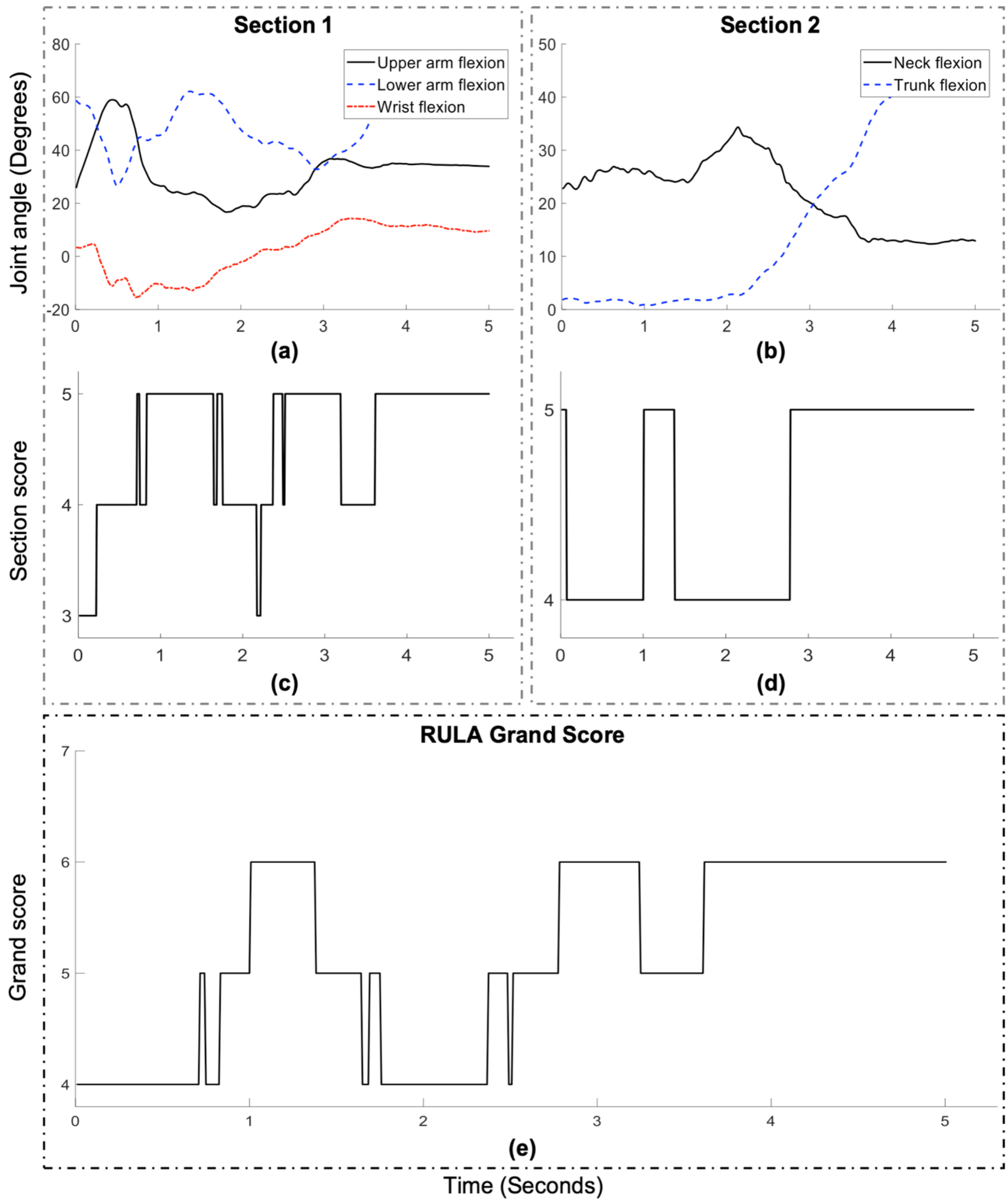

Figure 4-3: Calculation of RULA scores for a sample lifting. (a) joint angles for section 1, (b) joint angles for section 2, (c) section 1 score, (d) section 2 score, and (e) RULA grand score

4.4 RESULTS

The results of this chapter were obtained by utilizing a subset of the entire dataset, forty-three (43) masons' motion data (stature 180.3 ± 6.2 cm, total body mass 86.6 ± 13.2 kg). Seventeen of participants were a novice, seven participants were apprentices with 1 year of masonry experience, thirteen participants were apprentices with 1 year of masonry experience, and six of the participants were journeymen with more than 20 years of masonry experience. Each participant was instructed to complete a pre-built lead wall, which is described in the Chapter 3, Research Methods.

For each lift, the 'most critical posture' was defined as 1) the highest score for each assessment tool or 2) the highest lumbar compression force—the most critical load point (joint) in the trunk during bricklaying in a standard wall (Alwasel et al., 2017a). The highest measured scores and compression forces represented the peak loading of the task, which is significantly correlated to musculoskeletal injuries (Norman et al., 1998; Village et al., 2005). The peak loadings (i.e., most critical posture) were grouped according to the participant's level of experience and course height; then, the average and standard deviation of the peak loadings were investigated for each of the four levels of experience and each of the five-course heights, from 2nd to 6th course of the pre-built lead wall.

4.4.1 Rule-based Assessment

The average scores of RULA, REBA, and OWAS lifts were 6.949, 10.910, and 2.942, respectively. According to each tool's guideline, all overall scores indicated high musculoskeletal risks, which require users to investigate and implement changes in their posture. Figure 4-4 compares the average scores among the four experience groups. The average RULA score was highest for the 3-year group, whereas the average REBA and OWAS scores were highest for the journeymen. Furthermore, the novice group showed the lowest score across all assessment systems. However, the variance of average scores among the groups was insignificant in all three assessment systems. For example, the difference between the highest and lowest score in RULA was only 0.071.

To examine whether a relationship exists between the levels of experience and the risk evaluations obtained from RULA, REBA, and OWAS, a one-way Analysis of Variance (ANOVA) was carried out on the four experience groups using SPSS (version 21). The group size N, the mean grand score, its standard deviation, the ratio of variability among the groups, to the variability within group F, and the p-value are listed in Table 4-2, with the significance level set to 5%. The p-values were much larger than the required significance level ($p < 0.05$) indicating no significant difference among the groups for all three assessment systems.

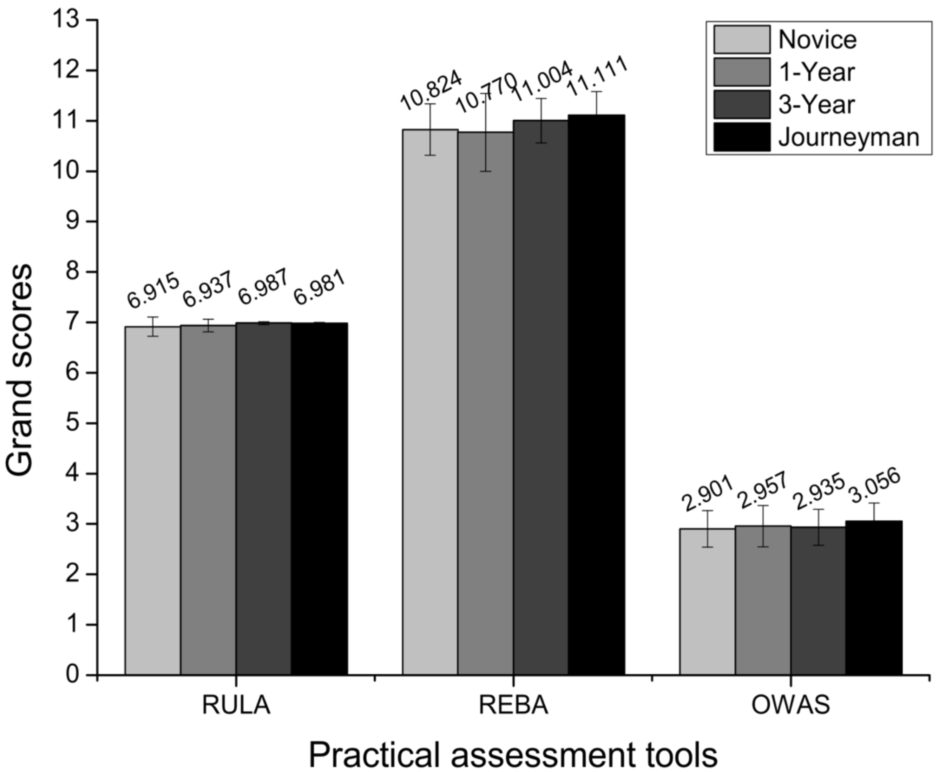

Figure 4-4: RULA, REBA, and OWAS scores averaged by experience level

Table 4-2: RULA, REBA, and OWAS scores averaged by experience level and the corresponding one-way ANOVA results

Assessments	Group (Level of Experience)	N	μ	σ	F	Sig. (p-value)
RULA	Novice (a)	17	6.915	0.191	0.858	**0.471**
	1-Year (b)	7	6.937	0.127		
	3-Year (c)	13	6.987	0.028		
	Journeyman (d)	6	6.981	0.022		
	Total	43	6.949	0.133		
REBA	Novice (a)	17	10.824	0.510	0.719	**0.547**
	1-Year (b)	7	10.770	0.770		
	3-Year (c)	13	11.004	0.441		
	Journeyman (d)	6	11.111	0.472		
	Total	43	10.910	0.530		
OWAS	Novice (a)	17	2.901	0.362	0.267	**0.848**
	1-Year (b)	7	2.957	0.411		
	3-Year (c)	13	2.935	0.355		
	Journeyman (d)	6	3.056	0.360		
	Total	43	2.942	0.358		

To build the lead wall, participants laid CMUs from the 2nd to the 6th course. Thus, their working postures varied with course height; participants bent their back much more to place a CMU on the 2nd course than they did on the 6th course. Table 4-3 shows the risk assessment scores averaged over course and experience group as well as the F and p-values comparing variation in average score for the five-courses within the same group at a significance level of 5%. This represents a fine-grained comparison of performance as opposed to what is presented in the preceding table. However, the variance in scores by course was also found to be insignificant for all three assessment systems with p-values much larger than the significance level ($p < 0.05$). The differences between the highest and lowest scores over the five-courses were 1.4%, 3.1%, and 10.5% for RULA, REBA, and OWAS, respectively.

Table 4-3: RULA, REBA, and OWAS scores averaged by course and experience group and the corresponding one-way ANOVA results

Groups	Average RULA scores (Std.)					F (p-value)
	2nd	3rd	4th	5th	6th	
Novice	6.94 (0.191)	6.876 (0.328)	6.854 (0.256)	6.928 (0.154)	6.938 (0.178)	0.508 **(0.730)**
1-Year	7.000 (0)	6.929 (0.189)	6.873 (0.252)	6.9 (0.183)	7.000 (0)	0.886 **(0.484)**
3-Year	7.000 (0)	6.988 (0.041)	6.960 (0.113)	7.000 (0)	6.981 (0.069)	0.901 **(0.470)**
Journeyman	7.000 (0)	6.917 (0.204)	6.889 (0.272)	6.876 (0.194)	7.000 (0)	0.702 **(0.598)**
Groups	**Average REBA scores (Std.)**					**F (p-value)**
	2nd	3rd	4th	5th	6th	
Novice	10.961 (0.473)	10.73 (0.725)	10.561 (0.792)	10.71 (0.581)	11.108 (0.533)	1.867 **(0.125)**
1-Year	10.724 (0.827)	10.696 (0.835)	10.835 (0.873)	10.823 (0.488)	10.926 (0.885)	0.095 **(0.983)**
3-Year	11.218 (0.486)	10.978 (0.577)	10.819 (0.567)	10.834 (0.594)	11.101 (0.598)	1.153 **(0.341)**
Journeyman	10.742 (0.882)	10.6 (0.903)	10.792 (0.935)	10.869 (0.504)	10.548 (0.942)	0.148 **(0.962)**
Groups	**Average OWAS scores (Std.)**					**F (p-value)**
	2nd	3rd	4th	5th	6th	
Novice	3.083 (0.223)	2.868 (0.393)	2.681 (0.791)	2.908 (0.493)	2.981 (0.449)	1.299 **(0.279)**
1-Year	3.092 (0.221)	2.858 (0.425)	2.718 (0.627)	2.991 (0.415)	3.135 (0.508)	0.980 **(0.433)**
3-Year	3.067 (0.202)	2.943 (0.373)	2.649 (0.5)	2.865 (0.612)	3.029 (0.44)	1.731 **(0.155)**
Journeyman	3.091 (0.265)	2.79 (0.425)	2.655 (0.63)	2.893 (0.329)	2.819 (0.985)	0.446 **(0.774)**

4.4.2 Biomechanical Analysis

Biomechanical studies have confirmed that low back injuries are associated with frequent lifting in industrial manual material handling tasks, particularly those where the lumbar compression force is in excess of the loading threshold, 3433N, defined by NOISH (Alwasel et al., 2017a; Arjmand & Shirazi-Adl, 2005). Figure 4-5 shows the lumbar compression force averaged and grouped by levels of experience. It also demonstrates two loading thresholds, namely the action limit set to 3433 N (dashed green line) and the maximum permissible limit set to 6376 N (dashed red line). Biomechanical analysis shows that the lumbar compression force was significantly lower for journeymen and novices than for 1- and 3-year apprentices. Although the novice group showed a similar lumbar compression force to journeymen, they took almost twice as long to complete the task. This finding indicates that a slower pace allowed novices to reduce the loads on their body compared to more experienced and productive apprentices. Furthermore, biomechanical analysis shows that while all groups experience back compression forces within NIOSH action limits at the fourth, fifth, and sixth courses, 1- and 3-year apprentices experience back compression forces beyond the action limit when they work on the 2nd and 3rd courses.

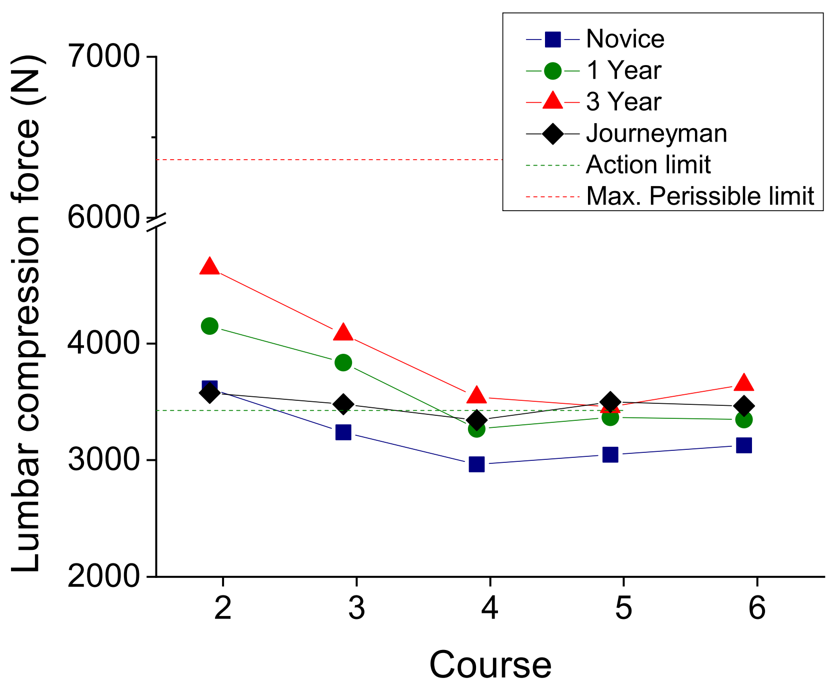

Figure 4-5: Lumbar compression force to complete each course by the levels of experience

4.4.3 Comparison Between Rule-based Assessment and Biomechanical Analysis

To compare the rule-based and biomechanical assessment results, each result was normalized by dividing the average score or force of the most critical posture of each participant by the corresponding maximum limit, namely 7 for RULA scores, 12 for REBA scores, 4 for OWAS scores, and 6376 N for lumbar compression force. The results are shown in Figure 4-6. The biomechanical metric shows significant variation among participants. The normalized RULA and REBA scores were almost constant regardless of the participant, and the normalized OWAS scores were scattered without obvious correlation to the biomechanical metric. For instance, the critical lumbar back compression force for participant #43 was less than that for participant #1 by 2431.45N. However, all three rule-based assessment scores for participant #43 were slightly worse than those for participant #1.

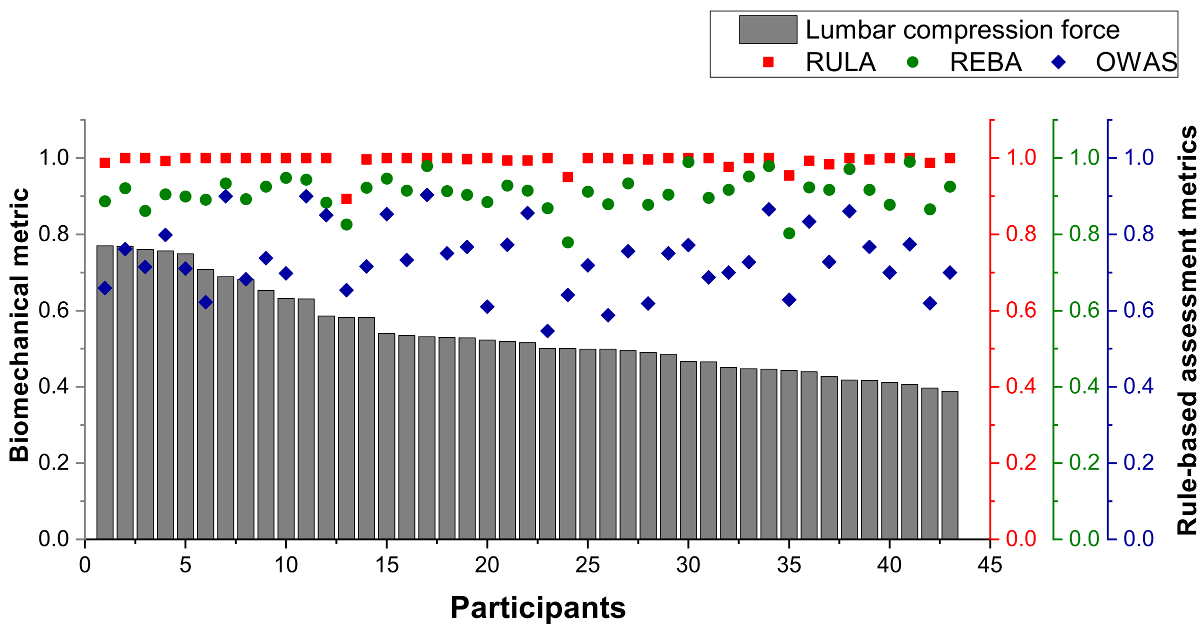

Figure 4-6: Normalized rule-based assessment average scores and the corresponding biomechanical metric

An independent sample t-test was conducted to examine whether rule-based assessments and biomechanical analysis results had statistically significant differences. To this end, participants were grouped into high and low groups based on their calculated lumbar back compression force. Lumbar compression forces and the grand scores of RULA, REBA, and OWAS were compared for three sample sizes comprised of the 5, 10, and 15 highest and lowest participants groups, corresponding to 25%, 50%, and 75% of the total sample size as demonstrated in Table 4-4. The t-test of the lumbar compression force found significant differences between the high and low groups regardless of the sample size, indicating significantly different lower back joint loads between the two groups. On the other hand, all rule-based grand scores showed no differences for all three group sizes indicating similar MSD risk levels for both groups.

Table 4-4: Independent sample t-test between the high and low groups

Assessments	Group	N	μ	σ	t value	Sig. (p-value)
RULA	Highest	5	6.971	0.042	-0.255	0.805
	Lowest	5	6.977	0.039		
	Highest	10	6.985	0.032	1.340	0.197
	Lowest	10	6.941	0.100		
	Highest	15	6.939	0.192	-0.207	0.838
	Lowest	15	6.950	0.089		
REBA	Highest	5	2.915	0.213	0.456	0.660
	Lowest	5	2.848	0.251		
	Highest	10	10.873	0.309	-0.533	0.600
	Lowest	10	11.000	0.685		
	Highest	15	10.866	0.408	-1.022	0.315
	Lowest	15	11.059	0.609		
OWAS	Worst	5	10.733	0.268	-0.855	0.417
	Lowest	5	10.980	0.587		
	Worst	10	2.914	0.313	-0.511	0.616
	Lowest	10	2.990	0.355		
	Highest	15	3.002	0.360	0.322	0.750
	Lowest	15	2.963	0.296		
Lumbar Compression Force (N)	Highest	5	4849.814	54.621	55.629	**0.000***
	Lowest	5	2575.705	73.297		
	Highest	10	4568.427	324.922	17.209	**0.000***
	Lowest	10	2673.557	125.152		
	Highest	15	4286.568	500.031	11.103	**0.000***
	Lowest	15	2766.308	176.657		

* Significant difference ($p < 0.05$) between the best and worst groups

4.5 DISCUSSION

This chapter examined the applicability of RULA, REBA, and OWAS to tasks involving heavy manual handling, specifically CMU bricklaying, by utilizing an automated rule-based assessment tool. A high-level of agreement among the evaluation results for all assessment systems was found. Despite the different scoring schemes, the most critical postures (i.e., the highest scored posture) indicated high level risk in all three systems, recommending posture changes as soon as possible. Furthermore, consistently high scores were found within each assessment system, irrespective of worker experience or work height. In each assessment system, no significant differences were found between experience levels or course heights.

However, the biomechanical analysis—a ground truth measure offering an explicit and quantitative assessment of actual joint loads—showed a range of evaluation results among the experience groups as well as course heights. Specifically, 3-year apprentices experienced the highest lumbar compression forces, while the journeymen and novices experienced relatively lower joint loads. In addition, the compression forces were lowest for all experience groups when completing the 4th course. These results are consistent with the results of the previous study (Alwasel et al., 2017a) conducted using a subset of the data in this study. The inverted-U-shape relationship between joint load (injury rates) and experience has been widely reported (Alwasel et al., 2017a; Frost & Andersen, 1999; Yerkes & Dodson, 1908). According to such studies, stimulus (e.g., peer pressure) on the first 5 – 8 years of apprentices' careers induce them to change their behavioral task performance to achieve higher productivity and proficiency while sacrificing ergonomic safety. However, after surviving the apex, they learn techniques allowing them to achieve increased productivity while maintaining ergonomic safety. It was also found that the main distinction between experienced and novice participants was not in safety but in productivity. Experts laid CMUs faster, completing the overall task (lead wall) in less time. Specifically, journeymen laid CMUs twice as fast as novices.

Biomechanical analysis provided sensitive risk evaluation that can distinguish the different degrees of risk (joint loads) arising from different motion patterns of the four experience groups while they performed the same tasks. Furthermore, even within the same experience group, the varying risks (joint loads) generated by different work heights were also distinguished by biomechanical analysis. However, rule-based assessment systems failed to distinguish these differences and only indicated that masonry work posed a significant risk to masons, regardless of experience and course height. Lastly, this study found that expanding the dataset used in biomechanical analysis, more than doubling the number of participants from the previous pilot study, produced results consistent with that study (Alwasel et al., 2017a). This shows that biomechanical analysis is an objective and robust method for risk assessment in heavy material handling tasks.

The contrast between rule-based assessment systems and biomechanical analysis can also be seen across all participants in Figure 4-6, where the grand scores of rule-based assessment systems are seen to be either saturated (RULA) or scattered (REBA and OWAS) irrespective of the biomechanically calculated back compression forces. For example, Figure 4-7 shows the lumbar compression forces and the grand scores for all frames captured throughout one lift. The red and blue circles in Figure 4-7 (a) indicate the frames where the lumbar compression forces were highest and lowest, respectively. The same frames are marked in Figure 4-7 (b), (c), and (d) which demonstrate the grand scores of RULA, REBA, and OWAS, respectively. While the lumbar compression force increases between these two frames, from 41% to 85% of the maximum permissible limit, the rule-based grand scores are saturated at 7 for RULA, decrease from 10 to 9 for REBA, and increase from 1 to 2 for OWAS.

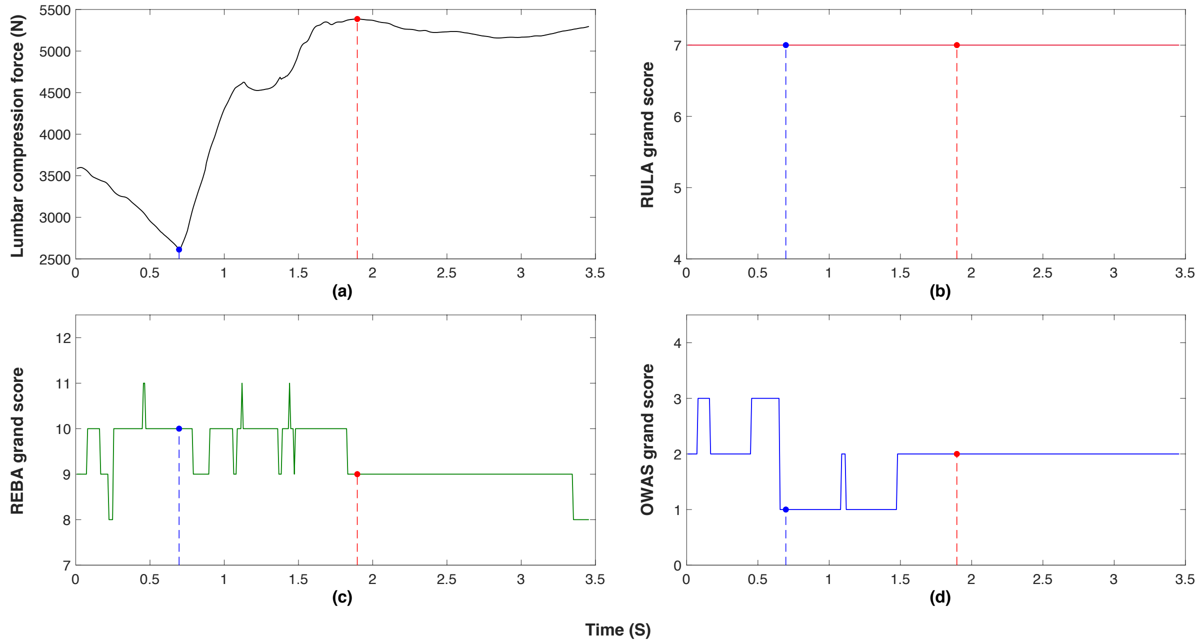

Figure 4-7: Results of biomechanical analysis and rule-based assessment from a sample lift. (a) Lumbar compression force, (b) RULA, (c) REBA, and (d) OWAS

An independent sample t-test was conducted to examine the discrepancy between biomechanical analysis and rule-based assessment systems (Table 4-4). The results of the t-test confirmed significant differences between high and low lumbar compression force groups for all sample sizes. However, the t-test results of all rule-based grand scores corresponding to the high and low lumbar compression forces showed no difference. These results illustrate that the inability of rule-based assessment systems to distinguish between risk levels in this task is due to score saturation, rather than an indicator of an across-the-board biomechanical risk

One factor driving up the grand score of rule-based assessments is the external load of the CMUs. Specifically, an external load greater than 10kg increases the RULA and REBA section scores by 3 and 2, respectively, and the OWAS section score by 1. Therefore, all rule-based assessment systems reported inflated (higher risk) grand scores regardless of the various body postures—even though the actual joint forces and moments were not consistently high.

With manual observation methods, it is only possible to analyze one or several distinct momentary posture(s) observed while performing the target task. Furthermore, depending on the viewpoint of the observer or the frame of the recorded video, the evaluator(s) may assess different levels of risk. This inherent error may, consequently, cause inter- and intra-observer variability of evaluation results. The developed automated rule-based assessment tool enabled accurate and continuous quantification of joint angles at 125 Hz, thereby overcoming the problem of evaluation variability. Specifically, the developed method can eliminate the problem of posture misclassification which undermines manual observation, particularly for joint angles near bin boundaries (Andrews et al., 2008b). Furthermore, the joint angles were estimated from the reconstructed 3D human skeleton model; thereby eliminating errors due to viewing angle variations (Sutherland et al., 2007).

However, in rule-based assessment systems, the discrete boundaries between the joint angle bins corresponding to each score can lead to discontinuous jumps between scores for consecutive frames (postures). Figure 4-8 illustrates the underlying reasons for the abrupt changes in the RULA upper limb section score over 0.2 seconds and 0.7 seconds, seen in Figure 4-3 (a) and Figure 4-3 (c), respectively. The score fluctuations occur due to upper arm and wrist flexion angle fluctuations around the bin boundaries. Specifically, a change of 0.762° in the upper arm angle from 44.9° in frame 26, to 45.8° in frame 27 shows the upper limb section score increase by 1 as it crosses the upper arm angle boundary at 45°. These discontinuous variations in risk scores are a fundamental shortcoming of rule-based assessment that cannot be overcome by automating angle quantification.

Frame	Shoulder Flexion	**Upper arm Score**	Elbow Flexion	**Lower arm Score**	Wrist Flexion	**Wrist Score**	**Table A**
26	44.990	3	53.168	2	4.681	1	**3**
27	45.752	4	52.444	2	4.564	1	**4**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	**⋮**
85	49.521	4	40.962	3	-14.615	2	**4**
86	48.556	4	41.512	3	-15.080	3	**5**
87	47.503	4	42.126	3	-15.364	3	**5**
88	46.354	4	42.809	3	-15.368	3	**5**
89	45.083	4	43.488	3	-15.291	3	**5**
90	43.740	3	44.058	3	-15.257	3	**4**

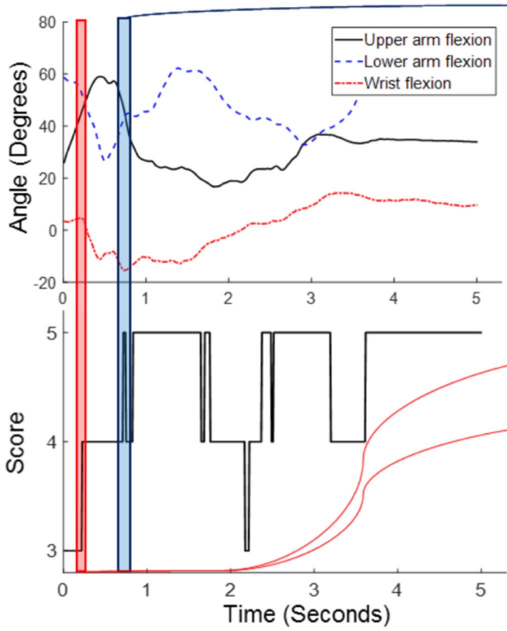

Table A		Wrist Score 1		Wrist Score 2		Wrist Score 3		Wrist Score 4	
Upper Arm	Lower Arm	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2
1	1	1	2	2	2	2	3	3	3
	2	2	2	2	2	3	3	3	3
	3	2	3	3	3	3	3	4	4
2	1	2	3	3	3	3	4	4	4
	2	3	3	3	3	3	4	4	4
	3	3	4	4	4	4	4	5	5
3	1	3	3	4	4	4	4	5	5
	2	3	4	4	4	4	4	5	5
	3	4	4	4	4	4	5	5	5
4	1	4	4	4	4	4	5	5	5
	2	4	4	4	4	4	5	5	5
	3	4	4	4	5	5	5	6	6
5	1	5	5	5	5	5	6	6	7
	2	5	6	6	6	6	7	7	7
	3	6	6	6	7	7	7	7	8
6	1	7	7	7	7	7	8	8	9
	2	8	8	8	8	8	9	9	9
	3	9	9	9	9	9	9	9	9

Figure 4-8: Joint score discrepancy between consecutive postures

The scope of the present study was limited to the investigation of ergonomic risk levels during the task of laying CMUs to a standard wall. This task represents the ergonomic risks in many masonry tasks involving repetitive and physically demanding manual handling. Future studies should assess the ergonomic risks of similar tasks in masonry (e.g., handling different size and weight blocks) and other trades. Moreover, in this study, risk evaluation was conducted on the most critical postures because the peak joint load is closely correlated to musculoskeletal injuries (Norman et al., 1998; Village et al., 2005). However, other studies have found that it was necessary to consider cumulative joint loads where critical loads were maintained over extended periods of time (Kumar, 1990, 2001; Norman et al., 1998). Therefore, researchers should investigate the cumulative joint loads in assessing risk levels for tasks where critical loads are maintained over several seconds.

4.6 CONCLUSIONS

This study investigated the applicability of three rule-based assessment systems, RULA, REBA, and OWAS, to a bricklaying task—laying 16.6 kg CMUs on a standard wall. An automated assessment tool was developed for those systems using static postures obtained from wearable motion capture systems. This tool was able to eliminate intra- and inter-observer variabilities, an inherent obstacle in manual rule-based assessment. The automated assessment tool also enabled accurate and continuous risk evaluation at a high-frame rate (125 postures per second) for the targeted task. It was used to assess risk levels encountered by forty-three masons during the bricklaying task. The evaluation results were compared among the three assessment systems and with the ground truth obtained from biomechanical analysis.

According to the guidelines of the three assessment systems, the results indicated that masons were exposed to high risk of injury regardless of their experience level and activity (course height) — no significant differences were found from one-way ANOVA. Despite their high-level of agreement, comparison with the ground truth showed that the results of these assessments were misleadingly saturated. Put another way, the assessment systems were unable to distinguish between safe and unsafe postures, finding both of them to be unsafe. For example, the difference between the highest and lowest lumbar compression forces was 2,431 N; however, the rule-based risk evaluations indicated high risk for both participants. In fact, the lowest loaded participant was 28% below the action limit for the joint while the highest loaded participant was 43% above the action limit. Further, all three assessment systems assigned higher risk scores to the lowest loaded participant than the highest loaded participant. In contrast, biomechanical analysis provided a range of risk evaluations that varied depending on experience as well as course height that the rule-based assessment systems failed to demonstrate. Specifically, journeymen and novices experienced low risk levels (joint loads) while 1- and 3-year apprentices encountered higher risk levels laying the CMUs on the 2nd and 3rd courses.

The present study is one of the first attempts to examine the applicability of rule-based assessment to tasks involving heavy manual material handling, such as bricklaying, via inter-methods reliability and comparison with ground truth, the results of biomechanical analysis. It has shown that rule-based assessment systems provide saturated risk evaluations for heavy material handling tasks because higher external forces can artificially inflate their scores, indicating higher risk, regardless of posture safety and actual joint loads. Over-inflated risk evaluations are not only inaccurate and insensitive to ergonomics but can also lead to unnecessary ergonomic interventions. In contrast, biomechanical analysis can provide robust risk evaluations that reflect the effects of external loads and distinguish between risk levels due to experience and course height. Therefore, biomechanical analysis should be adopted to evaluate ergonomic risks especially for tasks involving heavy material handling.

CHAPTER 5
ANALYSIS OF THE RELATIONSHIPS BETWEEN BODY LOAD AND TRAINING, WORK METHODS, AND WORK RATE[4]

5.1 INTRODUCTION

Skilled construction craft workers are supplied through various sources of craft training, such as apprenticeship programs, community colleges, and firm-sponsored training (Wang et al., 2008). Through these training programs, workers are taught essential work skills (e.g., proper use of tools) and work safety to reduce occupational risks (Albers et al., 1997; Wang et al., 2008). An evaluation of the effectiveness of training programs is usually done qualitatively using subjective means, including manual observation and surveying (Teizer et al., 2013). This evaluation, however, is limited by the absence of a quantitative score or index for apprentice performance. Furthermore, apprentices lack the necessary training loop feedback on postures and motions that would provide sufficient data to produce the functional adaptation. In particular, qualitative evaluations do not provide a full understanding of proper work methods for apprentices, thereby adding a layer of challenge to proactive injury prevention.

Collecting and analyzing data pertaining to apprentice work motions is essential to quantitatively evaluate their performance. Namely, working postures and movement patterns are primary inputs for evaluating ergonomic risks due to their association with joint load (joint force/ joint moment) in which there is a vulnerability to WMSDs (NIOSH, 2014; Punnett &

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[4] This chapter is adapted from **Ryu, J.**, Alwasel, A., Haas, C., and Abdel-Rahman, E. (2020) “Analysis of Relationships Between Body Load and Training, Work Methods, and Work Rate: Overcoming the Novice Mason’s Risk Hump”. *Journal of Construction Engineering and Management*. 146(8), 04020097. https://doi.org/10.1061/(ASCE)CO.1943- 7862.0001889

Wegman, 2004). Recent advanced sensing technologies, such as wearable inertial measurement units (IMUs), have enabled the acquisition of a broad range of accurate motion data (Chen et al., 2017; Valero et al., 2016). This data has allowed researchers to look at improving safety performance (Dzeng et al., 2017; Jebelli et al., 2016b; Yang et al., 2017; Zhang et al., 2019a, 2019b), work efficiency and productivity (Joshua & Varghese, 2014; Ryu et al., 2016, 2019), and ergonomic analysis (Nath et al., 2017; Ryu et al., 2018; Valero et al., 2016, 2017) within the construction industry. Collectively, the previous motion data studies show great potential for predicting and monitoring worker safety and productivity. Nonetheless, there has been little research into how workers interpret appropriate or inappropriate working methods, as well as how to reduce or eliminate the inappropriate working process.

In addition to the use of sensing technologies, the introduction of automation has been widely discussed to protect workers against repetitive and physically intensive tasks. For example, the manufacturing industry has shown that automation is well-suited for manufacturing tasks, such as repetitive mass-production assembly operations (Everett & Slocum, 1994). Although many parts of construction tasks are also repetitive, constant intervention by craft workers is inevitable due to the complexities of continuously changing construction sites (Everett & Slocum, 1994). As a result, the construction industry remains heavily dependent on craft workers and must prioritize workers' sustainability over automation by training workers to perform tasks safely.

Previous ergonomic studies have observed that workers develop beneficial work techniques as they gain experience. The primary consensus is that expert material handlers adopt different work techniques from those of inexperienced handlers and that the expert's techniques were advantageous in terms of safety and productivity (Alwasel et al., 2017a; Authier et al., 1995, 1996; Patterson et al., 1987). Indeed, researchers found a steady decline in work injuries as work experience increases from the data reported in the Occupational Health Supplement, National Health Interview Survey (Oh & Shin, 2003), and the Supplementary Data System (Siskind, 1982). So far, however, few studies have quantitatively investigated and compared how expert joint loads arising from work posture and motions differ from those of apprentices.

As a pilot study, Alwasel et al. (2017a) conducted combined biomechanical and productivity analysis on 21 masons recruited into four groups based on their experience: novices with no experience; apprentices with 1-year of experience; apprentices with 3-years of experience; and journeymen with more than 20 years of experience. All participants completed a pre-built standard concrete block wall using 45 CMUs. Then, they analyzed whole-body kinematic data collected from IMU motion capture systems. It was found that journeymen achieved not only low joint loads, but they also completed the task significantly faster than all other experience groups (Alwasel et al., 2017a). Furthermore, in a consecutive study, they found that masons have different work patterns that can be distinguished and classified, using machine learning, into different groups according to their experience (Alwasel et al., 2017b).

The pilot study (Alwasel et al., 2017a) hypothesized and confirmed that experienced masons adopt safer and more productive work methods than less experienced masons. The present study extends the pilot study by significantly increasing number of participants from 21 to 66 masons and analyzing the relationships among body loads, work experiences, and work methods. Exploiting the larger dataset, this study firstly evaluated a combined biomechanical-productivity analysis to improve confidence in the results. Further, this study examined the variations in work methods and their relationship to work height. Specifically, this study assesses how different work experience groups load their joints and adjust their work postures as the work height changes. Furthermore, it investigated the distinctive differences between journeymen's work methods and those of less experienced masons.

5.2 RESULTS

5.2.1 Joint Loads and Work Experience

Participants completed the prebuilt lead wall described in the Chapter 3. This analysis focused on the lumbar compression force at the L4/L5 disc level as it was found to be the most critical load point in the trunk, closely linked to lower back pain (Alwasel et al., 2017a). Better understanding of the lumbar joint load may also encourage the advancement of safe work methods (Plamondon et al., 2010).

Figure 5-1 shows the lumbar compression force arranged by levels of experience with the loading threshold defined by NIOSH (i.e., the action limits are 3433 N and the maximum permissible limits are 6376 N). Interestingly, journeyman and novice groups achieved lower lumbar compression force values than the mid-experienced groups. Particularly, the journeyman achieved a lumbar compression force lower than the action limits through all five courses. However, all groups experienced the lowest lumbar compression force when working on the 4th course. Statistical significance of the body of observations is explored later in this chapter.

Furthermore, the results of all major joints moments are shown in Figure 5-2. Joint moments at both the upper (elbow and shoulder) and the lower (hip and knee) body showed relatively high values for the 3-year apprentice group and low values for the journeymen. While joint moments in the lower body were at a similar level at the highest course, all groups experienced increasing joint moments in the upper body by completing higher courses.

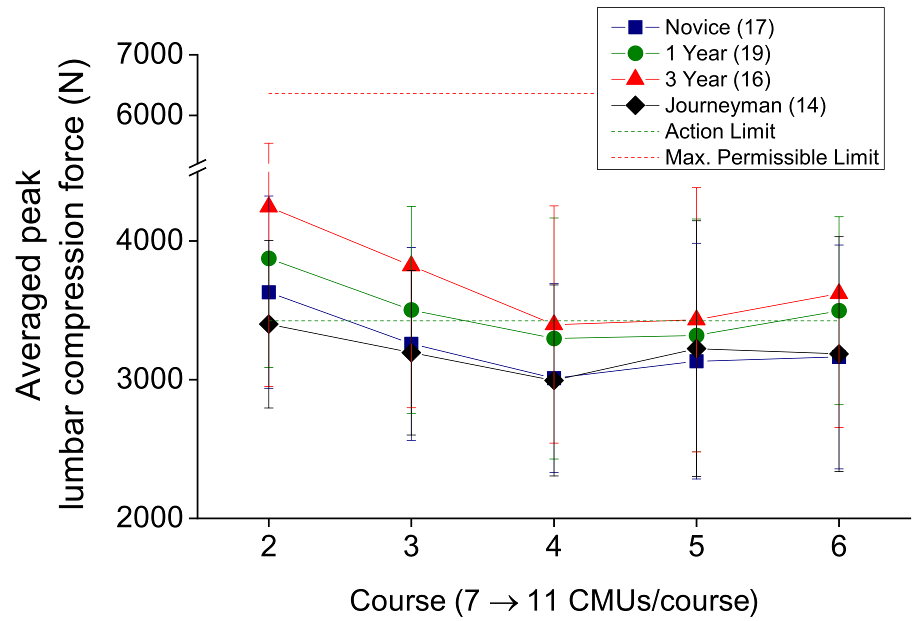

Figure 5-1: Peak lumbar compression force per course averaged by experience level

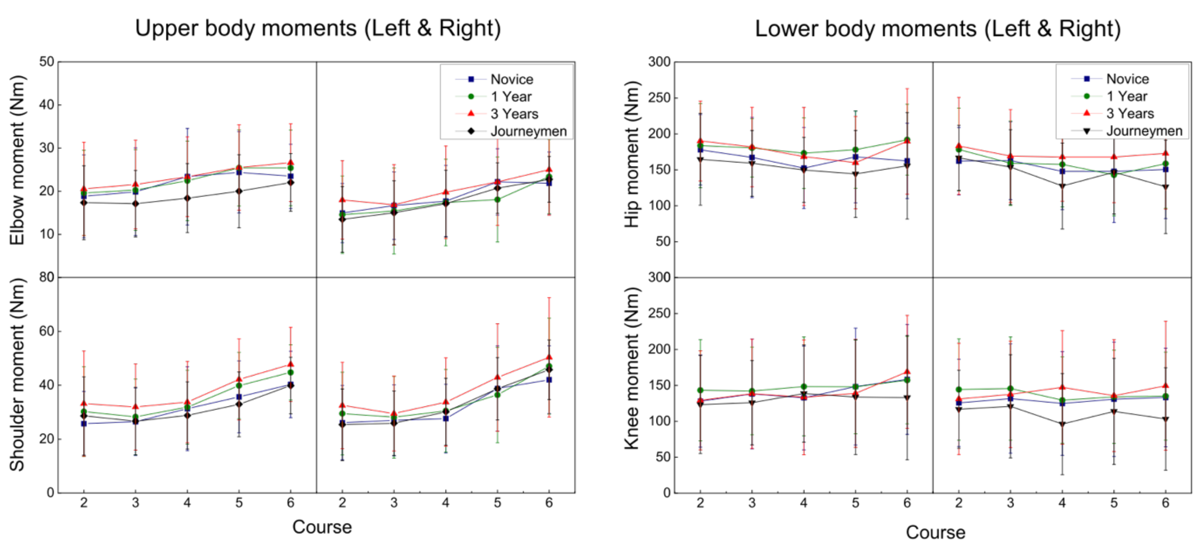

Figure 5-2: Peak joint moment per course averaged by experience level (Left: Upper body, Right: Lower body)

5.2.2 Joint Loads with Lift Types

In the current experiment, it was observed that participants used different lift types to handle CMUs (Figure 5-3). While most of the participants used a two-handed lift (70% of all lifting), 12.4% of all lifting was done one-handed, a method using only one hand from picking up to laying down CMUs. The remainder of the tasks involved mixed lifts, such as picking up a CMU with a one-handed lift and then switching to a two-handed lift at the halfway point of the lift. The same proportion of lift types was observed among experience groups, except for 1-year apprentices.

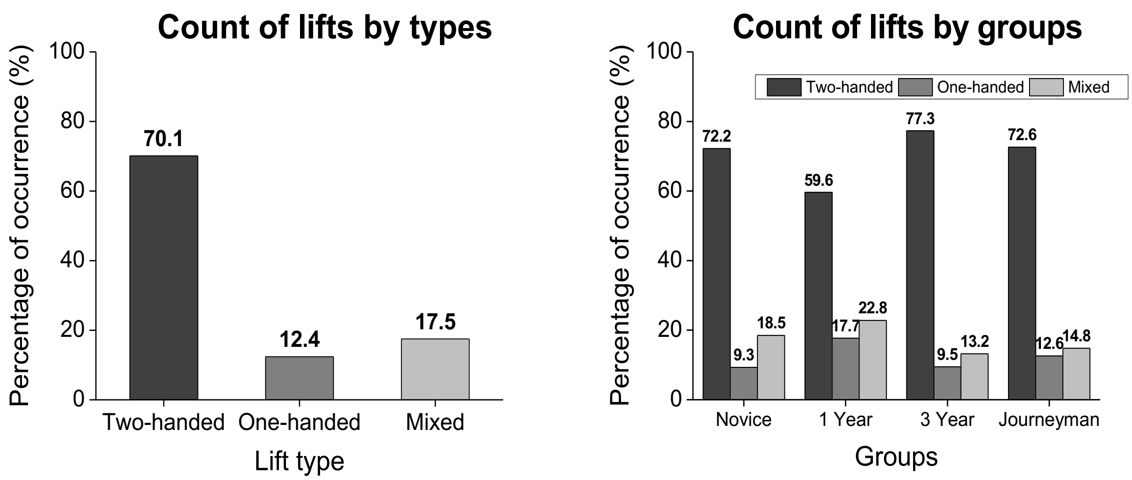

Figure 5-3: Count of lift by types (left) and count of lift type by groups (right)

Figure 5-4 shows the lumbar compression force by lift type for all experience groups. From this result, it is evident that the proportion of novice and apprentice groups experiencing lumbar compression forces above the action limit varies according to their lift type. For example, 3-year apprentices experience lumbar compression force above the action limit when they lift bilateral and mixed lift types. Conversely, the journeymen group consistently achieved lumbar compression forces below the action limit regardless of lift type.

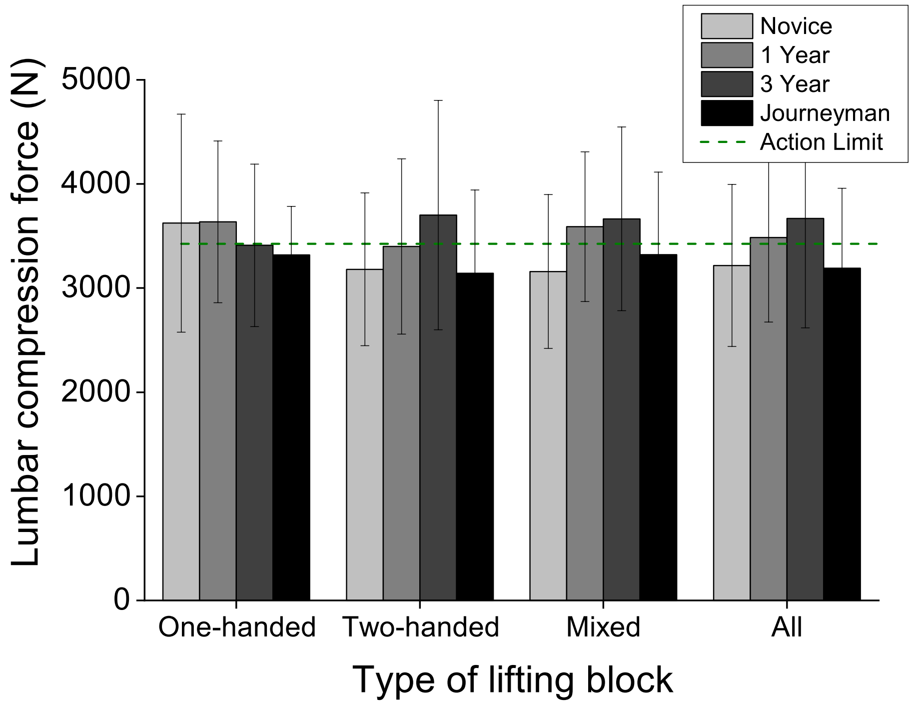

Figure 5-4: Lumbar compression force at L4/L5 level by lift type and experience level

Significant asymmetry occurs to the body when handling a CMU with only one hand. Thus, the joint moments between one- and two-handed lift types were compared. Specifically, considering that the participants have different dominant hands (e.g., right-handed and left-handed), joint moments on the side of the carried block and free-loading sides were examined. Figure 5-5 shows the upper and lower joint moments by lift type and level of experience. While all groups experienced symmetric joint moments on the right and left sides of the body during two-handed lifts, significant asymmetric joint moments were present between the carrying and the non-carrying sides during one-hand lifts.

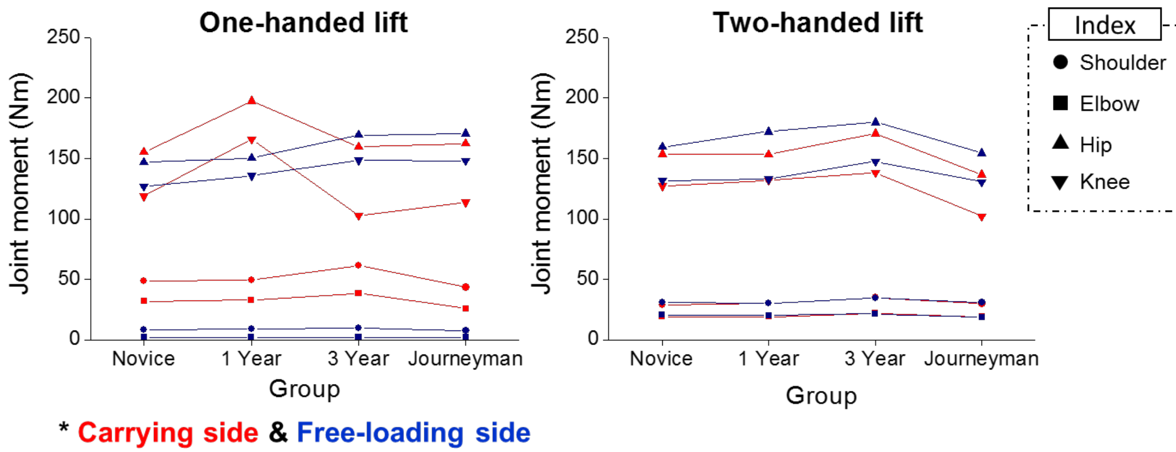

Figure 5-5: Joint moments averaged by level of experience during one-hand lifts (left) and two-hand lifts (right)

5.2.3 Productivity

While each participant placed the same number of CMUs during the controlled experiment, the completion time varied as per their work experience. Specifically, journeymen completed the wall in the shortest time, an average of 28 minutes, while novices, 1-year, and 3-year apprentices completed the wall in an average of 56 minutes, 37 minutes, and 40 minutes, respectively. Similarly, when converting the completion time to the number of CMUs laid per minute, journeymen laid approximately twice as many CMUs as novices (1.63 CMU/min. and 0.83 CMU/min.). These results follow the same trend shown in the initial report by Alwasel et al. (2017a), which was based on a subset of the data in this study. As discussed in their study, expert masons adopted safer working methods while maintaining high efficiency as their work experience increases (Alwasel et al., 2017a, 2017b).

This study also investigated productivity loss that occurred as the experiment progressed. The average time for each experience group to lay a CMU for each course was found from the 2nd to the 6th course. Then, the averages were normalized with respect to the 2nd course average (Figure 5-6). The normalized time taken to lay a CMU for each course indicates changes in pace throughout the task. While novice, 1-year, and 3-years apprentice groups dropped their pace at the end, journeymen maintained an almost constant pace from the 2nd to the 6th course.

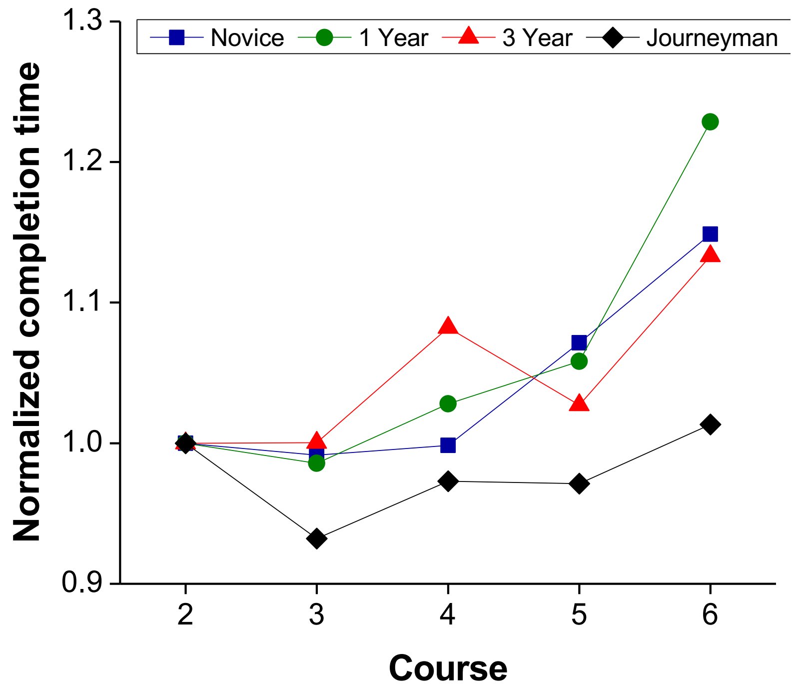

Figure 5-6: Normalized completion time per course for four experience groups.

5.3 DISCUSSION

This study carried out a combined biomechanical-productivity analysis on masons with varying levels of experience. It expands the number of participants from 21 in a previous pilot study (Alwasel et al., 2017a) to 66. Further, it extends the analysis of work methods to investigate the impact of course high and lift type (two-handed versus one-handed) on joint moments and the lumbar compression force. The results of this study show the experienced journeymen with more than twenty years of experience adopt similar work techniques distinct from those of less experienced workers. Specifically, it was found that 3-year apprentices experienced the highest lumbar compression forces, while novices and journeymen experienced lower forces. Furthermore, the journeymen group achieved the highest productivity, in terms of time taken to complete a lead wall, and were twice as fast as the novice group. The study, thus, finds that those work techniques were more productive and safer, suggesting their adoption in apprentice training to reduce the prevalence of occupational injuries and to improve productivity.

To examine the significance of differences between mean peak joint loads among the experience groups, this study carried out a one-way Analysis of Variance (ANOVA) using SPSS (version 21) with the significance level set to 5%. The name of the joint loads, experience groups, mean and standard deviation, the ratio of variability among the groups to the variability within group F, and the p-value are listed in Table 5-1. The analysis confirms that all joint loads of the journeyman group were significantly different than the less experienced groups. In particular, 3-year apprentices experienced significantly higher joint loads than journeymen, for all joints. It was concluded that these results accord with our earlier results, which showed that journeymen have distinguishable work postures causing low joint loads.

Table 5-1: Joint loads averaged by levels of experience, and corresponding one-way ANOVA results

Joint loads	Experience Group	Mean	Std. dev.	F value (p value)	Post Hoc Tests
Lumbar compression force (N)	Novice (a)	3217.61	779.01	47.812 **(0.00*)**	c > a,b,d b > a,d (Dunnett T3)
	1 Year (b)	3485.06	810.00		
	3 Year (c)	3668.19	1050.69		
	Journeyman (d)	3190.98	767.54		
Center of Hip moment (N·m)	Novice (a)	186.49	41.28	31.921 **(0.00*)**	c > a,b,d b > a,d (Dunnett T3)
	1 Year (b)	194.93	38.17		
	3 Year (c)	203.67	52.29		
	Journeyman (d)	182.42	40.80		
Right Elbow (N·m)	Novice (a)	19.04	8.10	13.107 **(0.00*)**	c > a,b,d (Dunnett T3)
	1 Year (b)	17.88	9.99		
	3 Year (c)	20.72	10.44		
	Journeyman (d)	18.34	7.55		
Left Elbow (N·m)	Novice (a)	22.26	9.78	28.787 **(0.00*)**	c > a,d a > d b > d (Dunnett T3)
	1 Year (b)	22.76	9.49		
	3 Year (c)	23.84	10.02		
	Journeyman (d)	19.24	8.05		
Right Shoulder (N·m)	Novice (a)	28.99	13.36	14.406 **(0.00*)**	c > a,b,d (Dunnett T3)
	1 Year (b)	30.20	15.55		
	3 Year (c)	33.89	17.38		
	Journeyman (d)	30.02	12.60		
Left Shoulder (N·m)	Novice (a)	32.60	14.34	26.873 **(0.00*)**	c > a,b,d b > a,d (Dunnett T3)
	1 Year (b)	35.22	14.81		
	3 Year (c)	38.48	16.92		
	Journeyman (d)	31.98	13.20		

Table 5-1: Joint loads averaged by levels of experience, and corresponding one-way ANOVA results (Continued)

Joint loads	Experience Group	Mean	Std. dev.	F value (p value)	Post Hoc Tests
Right Hip (N·m)	Novice (a)	153.44	60.80	25.732 **(0.00*)**	c > a,b,d a > d b > d (Dunnett T3)
	1 Year (b)	158.55	59.88		
	3 Year (c)	171.69	67.46		
	Journeyman (d)	142.40	59.27		
Left Hip (N·m)	Novice (a)	165.01	56.52	30.916 **(0.00*)**	c > a,d b > a,d (Dunnett T3)
	1 Year (b)	181.46	50.76		
	3 Year (c)	177.31	65.53		
	Journeyman (d)	154.02	59.92		
Right Knee (N·m)	Novice (a)	129.51	72.03	24.99 **(0.00*)**	c > a,d a > d b > d (Dunnett T3)
	1 Year (b)	137.45	65.85		
	3 Year (c)	140.83	80.38		
	Journeyman (d)	109.44	69.81		
Left Knee (N·m)	Novice (a)	142.47	75.57	6.084 **(0.00*)**	c > d a > d b > d (Dunnett T3)
	1 Year (b)	148.03	65.26		
	3 Year (c)	143.10	77.33		
	Journeyman (d)	131.52	74.06		

* Significant difference ($p < 0.05$)

Consistent with the literature, this research found that journeymen achieved low joint loads and high productivity compared with less experienced apprentices. A more significant finding is that the joint load-experience relationship keeps following the inverted-U-shaped trend from the pilot study. Higher joint loads in the 1-year and 3-year apprentice groups can be matched with those observed in earlier studies. For example, Frost and Andersen (1999) reported that the prevalence of upper extremity injuries among workers in jobs that require overhead work rose within their first 5 - 8 years on the job, decreased, then rose again after spending more than 25 years on the job. These results indicate that the injuries are cumulative, rather than individualistic or discrete incidents, since they appear as an outbreak after 5 - 8 years on the job. As a result, people who learned to do work safely tend to survive the longest without major injuries.

To investigate the dispersion of the dataset between the pilot study and the current study, we measured the normalized standard deviation for the lumbar joint forces, which is defined as the standard deviation for each group divided by the mean for all participants (Figure 5-7). For all groups, the overall results increased compared to the pilot study. Specifically, novice, 1-year apprentice and journeyman groups increased by 10%, 3%, and 5%, while 3-year apprentice groups showed an increase of 31%. Though the number of participants for each group increased approximately two or three times, the dispersion of the experienced lumbar compression force is similar, except for the 3-year apprentice groups. These findings also indicate that the highest diversity of working methods and motions exist in the 3-year apprentice groups.

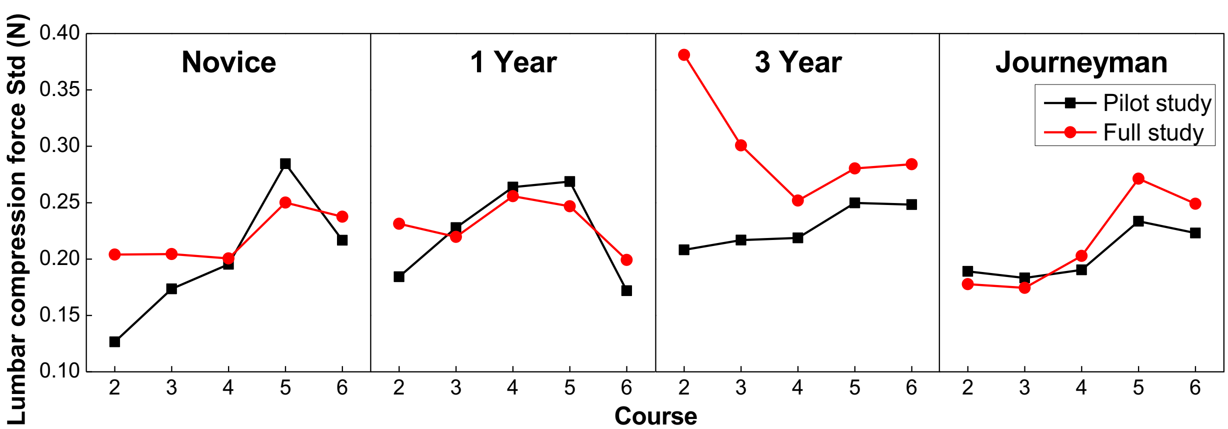

Figure 5-7: Normalized standard deviation of lumbar compression force comparison by courses

The lead wall was configured for the participants who laid CMUs at the 2nd to 6th courses, and participants adopted distinctly different postures to complete each course. Specifically, laying a CMU at the 2nd course required significant back bending (> 90^{o}), resulting in the highest lumbar compression force for all groups. Similarly, all groups experienced the lowest lumbar compression force at the 4th course because, at this course, the CMU pick up and lay down heights were between knee and waist height, approximately 80cm to 120cm, thereby avoiding excessive back bending.

Participants used different lift types, namely two-hand, one-hand, and mixed lifts. The lumbar compression force of the novice and apprentice groups exceeded the action limit during one-handed lifts. The apprentice groups exceeded the action limit during mixed lifts. The 3-year apprentices' lumbar compression force was always above the action limit, whereas the journeymen's lumbar compression force was below the limit regardless of the lift type, as shown in Figure 5-4.

The relationship between lift type and course height were examined (Figure 5-8). It was found that journeymen never use one-handed lifts to place a CMU at the 6th course and used mixed lifts more frequently than other groups. To place a CMU on the 6th course of the wall, participants needed to pick up a CMU near the ground level and lay down the CMU at a height of approximately 120cm. This significant height difference may result in excessive joint stress. Instead, the journeyman group used their momentum to pick up a CMU from the ground level in a one-handed lift and switched to a two-handed lift during the swing phase to increase stability and distribute the load on both sides of the body.

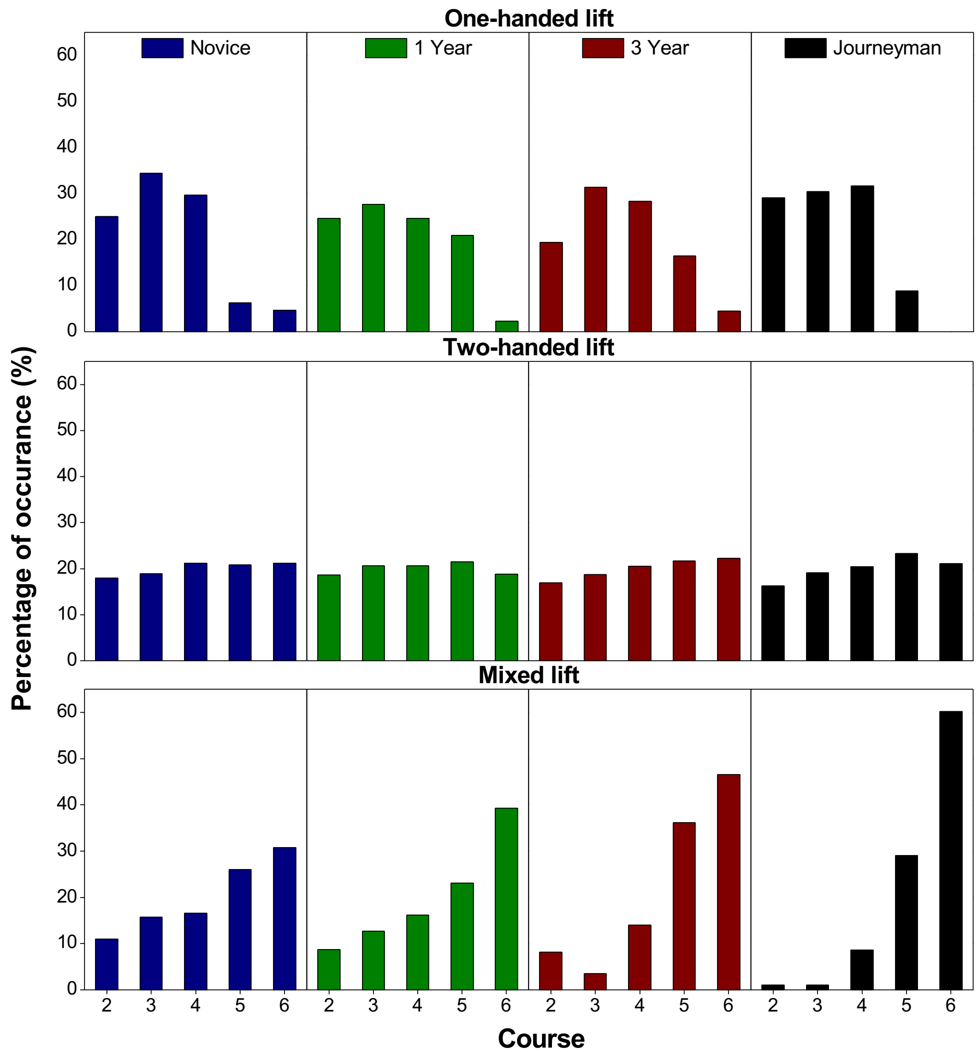

Figure 5-8: Percentage of each lift type by course for all experience groups

The statistical significance of the differences among the anthropometrics (height and weight) of the four experience groups was examined using a one-way ANOVA. A p-value of less than 0.05 was considered significant. The results confirm that there were no significant differences in height or weight among the groups, as the p-values were 0.182 and 0.805, respectively. Therefore, this data confirms that the variation in joint loads experienced by those groups was solely related to their work methods.

Regarding the relationship between productivity and levels of experience, journeymen achieved considerably higher productivity rates than less experienced groups. For example, journeymen had a CMU/min approximately two times higher than novices and were 30% more productive than the mid-experience groups. Further investigation was focused on determining productivity loss by tracking the working pace to complete each course (Figure 5-6). It was found that all novice and apprentice groups decreased their working pace as they progressed through the experiment, while journeymen maintained theirs. The productivity analysis indicated that journeymen adopted working methods that were not only efficient but also minimized the loss of productivity over time. The average completion times for 1-year and 3-year apprentices were similar, but the decline in productivity was greater among 1-year apprentices.

The recent study that utilized a subset of data of the present study examined the physical exertion of the bricklaying process by analyzing jerk values, which measure motor control (Zhang et al., 2019a). Journeymen marked the lowest jerk (the derivative of acceleration), indicating that they moved with smooth motions and a high degree of motor control while 3-year apprentices performed the lift tasks with the highest jerk values, indicating inferior motor control. Given these findings and the results of the biomechanical and productivity analysis in this study together, journeymen adopted working methods that help control their body properly, resulting in not only minimizing physical exertion but also maximizing productivity. Mid-experience groups performed with higher productivity than novices, but their working methods were accompanied by higher joint loads and poor motor control. The previous pilot studies suggested possible explanations to support these findings: 1) mid-experience groups appeared to be in competition with their peers during the experiment; also, 2) they perceived peer-pressure to reach their seniors' productivity level (Alwasel et al., 2017a, 2017b).

As skilled craft workers increasingly exit the workforce as a result of a workplace injury or aging, the recruitment of inadequately trained workers may cause higher injury statistics. Notably, the first baby boomers hit the retirement age in 2011, and industries are thus facing worker shortages in the labor force (Statistics Canada, 2011). Baby boomers, aged between 45 and 54 years of age, were reported to have suffered fewer injuries than their younger counterparts (BLS, 2015). Thus, there is a possibility that there will be an increase in workplace injury as more boomers retire. The findings have indicated that journeymen have more advanced working methods concerning safety and productivity that can help minimize the issues of workplace injury in the construction industry.

5.4 CONCLUSIONS

This study evaluated relationships between body loads, levels of experience, and work methods of masons. The results of this study have shown that the four experience groups adopted different motion patterns resulting in different levels of joint loads while they performed the same tasks. The levels of experience are also closely related to production rates. More specifically, journeymen and novices experienced relatively lower joint loads than 1-year and 3-year apprentice groups. The productivity rate tended to increase with more experience. Furthermore, it was found that the various experience groups adopted different CMU handling methods according to working height, namely one-handed, two-handed, and mixed lifts. Overall, these findings have indicated that journeymen adopt safer and more efficient working methods that are distinct from those of apprentices. The less-experienced groups had either higher joint loads increasing the likelihood of injury, as is the case for 1-year and 3-year apprentices, or lower production rates, as is the case for novices. The present study contributes to the body of knowledge on masons' safety and productivity by providing an in-depth understanding of the linkage between body loads, work experience, techniques, and productivity. Additionally, the findings in this study should inform apprentice-training methods and find application in other trades prone to higher risks of musculoskeletal-disorders.

CHAPTER 6
ERGONOMIC EVALUATION OF EXPERT MASONS WORK TECHNIQUES[5]

6.1 INTRODUCTION

Masons are aided by tools, processes, equipment, and materials, yet they continue to be subject to extreme physical demands. With advances in materials, design, and automation, the overall masonry work system may be redesigned to minimize the bodily harm associated with the industry. While ergonomic interventions have been introduced, masons are still required to perform diverse and hazardous tasks (e.g., placing a block overhead or lifting extremely heavy blocks) at the worksite. Less skilled masons exposed to these activities are at a high risk of injury and involuntary early retirement.

Analysis of the extensive motion data collected on masonry work enable us to understand the ergonomic risks of masonry tasks. In Chapter 5, the relationship between body joint loads, productivity, and work experience of masons was analyzed. It was found that expert masons adopted ergonomically safer and more productive work methods than less experienced masons. In this context, by analyzing expert masons' performance in different masonry tasks, we can identify the experts' knowledge about safer and more productive work methods.

When workers execute manual tasks (e.g. lift materials), they often select qualitatively different movement techniques (e.g. stoop- versus squat lifts) (Park et al. (2005). Alwasel et al. (2017b) proposed classifying working postures of masons into expert and inexpert classes

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[5] A part of this chapter is adapted from **Ryu, J.**, McFarland, T., Haas, C., and Abdel-Rahman, E. (2020) "Automatic Clustering of Proper Working Posture". *27th International Workshop on Intelligent Computing in Engineering*. Berlin, Germany. July 1-3, 2020. http://dx.doi.org/10.14279/depositonce-9977.

by applying machine learning techniques to joint location data. They generated a pose codebook based on a simplified set of six key-joint locations (C7/T1 disc, hip, right and left wrists, and right and left knees) then they identified a set of dominant poses within this codebook using *k*-mean clustering. They achieved the 92.04% of classification accuracy using Support Vector Machine classifier and 50 clusters codebook (k = 50).

These findings suggest that distinctive working postures and motion patterns identified from experts' work-techniques can be proactively used in apprentice training to improve the ergonomics and productivity of masons. Considering that apprenticeship programs mandate includes safety training, employing those work techniques in these programs may prove effective in minimizing safety and health hazard.

This chapter aims to (1) determine whether expert masons' work methods are safe and (2) identify the proper postures workers develop as they gain experience to increase safety. Specifically, this study evaluates joint loads in seven different masonry activities performed by expert masons (journeymen) and report on an automated posture clustering technique that applies a learning algorithm to whole-body motion data.

6.2 ERGONOMIC EVALUATION OF SEVEN MASONRY ACTIVITIES

Eight journeymen with over twenty years of experience were recruited to perform seven common masonry activities at CMDC in Mississauga, Ontario. The average participant was 179.63 ± 4.78 cm in stature and 90.84 ± 12.03 kg in body mass. The participants utilized three sizes of CSA – Type “A” CMUs to complete those activities.

In the first phase of the experiment, individual masons carried out four activities: laying out CMUs to construct (1) a standard wall, (2) a reinforced wall, (3) a wall in a constraint space (under a ceiling), and (4) a lead (first) course, in which the masons utilized 20cm hollow CMUs weighing 16.6 kg with dimensions of 0.19 x 0.19 x 0.39 m in these activities. In the second phase, (5) a wall was constructed by individual masons using heavy (30cm hollow) CMUs weighing 23 kg and measuring 0.29 x 0.19 x 0.39 m. The same task was also completed by two masons collaboratively lifting (6) the same 23 kg CMUs and (7) 30cm semi-solid CMUs weighing 35.2 kg and measuring 0.29 x 0.19 x 0.39 m. In the first four tasks, participants retrieved CMUs from three piles placed approximately one meter away from the lead wall and used mixed mortar provided by helpers in two mortar trays between the piles. In the final three tasks, the CMUs were placed in one pile approximately one meter away from the lead wall with one mortar tray placed next to the pile.

The journeymen completed all tasks over one day. First, each participant completed a standard prebuilt lead wall (activity 1) using 45 standard CMUs, Figure 6-1(a). Upon completion, seven units along the top course were removed by study personnel, and reinforcements were placed in the cells. The reinforcements were extended approximately 800 mm above the 5th course, Figure 6-1(b). Participants laid 2 courses, the 6th and 7th, using 15 CMUs—13 standard and 2 half units— to complete the activity (2). This study, however, focused on the handling of the standard CMUs and excluded analysis of the half units. This configuration represents the maximum height a mason would be required to perform a lift over reinforcement. Following completion, the reinforcements were removed, and a temporary ceiling was placed approximately 625 mm above the top of the 7th course, Figure 6-1(c). Participants laid courses 8 through 10 using 22 units—20 standard and 2 half units— to complete the activity (3). This set-up simulates the final courses of an unreinforced partition wall built up to the ceiling. All blocks being laid were above the shoulder/head height. After the completion of this activity (3), participants carried out the activity (4) by laying 7 standard CMUs to form the first course of a wall, Figure 6-1(d). Between activities, participants had a 15-minute break while helpers modified the configurations for the next activity. After completing the activity (4), the participants had an hour for break time.

Subsequently, the next phase of the experiment commenced with individual participants constructing a wall using 30cm hollow CMUs. The wall contained a steel rods for lead and had the lead course completed beforehand, Figure 6-1(e). Similar to the standard wall, participants laid units from the 2nd to 6th course. Each participant laid 20 of the 30cm hollow CMUs—15 full and 5 half units. Subsequently, participants repeated construction of the same wall with

30cm hollow and 30cm semi-solid CMUs laid collaboratively, in a two-person lift, Figure 6-1(f).

Figure 6-1: Experimental configurations: (a) standard wall; (b) reinforced wall; (c) constraint wall; (d) first course; (e) one-person lift of 23 kg CMUs; and (f) two-person lifts of 23 kg & 35.2 kg CMUS

6.2.1 Results: Standard Weight Blocks

The first four activities employing standard weight CMUs span wall course heights from 1 to 10. Figure 6-2 shows the peak lumbar compression forces at each of these activities and courses, namely first course (F. 1), standard wall (S. 1-6), reinforced wall (R. 6-7), and constraint wall (C. 8-10), averaged over all subjects. The green dashed line represents an action limit (load threshold) of 3433 N (NIOSH, 1981). Expert masons were found to maintain the lumbar compression forces below the action limit, except when they completed the first course where it reaches 3893 N. Further, it was found that the subjects experienced similar or lower compression forces in the higher course reinforced and constraint walls than those of the first course and standard wall.

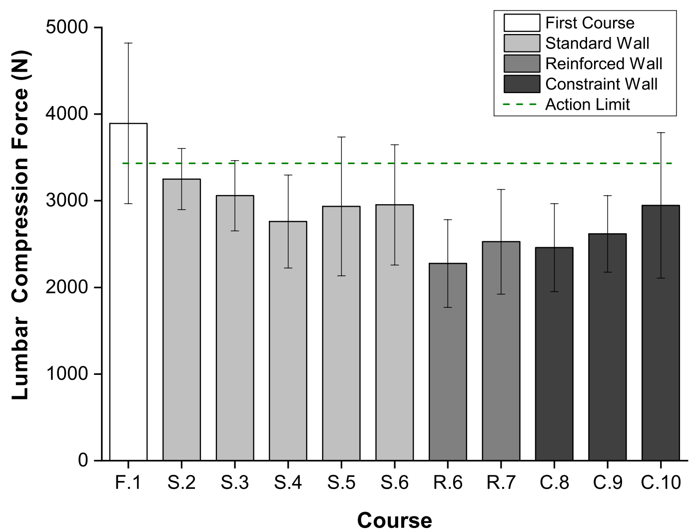

Figure 6-2: Average peak lumbar compression force by activity and course

The average peak of the shoulder, elbow, hip, and knee joint moments for each course are shown in Figure 6-3. Shoulder moments were consistently higher than elbow moments and both of them increased gradually with course level. In contrast to the upper limb joint moments, the lower limb joint (hip and knee) moments remained relatively constant demonstrating no correlation with the activities or course levels except that the hips experience elevated joint moment in the first two courses.

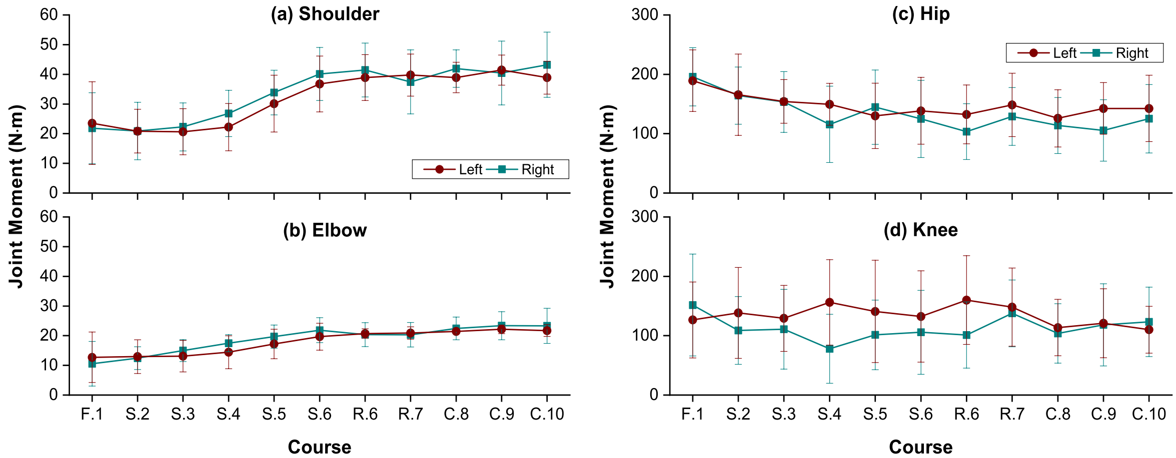

Figure 6-3: Average peak joint moment for the (a) shoulder, (b) elbow, (c) hip, (d) and knee joints

6.2.2 Results: Heavy Weight Blocks

Figure 6-4 shows the average peak lumbar compression force during lay down of courses 2 to 6 of a standard wall while employing individual lifts of 20cm hollow and 30cm hollow CMUs and collaborative (two-person) lifts of 30cm hollow and 30cm semi-solid CMUs. The subjects experienced the highest lumbar compression force (3915.74 N) when they handled individually 30cm hollow CMUs. This was approximately 14% in excess of the action limit. The difference in the lumbar compression force between collaborative lifts of 30cm hollow and semi-solid CMUs was small despite a 50% difference in their weight.

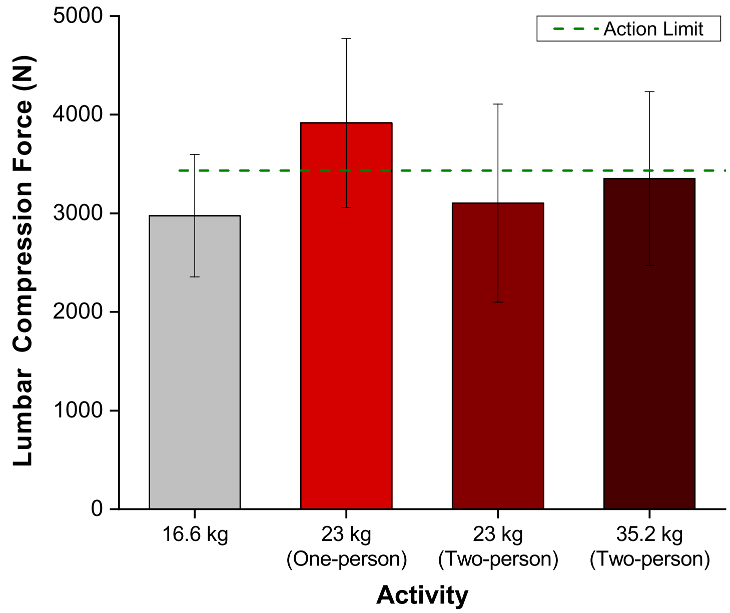

Figure 6-4: Lumbar compression force for by CMU weight

Comparing the peak lumbar compression forces averaged by course, Figure 6-5, shows that lifting heavier CMUs results in higher lumbar compression forces. It also shows that the force variation with course height for individual lifts, both of 20cm and 30cm hollow CMUs, were similar. Likewise, the force variation with course height for the collaborative lifts, both of 30cm hollow and 30cm semi-solid CMUs, were similar. However, individual force variation pattern was different from the collaborative force variation pattern. Moreover, the lumbar compression forces during placement of CMUs at the fourth course were below the action limit across all three CMU weights and similar to that when placing 20cm hollow CMUs at the 2nd course.

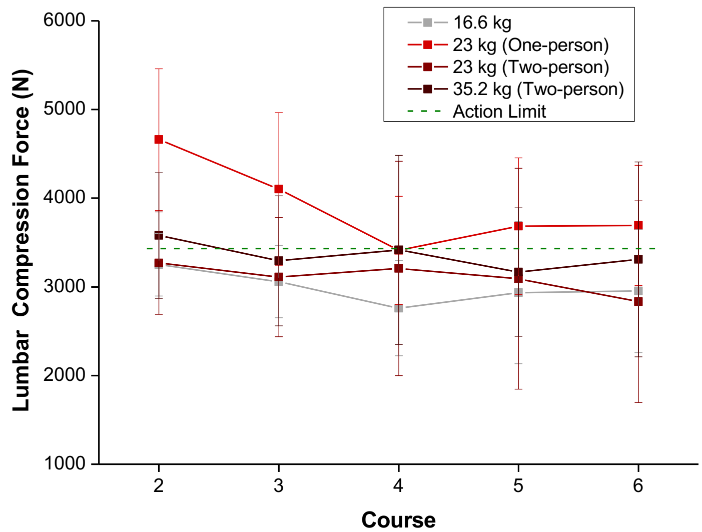

Figure 6-5: Lumbar compression force averaged by CMU type-lift method and course height

The shoulder and elbow joint moments increased with course height, Figure 6-6, in all lift cases irrespective of CMU type or lift method. In contrast, knee and hip joint moments were relatively unaffected by course height. Upper and lower limb joint moments were highest for individual lifts of 30cm hollow CMUs regardless of course height.

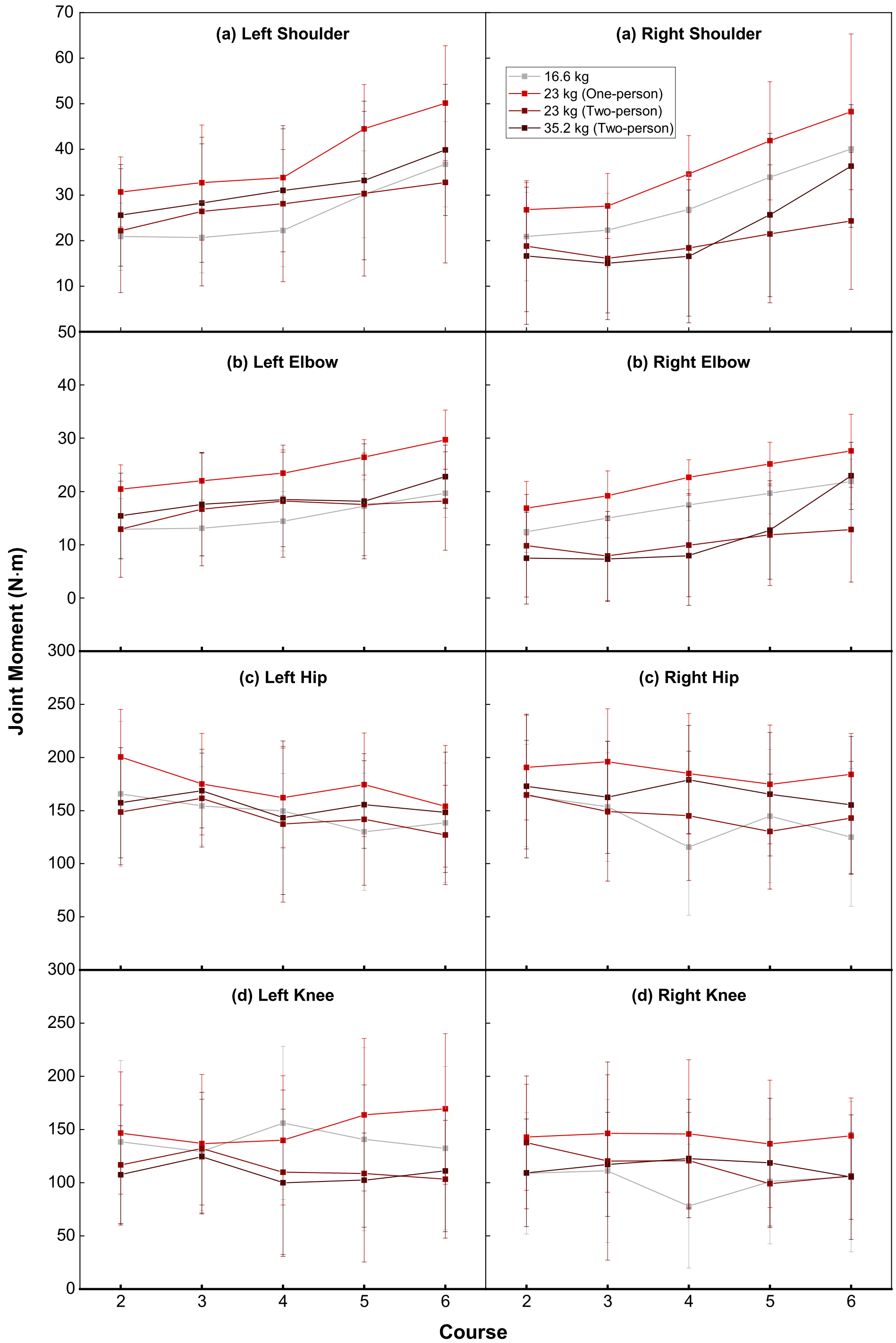

Figure 6-6: Average peak joint moment for the (a) shoulder, (b) elbow, (c) hip, (d) and knee joints during individual and collaborative lifts of three CMU weights

6.3 AUTOMATED PROPER POSTURE CLUSTERING

In this analysis, different lifting postures frequently adopted by experts and apprentices were investigated using *k*-mean clustering. The analysis focused on the 45 CMU lifts required to complete the standard wall (activity 2). Forty-five masons grouped into experts (journeymen) and three apprentice groups (novices with no experience, 1-year and 3-year apprentices), participated in this experiment as described in Chapter 3.

6.3.1 *k*-means Clustering

The *k*-means clustering algorithm was introduced in 1967 by MacQueen (MacQueen, 1967). It is one of the most commonly used clustering algorithms for many practical applications (Aggarwal & Aggarwal, 2012; Jain et al., 1999; Johnson & Wichern, 2002). The algorithm partitions a given set of data into *k* disjointed clusters around the nearest *k* means. The value of *k* is fixed in advance (MacQueen, 1967).

In this study, each CMU lift is composed of a sequence of postures. Since the sampling rate was held constant, the number of those postures is dependent on the duration of the lift only. For example, a CMU lift lasting 4 seconds consists of a sequence of 500 postures (frames). Each posture is represented by a 78-component vector comprising the coordinates of 26 major body joints. The posture dataset was categorized into *k* clusters by minimizing the sum of the squared Euclidian distance between the individual postures represented by the locations of those joints. The initial center points for the clusters were randomly selected and iteratively updated to obtain the final cluster locations (Singh et al., 2013).

Each cluster has a posture centroid represented by a vector of joint centers. Each bin contains the closest, most similar, postures to the centroid posture irrespective of whether they belong to experts and apprentices.

6.3.2 Posture Classification

The clustered postures were classified as distinctive to experts or apprentices by assessing the proportion of expert and apprentice postures present in the population of each bin. Specifically, bins were categorized as:

- 'Expert-dominated' where more than 65% of the postures belonged to journeymen.
- 'Apprentice-dominated' where more than 65% of the postures belonged to apprentice masons.
- Otherwise, the bins were labeled as 'equally represented'. Those clusters indicate postures common to human locomotion and trade.

Furthermore, to enable objective comparison between expert and apprentice-dominated postures, each bin was further labelled according to the lift phase where it appears during a CMU lift, namely pick up, moving, or lay down. These labels allowed us to deduce how different masons perform similar functions. Since most lifts were completed within 3 to 5 seconds, 360 to 600 frames, the first and last 150 frames were defined as pick up and lay down phases, and the frames in between were defined as moving phase.

6.3.3 Results: Automated Proper Posture Clustering

Figure 6-7 shows the clusters obtained for k = 50 and the proportion of expert and apprentice postures in each cluster. Figure 6-8 shows representative postures for each annotation. Each row shows the similar postures among the annotations. Interestingly, expert postures were limited to 10 clusters out of all 50 clusters. In contrast, apprentice postures were present in most clusters. There were 24 apprentice-dominated clusters and 16 equal representation clusters. This finding indicates that expert masons adopt a limited set of simple motions when performing repetitive lift tasks. At the same time, apprentices appear to utilize more complex and varied lift techniques when carrying out the same tasks. Appendix D summarizes the 5 representative postures selected from each category.

Two clusters (5 and 46) were almost exclusively populated by experts and ten clusters (3, 10, 15, 19, 25, 32, 39, 40, 47, and 48) were almost exclusively populated by apprentices. Sixteen cluster histograms had similar proportions of expert and apprentice postures, for example cluster 11 was populated by 48% of expert and 52% of apprentice postures. These results are in accord with our previous conclusion that expert masons adopt a distinctive and simple set of work postures and motion pattern different from those of apprentice masons.

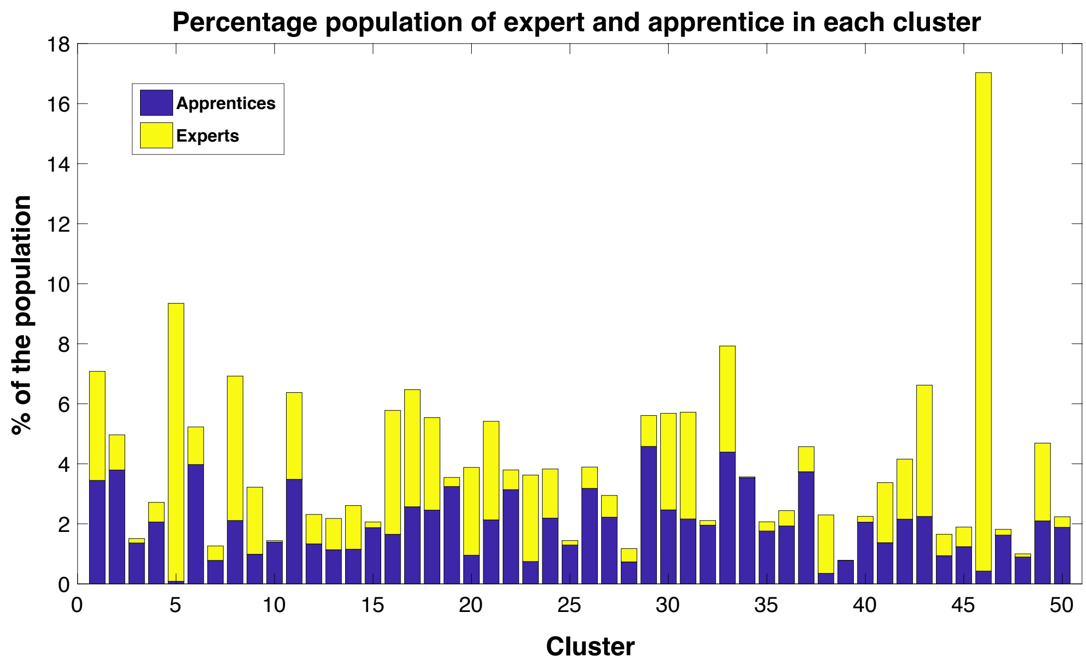

Figure 6-7: Posture clusters obtained from k-means clustering

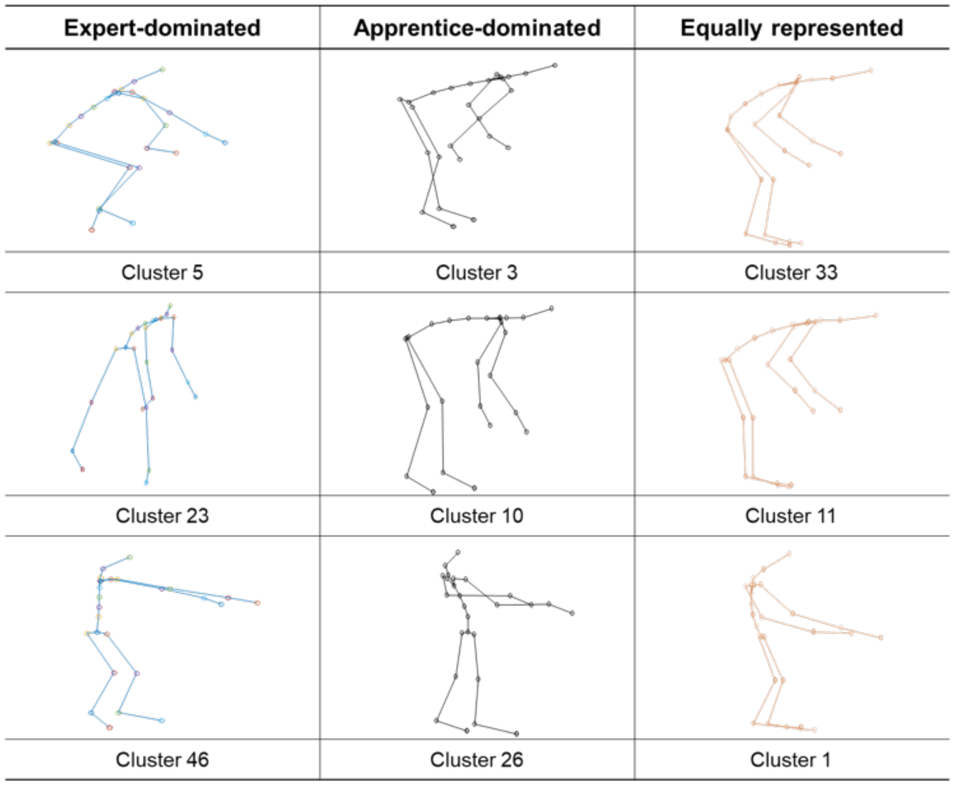

Figure 6-8: Examples of postures representing each annotation

To enable objective comparisons among various postures, this study identified the function associated with each cluster based on the frame numbers of postures in its population. Figure 6-9 compares the centroid postures of an expert-dominated bin (# 8) to that of an apprentice-dominated bin (# 15) belonging to the moving phase. The figure shows two projections of each posture in the sagittal and frontal planes. Comparing the postures in the sagittal plane, it was found that the expert mason positioned the CMU closer to the centre of body mass using smaller back and knee flexion angles. In the frontal plane, it was found that the expert maintained better body symmetry than the apprentice mason.

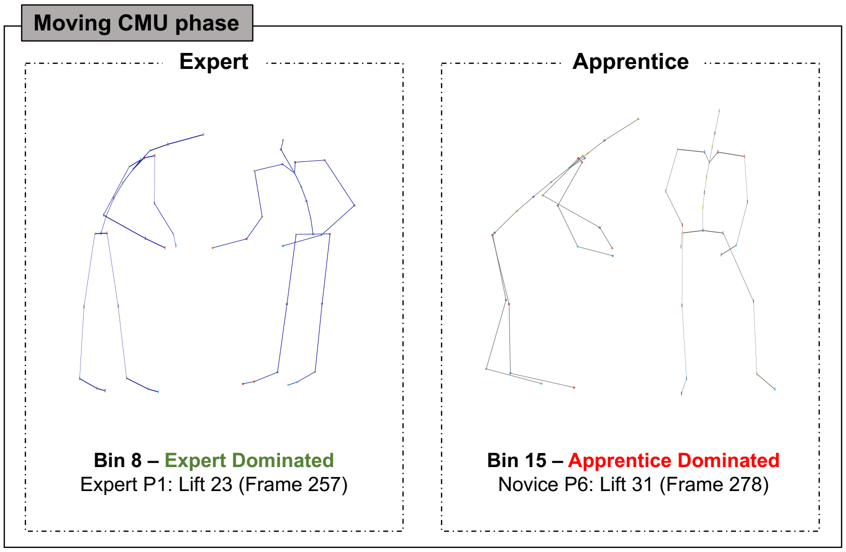

Figure 6-9: Comparison of expert-dominated and apprentice dominated postures during moving the CMU phase

6.4 DISCUSSION AND CONCLUSIONS

Masons are at a high risk of WMSDs and premature retirement due to a lifetime of repetitive bodily strain, heavy lifting, and awkward postures. By analyzing the expert performance, in terms of body kinematics and biomechanical force levels, during various masonry activities, we can formulate guidance for the training of a safer and more productive generation of masons. Furthermore, identifying working postures adopted by experts can provide insight into the factors underlying safer work methods.

To achieve these goals, this study first carried out biomechanical analysis of eight expert masons during seven masonry activities using three types of CMUs. The study found that the most critical body joints were in the lower back and upper limbs (shoulders and elbows). Strain to these joints specifically may lead to lower back pain and other injuries requiring days away from work or, in severe cases, leading to retirement (Adams 2004).

The critical joints were dependent on the activity. In standard wall tasks, lumbar compression forces were more critical than upper limb joint moments. Assuming safer postures, where masons maintain a straight back and hold the CMU closer to body center, these forces remained with the safe (action) limit regardless of course height. In reinforced and constraint walls, the shoulder joins were at a higher risk than the lower back. In these activities, masons must raise CMUs above their shoulders or over their heads. Maintaining a straight back in these activities does not protect the shoulder and elbow joints from absorbing the awkward lift strain. Lower limb joints (hips and knees), however, do not appear exposed to risk during these activities. The experience similar loads regardless of activity or course height. This is reflected by near-constant joint moments between activities and courses, except for individual lifts of 30cm hollow CMUs where they experienced elevated joint moments. Further analysis reveals a constant increase in shoulder moments when heavyweight CMUs (23 kg and 35.2 kg) were lifted individually as well as collaboratively.

The weight of a 30cm hollow CMU (23 kg) is equal to the Recommended Weight Limit for a one-person lift established by NIOSH (Waters et al., 1993). However, the average peak lumbar compression forces for individual lifts of 30cm hollow CMUs was 15 % higher than NIOSH action limit which poses increased risks of lower back pain (Waters et al., 1993). On the other hand, the lumbar compression forces resulting from individual lifts of 20cm hollow CMUs (16.6 kg) were below the action limit for all course heights.

Individual lifts of 20cm hollow and 30cm hollow CMUs generated the highest and lowest back compression forces during the completion of the 2nd and 4th courses, respectively. The height of the 2nd course is 40cm. Placement of CMUs at this height required excessive back bending, resulting in significant lumbar compression forces regardless of the CMU weight. On the other hand, the height of the 4th course is approximately 80cm, which corresponds to the waist level for a 50% male. Participants maintained a straight back posture while slightly bending their knees when placing CMUs at the fourth course. This posture enabled them to hold even the heavy 30cm hollow CMUs close to the center of the body. As a result, participants experienced the lowest lumbar compression force at the 4th course. In fact, the lumbar compression force during individual laying of 30cm hollow CMUs at the 4th course (3411 N) was below the action limit and similar to the force during laying of 20cm hollow CMU at the 2nd course (3298 N).

The lumbar compression force trends for collaborative (two-person) lifts of 30cm hollow and semi-solid CMUs (23kg and 35.2kg) were similar to each other but dissimilar to those of individual lifts. This is expected since body loads are function of body posture and the relative position of the CMU with respect to the body. Specifically, in individual lifts participants maintained a symmetric posture with respect to the unit. In contrast, in collaborative lifts participants frequently showed asymmetric body postures.

Finally, expert masons used different CMU handling techniques as summarized by the percentages shown in Table 6-1. Single-handed lifts were primarily used in the first course of a standard wall as they lifted unit from the top of a pile and laid them at the bottom of the wall. They were also employed during two-person lifts at all course heights. Expert masons opted for two-handed or mixed lifts in higher courses completed individually (including reinforced and constraint walls). It is noted that an investigation of the body loads caused by asymmetric lifts (e.g., single-handed and mixed lifts) is not included in this chapter but should be investigated in future studies.

Table 6-1: CMU handling techniques

	Usage (%)		
Activity	Single-handed Lift	Double-handed Lift	Mixed Lift
First Course	64.81	27.78	7.41
Standard Wall	8.36	70.47	21.17
Reinforced Wall	0.00	58.91	41.09
Constraint Wall	0.00	83.67	16.33
Individual lift (23kg)	0.00	78.33	21.67
Collaborative lift (23 kg)	64.71	25.00	10.29
Collaborative lift (35.2 kg)	56.20	35.54	8.26

This chapter also introduced an automated posture clustering method proposed to identify proper working postures that workers develop as they gain experience. This method utilizes whole-body motion data and the *k*-means clustering algorithm. The motion data was collected from forty-five masons with different experience levels while they carried out an indoor masonry task, namely completing a lead wall using 20cm hollow CMUs.

The results show that the proposed method can automatically cluster the most frequent working postures among two experience groups: expert and apprentice. Expert-dominated and apprentice-dominated postures were determined by evaluating the population belonging to the two groups in each cluster. Identifying the lift phase where each cluster appears, based on the frame numbers of the postures it contains, enabled objective comparison among clusters corresponding to the same function. This is a significant advantage over manual observation work assessment, commonly used at worksites, where it is almost impossible to accurately obtain and compare postures occurring during continuous body motion. Furthermore, visualization of the clustered postures allows for an intuitive understanding of the differences between ‘good’ and ‘bad’ postures undertaken to carry out the same function. A sample of training literature, a Safe Posture poster, was developed based on comparison of the expert-dominated and apprentice-dominated frequent postures (Appendix E). The poster was delivered to the research partner (CMDC) for use in training.

The methods and results proposed in this chapter provide important insights into expert masons' distinctive work techniques through ergonomic evaluation of various masonry tasks and automated clustering of working postures. In particular, these findings suggest a configuration of optimized working height to minimize musculoskeletal stress. Although 30cm hollow CMU is 40% more in weight and volume than standard CMUs, they result in joint loads similar to standard CMUs when placed individually at the 4th course height (waist). Therefore, it is proposed that the optimal working height for tasks involving CMU handling is at the waist level. In summation, identification of proper postures adopted by experts has clear potential to serve as a straightforward method to provide apprentice workers with training techniques and training materials.

CHAPTER 7
A METHODOLOGY TO EVALUATE THE IMPACT OF SEMI-AUTOMATED WORK SYSTEMS IN CONSTRUCTION[6]

7.1 INTRODUCTION

Despite being one of the oldest industries, the level of automation and robotics in the construction industry has only begun to advance in the past few decades, lagging behind other industries such as automotive and manufacturing (Balaguer & Abderrahim, 2008; Bock, 2015; Hasegawa, 2006). Furthermore, continuous changes in construction sites demand manual intervention by laborers, which is a concern due to the high number of injuries and WMSDs associated with the trades (Everett & Slocum, 1994). Therefore, flexibility of semi-automated work system, where operators work in conjunction with machines and robots, is an attractive alternative.

In this chapter, semi-automated work systems are defined as an equipment which automates a component of a task and is designed to be used in conjunction with manual laborers to complete the task, with a focus on force-assist systems. This study targets the implementation and integration of semi-automated systems with traditional working processes. Previous methodologies have been proposed to assess the value of integrating new work systems into traditional systems in a construction context. Those methodologies focused on either project-level evaluation of full automation (Paulson Jr, 1985; Slocum, 1986) or were limited to worker productivity (Grau et al., 2009; Zhai et al., 2009). This work proposes a

[6] This chapter is adapted from **Ryu, J.**, McFarland, T., Banting, B., Haas, C., and Abdel-Rahman, E. (2020) "Health and Productivity Impact of Semi-Automated Work Systems in Construction". *Automation in Construction*. 120, 103396. https://doi.org/10.1016/j.autcon.2020.103396.

systematic and objective methodology to assess the value of semi-automated work systems in a construction context, where value is assessed in terms of both reduction in risk exposure to MSDs and improvements in productivity. A broader and more complete assessment of value prior to implementing such a system would also include analysis of: (1) net present value, (2) safety impact, (3) morale impact, (4) quality effects, (5) competitiveness impacts, and (6) process changers required. Validation of this methodology is demonstrated through an experimental evaluation of a force-assist self-leveling pallet in a masonry task.

7.2 METHODOLOGY

The flowchart of the methodology to evaluate semi-automated work systems is outlined in Figure 7-1. The general steps of the methodology involve the following components: the identification of at-risk tasks within the job; a quantitative assessment of biomechanical demands and productivity; a proposal of semi-automated work systems and their integration into current work processes; experimental evaluation of the proposed equipment; and a final implementation decision and plan. Expanding the system boundaries of this type of evaluation is possible by carefully aggregating the basic health and productivity elements of the methodology in a way that accounts for all tasks and activities within the bounded system. An early perspective on this was published by Skibniewski (1988).

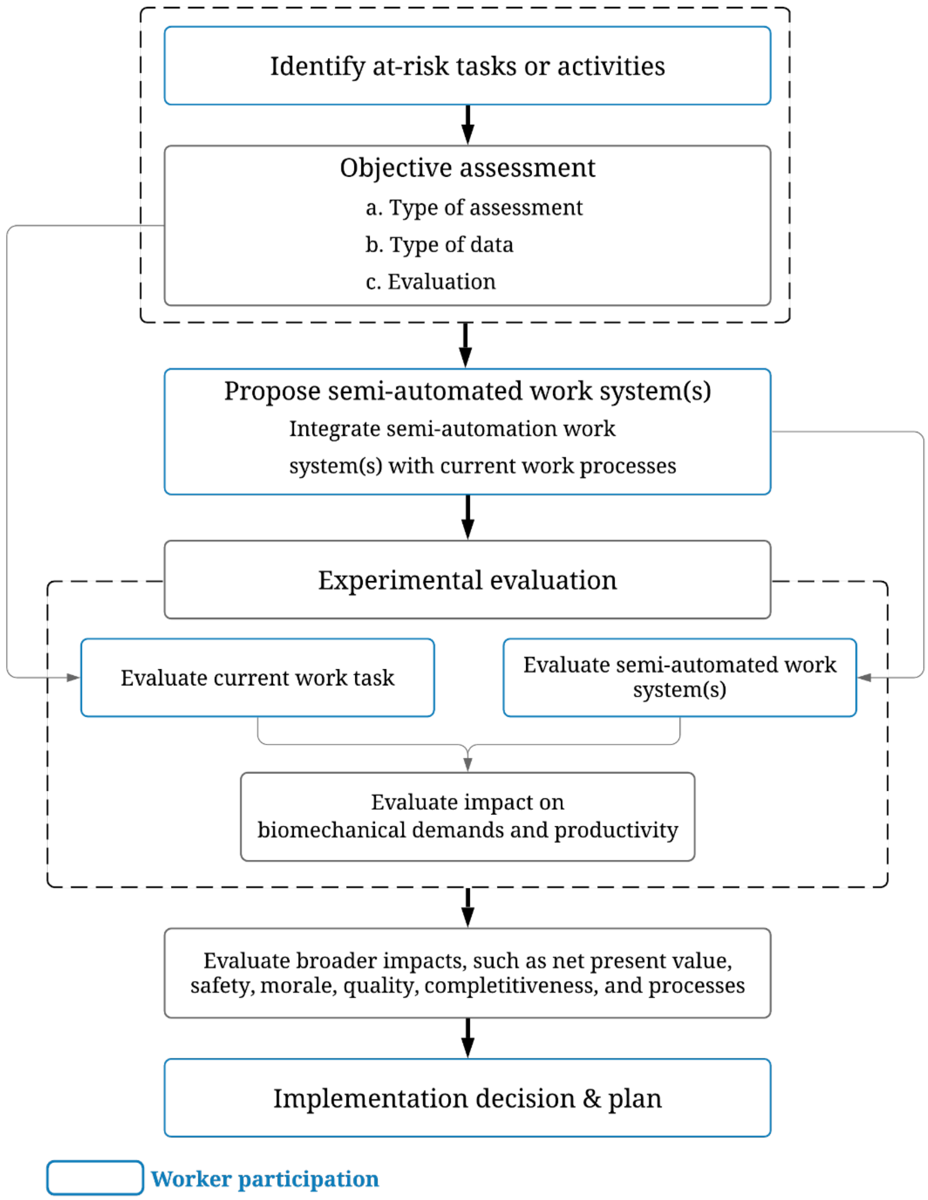

Figure 7-1: Flowchart of methodology to evaluate semi-automated work systems

7.2.1 Identify At-Risk Tasks or Activities

The first step is to identify which tasks should be prioritized for the introduction of automation in the workplace. The presence of risk factors such as force, repetition, duration, awkward posture, contact stress or vibration, can point to at-risk tasks (Kumar, 2001; Wang et al., 2015). Furthermore, reported occupational injury data (e.g., the incidence rate of nonfatal occupational injury and illness cases reported by the U.S. Bureau of Labor Statistics) may indicate high-risk areas for MSDs. Lastly, critical bottlenecks that affect productivity are also areas where automation can be introduced. Production bottlenecks may be caused by undesirable ergonomic standpoints (Dempsey, 2007), therefore, the introduction of automation has the potential to mitigate the adverse effects that impact health and productivity concurrently.

7.2.2 Objective Assessments

The current biomechanical demands and productivity of the chosen task need to be assessed to: (1) determine the parts of each task which may pose a hazard, and (2) provide valuable baseline data for later comparative analysis (Step 4: Experimental evaluation). Quantitative measurements enable the creation of objective benchmarks by which variables of critical importance to management are established and the performance of the semi-automated work system is evaluated.

7.2.2.1 Types of Assessment

To evaluate biomechanical exposures in the field of construction, practitioners and researchers have developed different assessment methods and tools. The approaches can be divided into four groups according to the data measurement techniques: self-reports, observational assessments, direct measurements (Li & Buckle, 1999), and simulation-based methods. In addition, due to several benefits—such as low-cost and its ease of use—both self-reports (e.g., checklists and diaries) and observational assessments (e.g., direct observation through ergonomic experts) are widely used in most worksites (David, 2005). However, self-reports can be subjective and unreliable (Plantard et al., 2015) while observational assessments can be prone to inaccuracies and inconsistencies due to human error and missing information (Valero et al., 2016).

Simulation-based methods can also be used to evaluate task demands such as joint loads and internal forces without directly measuring a worker. In simulation-based methods, a digital human model can be incorporated into a virtually reconstructed environment to estimate the biomechanical loads that an operator might face during a prescribed task (Golabchi et al., 2015; Jayaram et al., 2006). This is useful for evaluating the potential impacts of workplace redesign without the costs and time for changing the physical environment. However, the accuracy of the simulation can vary according to the accuracy of inputs and the assumptions made by the model. Furthermore, humans have large variability in movement decisions and simulations cannot always accurately predict the way an individual may move in a complex environment or task (Reed et al., 2006). An example of this is showcased in a study carried out by Alwasel et al. (2017a, 2017b), in which they found that expert masons moved in significantly different ways than apprentice masons while performing the same task (e.g., building a concrete masonry block wall). Consequently, experienced masons suffer fewer joint loads and injury risks than the apprentices as they have fewer wasted motions, which also leads to higher productivity than apprentice masons (Alwasel et al., 2017b). Therefore, direct measurements may facilitate the capture of more detailed and nuanced information with respect to the real scenario, whereas a simulation may disregard these crucial elements.

7.2.2.2 Types of Data

The quantification of injury risk is a complex challenge due to the many factors which influence injury, such as individual traits (e.g., genetics, morphology, and psychosocial factors), biomechanical risk factors (e.g., force, repetition, duration, and posture), and the integration of these factors acting on the tissues of the body (Kumar, 2001). Since individual risk factors will vary between workers, the best estimate of occupational demands stems from analysis of biomechanical exposures, namely force, posture and time (i.e. repetition or duration). While repetition and external loads can be easily measured, internal demands (e.g. joint forces or muscle contractions) and postures are harder to quantify without the appropriate tools. Injury rates are typically easier to track and have a direct relationship with worker compensation. However, they are less useful for collecting data on the immediate impact of the intervention, raise research ethics issues, and may not be sensitive enough to evaluate smaller task changes.

They are, therefore, not recommended for this methodology. Expected quantitative data collection and analysis is preferable. Quantitative data collection methods include the direct measurement of forces, body motions (kinematic data), and muscle activity.

7.2.2.3 Evaluation

Quantitative and objective evaluation is required to assess the value of a semi-automation work system(s) into the current process. Biomechanical analysis can be an effective solution, because it estimates a quantitative load on the body segments (e.g., inertial forces and moments) using a 2D or a 3D biomechanical model (Radwin et al., 2001). Furthermore, several loading thresholds exist to evaluate the risk of MSDs, such as the action limit for lower back compression force defined by the NIOSH (Waters et al., 1993). In terms of productivity, the best measure of productivity will vary by construction discipline and be unique to both the job site and its management values. Nevertheless, quantitative productivity measures will often take the form of either completion rates (labor productivity) or task completion times, since this information can be included in broader analysis of the business value proposition represented by substituting a semi-automated work system for a manual system.

7.2.3 Propose Semi-Automated Work System

After the initial assessment and evaluation of the at-risk tasks, stakeholders should propose potential semi-automated work systems to reduce or eliminate the risk factors identified in the previous steps. Low-impact and cost-effective solutions should be prioritized. Once a potential intervention(s) has been selected it will be necessary to determine the optimal integration method into the current work processes. To achieve this, work layout, procedures, and steps should be considered.

7.2.4 Experimental Evaluation

During this portion of the methodology, the original work task should be re-evaluated with the semi-automated work system integrated into the work process. Except for the activity that has been replaced by the introduction of the semi-automatic system, all processes should be under the same condition as the original work tasks. Then, the same biomechanical and productivity analysis performed at the baseline should be repeated and compared to evaluate the impact of the intervention.

7.2.5 Implementation Design and Plan

The value and effectiveness of the semi-automated work system(s) should be determined and compared against alternative solutions based on the impact of biomechanical demands and productivity. Management should make a final decision on whether the system fits their needs and budget, among other factors. Skibniewski (1988) suggested that the final implementation decision for the employment of robotics in construction should be based upon the consideration of a wide number of elements such as the type of future projects and location, labor costs, availability and projections, market volume estimations, tax advantages, and other preferences to determine the desirability of the robot (Skibniewski, 1988).

Where management decides not to implement the work system, alternative solutions should be explored, and the process can be repeated from Step 3: Propose semi-automation work system(s) until an acceptable solution has been found. Once management decides to move forward with a solution, a comprehensive implementation plan should be formulated. The implementation plan should be specific and systematic and include the following components: policy changes (where applicable), maintenance guidelines, appropriate training of both management and workers, effective communication and knowledge dissemination, adequate time and resources, and management support and commitment (van Eerd et al., 2010; Yazdani & Wells, 2018)

Worker participation is implicated in Step 1: Identify at-risk tasks or activities; Step 3: Propose semi-automated work systems; Step 4.1: Evaluate semi-automated work systems; and Step 5: Implementation decision & plan of the proposed methodology. A systematic review of participatory ergonomic (PE) interventions, in which worker participation is involved heavily in the evaluation, problem-solving and decision-making process of ergonomic improvements, found partial to moderate evidence that PE interventions were successful in reducing MSD symptoms, injuries, compensation claims and lost work days (Rivilis et al., 2008; van Eerd et al., 2010). Worker participation and feedback are also noted by several studies as critical in increasing the effectiveness of MSD interventions (Hess et al., 2004; Selby, 1992; Yazdani & Wells, 2018). Worker feedback provides an important insight into the practical implementation of the proposed work system through its usability and compatibility with current work processes, which will influence the adoption of the work system by workers and its consequent successfulness.

7.3 VALIDATION OF THE METHODOLOGY

To experimentally validate the proposed methodology, masonry tasks and biomechanical analysis were selected as the methods for the identification of at-risk tasks and quantitative assessment respectively. The study protocols were approved by the Research Ethics Committee at the University of Waterloo. In this case, a self-leveling pallet was used both for force assistance and improved positioning while building a standard wall out of 20cm CMUs.

7.3.1 Propose Semi-Automated Work System

Masons spend up to 53% of their working time in a bending posture to pick and place materials at ground or knee levels (Boschman et al., 2012). In Chapters 5 and 6, it was found that picking up and laying down CMUs at heights between 80cm and 120cm was optimal, avoiding excessive back bending and resulting in the lowest lumbar compression force. Therefore, to reduce lifting demands on the operator, particularly to avoid picking up CMUs at or below knee level, while building a standard wall, a self-leveling pallet was proposed as an intervention. The self-leveling pallet is an automatic load leveler that uses a mechanical spring system to adjust its height based on the weight of the materials placed on the pallet, allowing the pick-up height of the CMUs to remain at waist height as the number of CMUs, and consequently the weight of the load, decreases.

In this study, the self-leveling pallet—manufactured by Southworth Products Corp. (Southworth, Portland, USA)—had a 2041.17 kg (4500 lb.) load capacity with a rotating platform measuring 1.11 m in diameter (Figure 7-2). The self-levelling pallet had a fully automatic, spring-actuated mechanism calibrated to a height range between 29.5cm (fully loaded) and 70.5cm (unloaded). As safety features, it also includes bellow skirting, which wraps around the entire unit to keep the area under the pallet free of debris, and a sold disc cover on top. The goal of this equipment was to reduce the height and reach distance while unloading CMUs from the pallet, thereby reducing the arm movement and movement of the lower back as well as reducing wasted motions during lifting to reduce task completion time.

Figure 7-2: Self-leveling pallet utilized in the experiment (Southworth, Portland, USA)

7.3.2 Experimental Evaluation

7.3.2.1 Evaluate Semi-Automated Work System

A controlled experiment was conducted to objectively evaluate the performance of the proposed semi-automated work system. Thirteen healthy male masons (aged 26.4 ± 6 years, stature 181.0 ± 4.7 cm, total body mass 88.5 ± 12.1 kg) were recruited from the Ontario Masonry Training Centre (Mississauga, Ontario). Ten of the participants were apprentices with 1 year of masonry experience, while three of the participants were apprentices with 3 years of masonry experience.

7.3.2.1.1 Protocol

The study was comprised of control wall sessions and self-levelling pallet sessions. Participants took part in one session per day. In day one, they were randomly assigned to either the control wall session or the self-leveling pallet session. In day two, they completed whichever session they had not yet completed. This randomization was meant to minimize the impact of a learning curve on the results. Each participant was instructed to complete a pre-built lead wall, which is described in the Chapter 3, Research Methods.

During the control wall construction session, the materials were arranged to simulate a typical job site set up (Figure 7-3, left). In the self-leveling pallet construction session, the CMUs were placed on a self-leveling pallet approximately one meter from the lead wall and the two mortar boards were placed beside the self-leveling pallet (Figure 7-3, right). During the self-leveling pallet construction session, CMUs were stacked on the self-leveling pallet in stacks of 3 layers of 16 CMUs each.

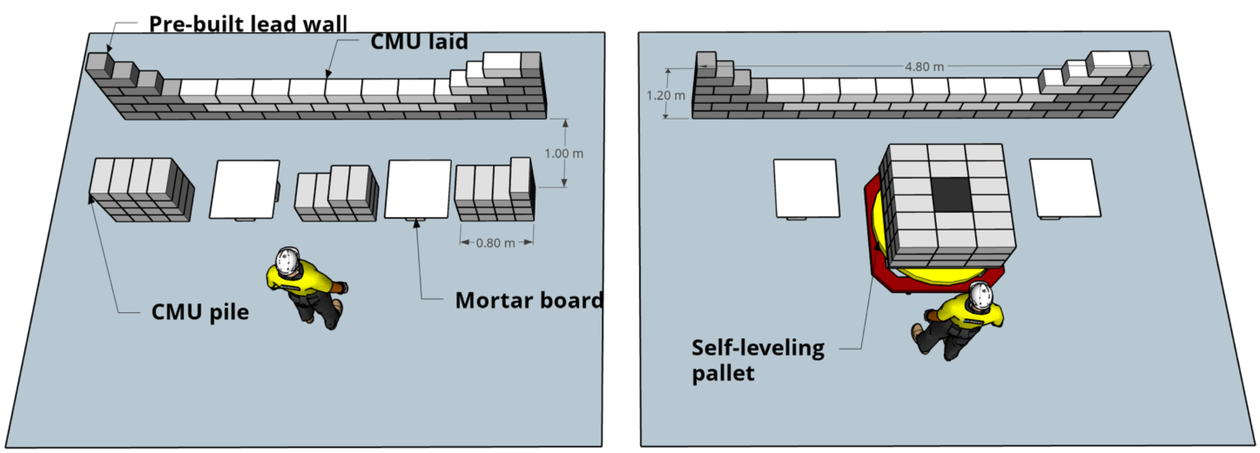

Figure 7-3: Layout of the experimental setup: conventional workspace (left) and semi-automated workspace (right)

The initial CMU pick-up height in the control wall construction session was 76 cm for each pile, Figure 7-4 (a). Participants picked up CMUs at lower levels as they proceeded with the experiment to a minimum of 19 cm for the bottom layer. In the self-leveling pallet construction session, pick-up heights for each layer moved between 105 cm, 97 cm, and 90 cm in sequence, which were shown in Figure 7-4 (b), (c), and (d).

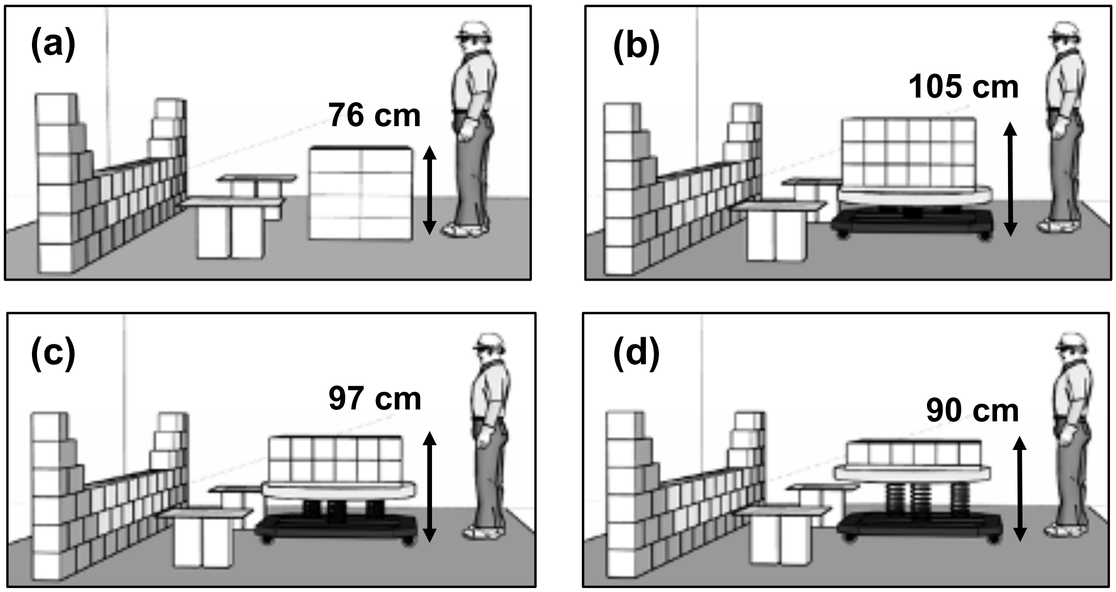

Figure 7-4: Pick-up height of the CMUs (a) resting on a pile on the floor, (b) on top of the self-leveling pallet stacked 3 blocks, (c) 2 blocks, (d) and 1 block high

7.3.2.2 Evaluate Impact on Biomechanical Demand

Peak lumbar compression force at the L4/L5 disc level was the primary focus in this study due to the direct representation of the physical demands on the back. In this section, peak lumbar compression force was compared during the 1) lifting and 2) pick-up phase.

Figure 7-5 shows the average peak lumbar compression force, at pick-up and during the lift, for all 13 participants. While using the self-leveling pallet, the overall average peak lumbar compression force was reduced by approximately 20% during the lifting phase, and 40% at pick-up. NIOSH defines the action limit (3433 N) as the threshold below which 99% of male workers and 75% of female workers have the strength capability to perform the task with nominal risk (NIOSH, 1981; Waters et al., 1993). While completing the task manually (without the self-leveling pallet), participants were exposed to lumbar compression forces close to the action limit during lifting. However, significantly lower lumbar compression forces were found when using the self-leveling pallet both during lifting and at pick-up. Notably, participants were only exposed to lumbar compression forces that were ~50% of the action limit during the pick-up phase with the self-levelling pallet. It was determined that the differences in lumbar compression forces between the two work conditions were significant by conducting an independent sample t-test ($p < 0.05$).

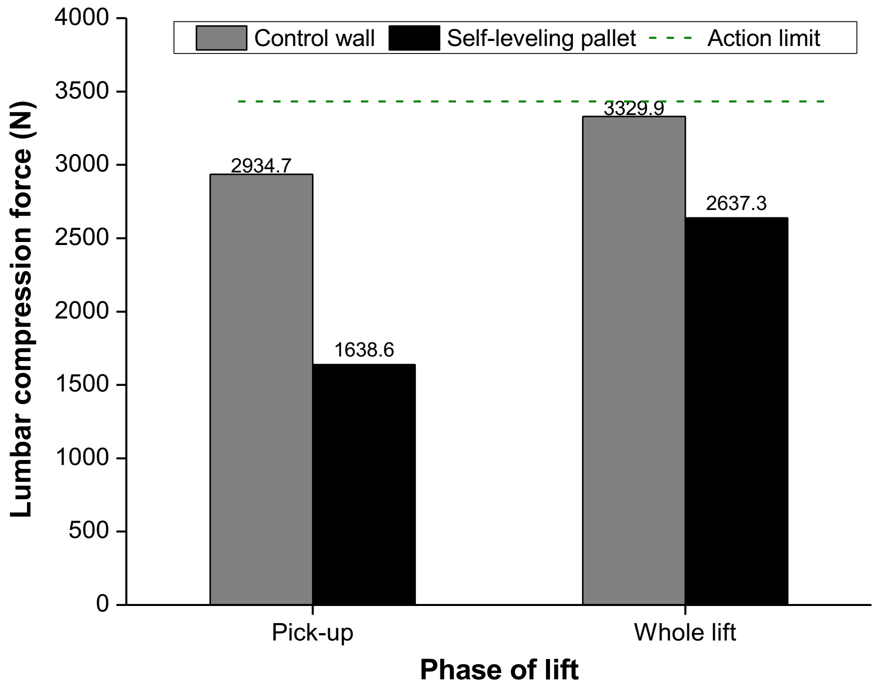

Figure 7-5: Peak lumbar compression force (N) during lifting and at pick-up with and without the self-leveling pallet

To complete the pre-built lead wall, participants laid CMUs from the 2nd to the 6th course; therefore, their working postures varied according to course height. Specifically, participants bent their back significantly more to place a CMU at the 2nd course than they did to place it at the 6th course. Figure 7-6 shows the peak lumbar compression forces during the lifting phase by course height. Due to significant differences in trunk flexion according to course height, participants experienced the highest lumber compression at the 2nd course for both conditions (with and without the self-levelling pallet). However, lumbar compression forces decreased with progressive course heights for participants while using the self-leveling pallet. Particularly, the peak lumbar compression force at the sixth course is 37.9% lower compared to forces experienced at the 2nd course and 38.5% lower compared to the control wall at the sixth course.

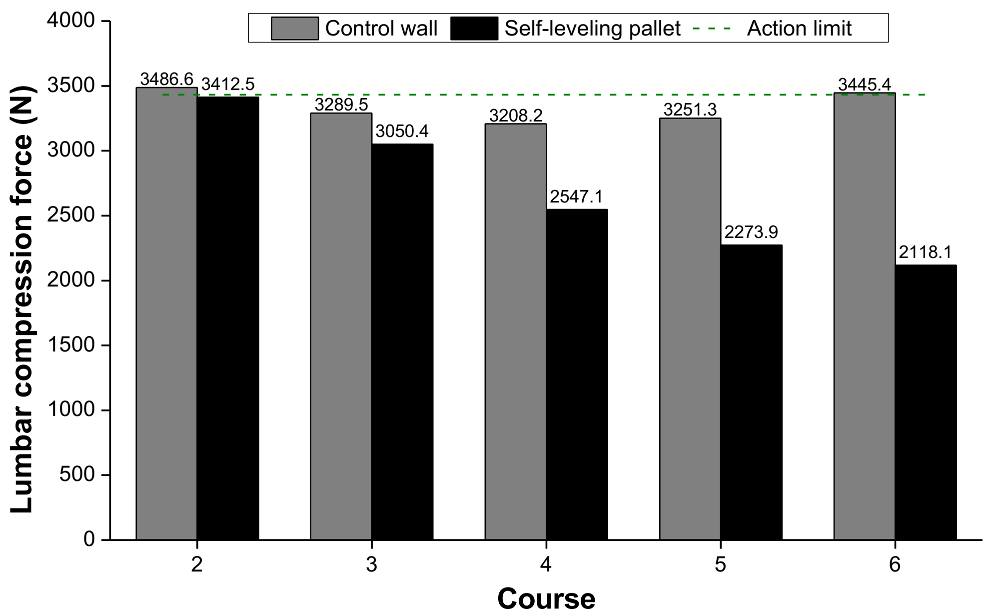

Figure 7-6: Averaged peak lumbar compression force (N) during whole lift for the control wall and the self-leveling pallet by course

The difference in lumbar load due to the presence or absence of the self-leveling pallet was most significant during the CMU pick-up phase of the “lift”. Figure 7-7 compares lumbar compression forces by course at pick-up only. In the control wall construction session, the CMUs were picked up from a decreasing height as participants removed CMUs from the stacked piles to complete the wall. As a result, the lumbar compression force increased as they worked on higher courses. On the contrary, with the use of the self-levelling pallet, participants were able to maintain similar CMU pick-up height regardless of the course of the wall, so their lumbar loads remained consistent throughout.

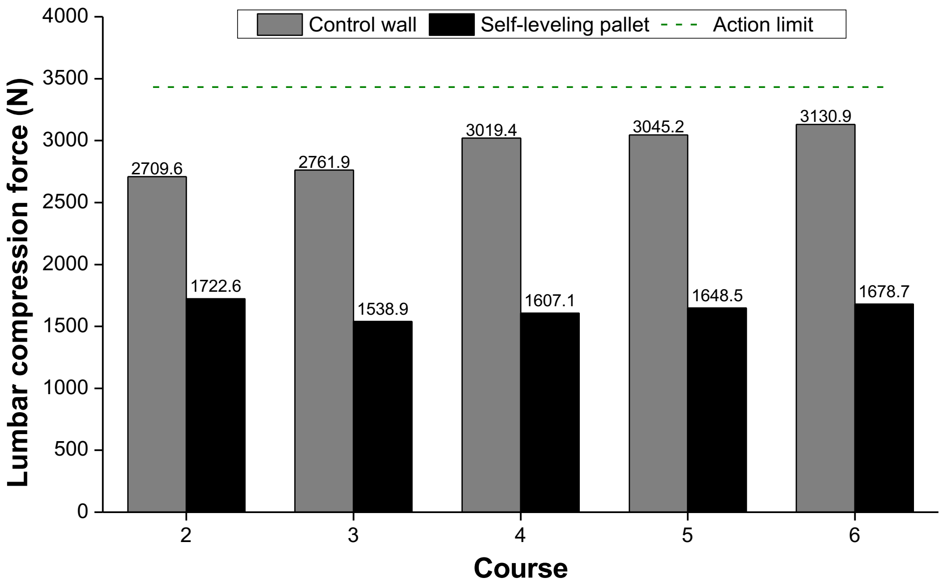

Figure 7-7: Averaged peak lumbar compression force (N) during pick-up phase for the control wall and the self-leveling pallet wall by course

Significant posture variations were observed during the pick-up phase of the CMUs. Figure 7-8 shows the postural differences when a participant picked up a CMU manually (left) and with the self-leveling pallet (right). To examine significant differences of postures occurring between the use and non-use of the self-leveling pallet, an independent sample t-test was conducted. Mean body joint angle (trunk, right and left shoulder, right and left knee), its standard deviation, t and p values are listed in Table 7-1 ($p < 0.05$). Significant differences were found for all five joint angles between the use and non-use of the self-leveling pallet. Both mean and standard devotion of all five joint angles were lower when using the self-leveling pallet than when using traditional methods. One interesting finding is that the mean and standard deviation of trunk angle without using the self-leveling pallet were approximately seven- and ten times larger than the angles using a pallet, respectively. These results indicated that participants can create safer posture patterns at the pick-up phase with the self-leveling pallet.

Figure 7-8: Postural differences: picking up a CMU manually (left) and with the self-leveling pallet (right)

Table 7-1: Mean and standard deviation of joint angles in the sagittal plane at pick-up with and without the self-levelling pallet (significant p-values denoted in bold)

Joint	Group	Mean	Std. Dev.	t-value	p-value
Trunk	Control wall	54.35	41.75	25.22	**0.00***
	Self-leveling pallet	8.06	4.92		
Right Shoulder	Control wall	59.14	36.91	15.38	**0.00***
	Self-leveling pallet	23.69	36.58		
Left Shoulder	Control wall	53.58	25.06	19.31	**0.00***
	Self-leveling pallet	24.21	23.38		
Right Knee	Control wall	26.15	12.90	16.08	**0.00***
	Self-leveling pallet	14.90	9.24		
Left Knee	Control wall	28.43	12.95	12.35	**0.00***
	Self-leveling pallet	19.19	10.88		

* Significant difference ($p < 0.05$)

7.3.2.3 Evaluation Impact on Productivity

In both experimental sessions, participants completed the lead walls with the same number of CMUs. On average, the completion time with the self-leveling pallet was 10% faster than without the pallet. Specifically, eleven out of thirteen participants completed the self-leveling pallet construction session at a similar duration or faster than the control wall. Since the self-leveling pallet directly affected a participant's CMU lifts rather than other actions, such as spreading mortar, it was compared the time to complete a lift in both conditions. With the self-leveling pallet, participants were able to complete lift motion approximately 22% faster than the original work condition (Figure 7-9). The result indicates that participants moved CMUs with concise motions and paths resulting in shorter completion times.

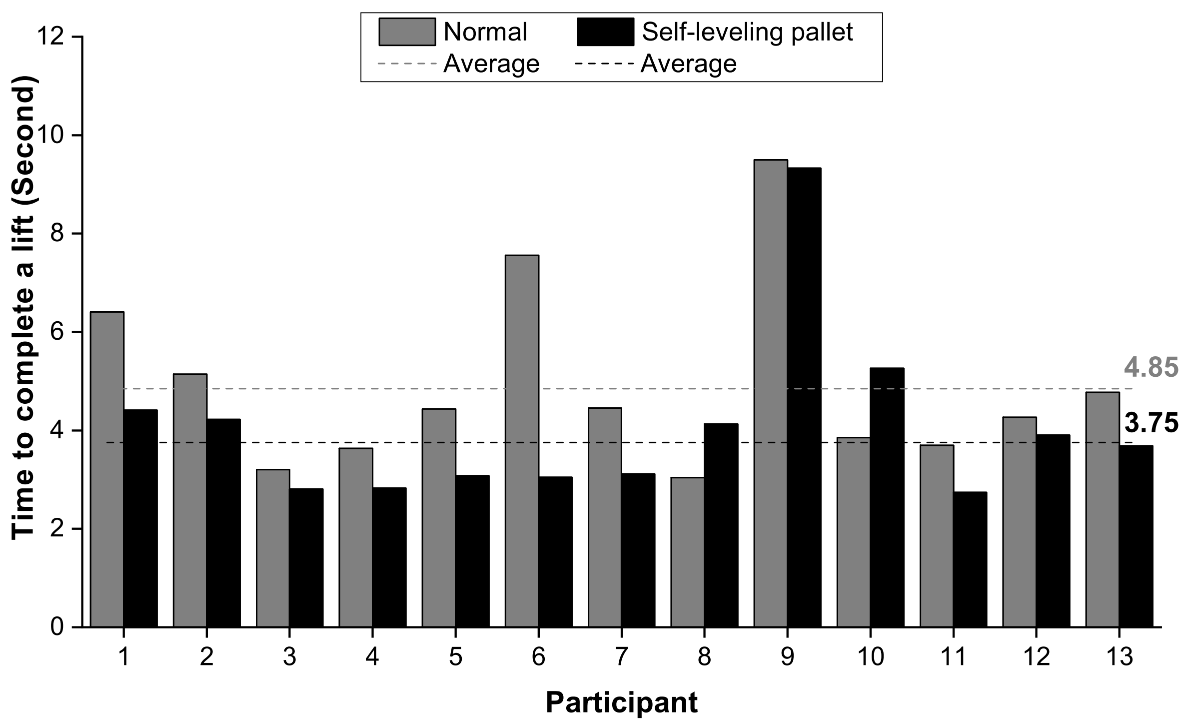

Figure 7-9: Average time to complete a CMU lift by participant

7.3.3 Implementation Decision & Plan

The results of the comparative evaluations show that the self-leveling pallet has great value and effectiveness in terms of reducing biomechanical demands and increasing labor productivity. Specifically, the intervention eliminated excessive back bending postures when masons picked up a CMU, resulting in significantly reduced lumbar compression forces over course heights and significant overall average load reductions. Moreover, the self-leveling pallet helped participants to accelerate their work process (10% increased overall productivity and 22% faster lift completion time) safely.

Due to the cost-driven nature of the industry, demonstration of the economic value of the work system is critical for management consideration. For the cost-justification of ergonomic intervention, the potential impact on injury risks must be considered with regard to costs and productivity measures. For example, the National Safety Council reported that the average total incurred medical costs per injuries to the lower back for the years 2016-2017 was $17,583 (National Safety Council, 2017). In addition to the medical expenses, indirect costs (e.g., time loss on the day of injuries and reduced output of replacement employee(s)) can also be incurred, estimated at four times the direct cost in the U.S. (MacLeod, 1994). Connecting with the current study, the self-leveling pallet effectively reduced risk factors related to lower back injuries (i.e., excessive back bending). Furthermore, productivity increased. As a result, significant financial benefits, can be expected from the implementation of the semi-automated work system. The data from the comparative analysis can be used to evaluate the expenses associated with the intervention (e.g. training, maintenance, purchase costs etc.) with cost-savings from increased productivity, reduction in injuries, workers' compensation, turnover and training costs to estimate the payback period and help support the case for adoption of the semi-automated work system (Oxenburgh, 1997). Factors identified in the introduction would also need to be considered in the overall business value proposition.

According to the participant's feedback, mortar boards should be placed at a height similar to the self-leveling pallet. Due to the lower height of the mortar boards than the pallet, participants had to slightly bend their back to get mortar on their trowel and apply it to the CMU. In addition, while the control workstation had three CMU piles, the semi-automated work system had only one self-leveling pallet in the center of the workstation, so the participants were required to follow a longer path to place CMUs at the end of each course of the lead wall. Replacement with a wider rotating cover-top of the self-leveling pallet or placement of additional pallets could be a complementary addition. Therefore, a final implementation decision and plan should consider this feedback.

7.4 DISCUSSION AND CONCLUSIONS

This study presented a methodology to evaluate the impact of semi-automated work systems on health and productivity in the construction industry. The proposed methodology integrates wearable motion capture suits and analytical tools in the assessment of masonry tasks. The methodology was implemented to assess the use of a self-leveling pallet in masonry tasks. Thirteen participants completed a standard wall using 45 CMUs under two conditions: traditional and semi-automated workstations. Biomechanical and productivity analyses were carried out to assess and compare the participants' lumbar compression forces and productivity in each experimental condition.

The current study has shown that the proposed methodology provided an objective evaluation of semi-automation showing a 40% reduction in lumbar compression force and 22% increase in lift motion speed. Labor productivity was improved by 10%. Therefore, it offered a quantitative evaluation of the semi-automated work system's contribution to reducing exposure to MSD risk factors associated with lower back injuries and increasing CMU pickup speed. This evaluation process also provides much of the quantitative basis necessary to carry out an objective cost-benefit analysis to estimate the potential financial benefits of ergonomic interventions (Goggins et al., 2008; Oxenburgh, 1997).

The adoption of full automation in construction is an active area of research. Particularly, in masonry, bricklaying robots, SAM 100 (Construction Robotics) and In-situ-Fabricator (Giftthaler et al., 2017), are currently being introduced. Such masonry automation promises improvements of masons' health and productivity by taking over physically demanding and repetitive tasks. Full automation is still challenging in many situations because of limitations such as intrinsic dynamic changes in worksites, the need for continued worker interventions, and regulations. Therefore, until construction sites are fully automated, collaboration among robots, machines and workers is inevitable. As such, semi-automation is a feasible alternative for the foreseeable future. In fact, a recent surge in the popularity of exoskeletons has introduced this technology to the construction industry, such as robotic exoskeletons (FRACO) designed to augment masons' physical capabilities. As the popularity of these systems grow and they are adopted onto worksites, management increasingly needs resources to systematically evaluate their impact on health and productivity. Consequently, the methods proposed in this study play an important role in bridging the gap between traditional and fully automated work systems.

The proposed methodology can also be integrated into broader continuous improvement frameworks within organizations, such as MSD prevention programs, occupational health and safety frameworks and integrated management systems, which follow a common framework for continuous improvement e.g. Deming's Plan-Do-Check-Act cycle (Deming, 1951, 1986; Moen & Norman, 2006; Yazdani et al., 2015). This allows the evaluation process to integrate seamlessly into previously established internal organizational tools. The compatibility of this methodology with existing processes increases its value and applicability as a pathway for management to undertake health risk reduction activities while promoting a continuous improvement model for MSD prevention and productivity enhancement.

The proposed methodology emphasizes the importance of evaluating not only productivity increments incurred from the implementation of a semi-automated work system, but also the impact on workers' physical exposures as an equally important component. Often, ergonomic principles are neglected in workplace design or the planning phase of new projects, such as the installation of semi-automated work systems, due to a lack of consideration or a deficit in knowledge (Broberg, 2007; Jensen, 2002; Skepper et al., 2000). The introduction of robotics and automation into a workplace may introduce new risks, if human factors and ergonomics principles are not integrated in the design, work processes, and operation and maintenance requirements (Helander, 1990). This methodology presents a proactive approach to the evaluation of both health and productivity of semi-automated work systems, which fill this deficit.

CHAPTER 8
CONCLUSIONS

8.1 SUMMARY AND CONTRIBUTIONS

This research effort started with an overarching goal to identify opportunities for human-centric advanced work systems that can

1) objectively and simultaneously evaluate ergonomic risk levels and productivity in construction tasks involving heavy material handling,
2) effectively identify safe and productive working postures and techniques that workers develop as they gain experience, and
3) evaluate the impact of new, semi-automated work systems on health and productivity in a construction context.

Considering this goal, the principal findings of this research effort can be summarized in the context of the four specific objectives outlined in Chapter 1:

Objective 1: Investigate comprehensive methods for WMSD assessment that can objectively evaluate risk levels in construction tasks involving heavy material handling. Chapter 4 investigated the applicability of three rule-based assessment system (RULA, REBA, and OWAS) to a bricklaying task. An automated assessment tool to implement those systems on whole-body motion datasets consisting of static postures. Using this tool, risk levels encountered by 43 masons during laying of 16.6 kg standard CMUs in a wall were assessed. Biomechanical analysis of the same datasets was carried out and utilized as ground truth to evaluate their results. It was found that rule-based assessments may lead to erroneously inflated risk scores in heavy manual handling tasks. In contrast, biomechanical analysis provided sensitive risk evaluations able to distinguish the different degrees of risk arising from different motion patterns while participants performed the same tasks. These findings suggest using automated biomechanical analysis as an objective and robust method to evaluate risks encountered in tasks involving heavy material handling.

Objective 2: Analyze the relationship between body loads, experience, and work methods. Chapter 5 carried out a combined biomechanical-productivity analysis to determine the loads experienced by major body joints. Exploiting the motion datasets of 66 masons with various work experiences, this study assessed how different experience groups load their joints and adjust their work techniques as the work height changes. The results show that experienced journeymen with more than 20 years of experience adopt similar work techniques distinct from those of less experienced workers. Specifically, those work techniques were more productive and safer, suggesting their adoption in apprentice training to reduce the prevalence of occupational injuries and to improve productivity. This study contributes to the body of knowledge on masons' safety and productivity by providing an in-depth understanding of the linkage between body loads, work experience, techniques, and productivity. Additionally, the findings of this study are expected to have a greater impact when they are adopted to apprentice-training methods and applied to other trades exposed to high musculoskeletal-disorders-risks.

Objective 3: Identify the proper working postures and techniques that workers develop as they gain experience to increase safety and productivity. Chapter 6 investigated the expert masons' work methods in carrying out seven masonry activities to determine the associated risks. Further, the study identified proper working postures adopted by experts using a joint location-based clustering algorithm. The results provided insights into expert masons' distinctive work techniques through ergonomic evaluation for various masonry tasks and automated clustering of working postures. Particularly, it was found that an optimized work configuration (working height for picking up and laying down material) can minimize musculoskeletal risk. Specifically, it was found that the optimal working height for CMU handling is at the waist level. Furthermore, automatic proper posture clustering provides significant advantages over manual observation work assessment. It also provides an intuitive understanding of the differences between ‘good’ and ‘bad’ postures undertaken to carry out similar block handling tasks. These findings would open the door not only to redesign masonry work systems for a safer generation of masons but also to provide apprentice-level workers with easy-to-understand training materials.

Objective 4: Develop a systematic and objective methodology to assess the value of semi-automated work systems in a construction context. Chapter 7 proposed a systematic and objective methodology to assess the value of a semi-automated work system in a construction context, as it pertains to reduced exposure to musculoskeletal disorder risks and productivity improvements. The flexibility semi-automated work systems offer is attractive. However, it is critical to estimate the anticipated effectiveness of these interventions before integrating them into current work processes. The proposed methodology was validated through an experimental evaluation of a force-assist self-leveling pallet in a masonry task. It provides an objective evaluation of impact on the task showing 40% reduction in joint loads and 10% increase in productivity. The methodology emphasized the importance of simultaneous evaluation of the semi-automated work system’s impact on workers' physical exposure and productivity. Additional assessments are also suggested for a complete analysis of efficacy.

8.2 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Motion data-driven work assessment systems will help tradesmen work better, faster, and safer. This will have direct impacts not only on maintaining health and improving workers' well-being but also on preventing WMSD risk factors and enhancing productivity. However, many methodological and technical challenges remain which still warrant further attention in future research efforts. Certain limitations of this research are discussed, particularly in the context of directions for future research.

1. **Task Type:** The scope of this study was limited to the investigation of ergonomic risk levels and productivity for masonry tasks that involve lifting of CMUs. Although these tasks are integral to masonry work, other types of masonry tasks were excluded from this study, could also negatively affect masons in terms of health and productivity, e.g.,

mixing and spreading of mortar, handling of bricks etc. Future studies should assess the ergonomic risks of these tasks. Moreover, given that ergonomic risks are commonly encountered in other construction activities and other trades, the research methods introduced in this thesis have the potential to expand their scope to other construction subsectors (e.g., concrete, carpentry, plumbing, and roofing) as well as other industries (e.g., manufacturing and automation).

2. **Task Duration:** In this study, risk evaluation was conducted on the most critical postures because the peak joint load is closely correlated to musculoskeletal injuries (Village et al., 2005; Norman et al, 1998). However, other studies have found that it was necessary to consider cumulative joint loads where critical loads were maintained over extended periods of time (Norman et al, 1998; Kumar 1990, 2001). Therefore, further research should investigate the cumulative joint loads in assessing risk levels for tasks where critical loads are maintained over several seconds or more.

3. **Static Analysis:** This research only considered static postures in assessing risk levels. Specifically, static biomechanical loads were evaluated using 3DSSPP. It did not account for inertial forces caused by accelerations of body segments and CMUs. Dynamic biomechanical analysis, which accounts for those inertial forces, can draw out additional loads imposed by the motion patterns of a given task. Further studies applying dynamic estimates of joint loads could help to enhance the understanding of how movements affect joint loads, better account for the load thresholds (e.g., action limit and maximum permissible limits defined by NIOSH), and study energy expenditure patterns.

4. **Training System:** Traditional apprenticeship programs do not provide sufficient feedback on postures and motions to inform the trainees' functional adaption as they gain skill in their trade. In other fields (e.g., athletics), novices are encouraged to learn the intricacies of effective movement techniques through professional instruction. One such example is golfer learning an effective swing. Using professional feedback, novice golfers learn and practice the proper form for a safe and effective swing. Additionally,

through this practice, they learn to avoid countless forms of improper swings which may be inefficient or harmful. Therefore, as an extension of the proper working posture identification methods introduced in chapter 6, further studies are needed on how apprentices may learn and practice proper working techniques to intuitively understand how to move safely and efficiently.

5. **On-site Risk Monitoring Tool:** Wearable motion capture system presents an unprecedented opportunity for real-time assessment and feedback about workers' exposure to biomechanical risk to trainers, supervisors or managers. However, the analysis methods utilized in this thesis required a significant amount of time and effort to go through multiple data processing steps in order to provide evaluation results. This is a limitation in monitoring ergonomic risks at the worksite. Therefore, research is needed to better understand use-cases and to develop real-time techniques for motion data-driven on-site risk monitoring and feedback systems.

8.3 PUBLICATIONS

The peer-refereed publications, directly related to this scope of this thesis, and authored by the candidate are listed below:

8.3.1 Peer-refereed Journal Articles

1. **Ryu, J.**, Diraneyya, M. M., Haas, C. T., Abdel-Rahman, E. M. (2020) "Analysis of the Limits of Automated Rule-based Ergonomic Assessment in Bricklaying". *ASCE Journal of Construction Engineering and Management*. 147(2) 04020163. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001978

2. **Ryu, J.**, Alwasel, A., Haas, C. T., Abdel-Rahman, E. M. (2020) "Analysis of Relationships Between Body Load and Training, Work Methods, and Work Rate: Overcoming the Novice Mason's Risk Hump". *ASCE Journal of Construction*

Engineering and Management. 146(8), 04020097. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001889

3. **Ryu, J.**, McFarland, T., Banting, B., Haas, C. T., Abdel-Rahman, E. M. (2020) "Health and Productivity Impact of Semi-Automated Work Systems in Construction". *Automation in Construction*. 120, 103396. https://doi.org/10.1016/j.autcon.2020.103396

8.3.2 Peer-refereed Conference Papers

1. **Ryu, J.,** McFarland, T., Banting, B., Haas, C., and Abdel-Rahman, E. (2020), "Automatic Clustering of Proper Working Posture" *27th International Workshop on Intelligent Computing in Engineering*, Berlin, Germany. July 1-3, 2020. http://dx.doi.org/10.14279/depositonce-9977

2. **Ryu, J.**, Zhang, L., Diraneyya, M, Banting, B., Haas, C., and Abdel-Rahman, E. (2019) "Ergonomic assessment of standard vs. heavy-weight CMU lifts" *13th North American Masonry Conference*, Salt Lake City, UT. June 16-19, 2019.

3. **Ryu, J.**, Zhang, L., Haas, C., and Abdel-Rahman, E. (2018) "Motion Data Based Construction Worker Training Support Tool: Case Study of Masonry Work" *35th International Symposium on Automation and Robotics in Construction (ISARC)*. Berlin, Germany. July 20-25, 2018. https://doi.org/10.22260/ISARC2018/0150

4. Alwasel, A., **Ryu, J.**, Abdel-Rahman, E., Haas, C. (2017) "Improving Health and Productivity of Construction Workers: A New Toolkit" *13th Canadian Masonry Symposium*. Halifax, NS, Canada. June 4-7, 2017.

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APPENDICES

APPENDIX A

Consent Form

Department of Systems Design Engineering

Date: July 11, 2019

Title of Project: ***Identification of Good Form among Construction Trade Workers***

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Purpose of this Study

This study is being carried out as part of the PhD program requirements of Mr. JuHyeong Ryu's. Injury is one of the reasons that remove workers off the workforce early in their careers. These injuries are usually a result of working in dangerous postures that overtime lead to injury. Workers often use these postures as part of their daily work without realizing their long-term implications.

This study hypothesizes that experienced workers have adopted a healthy way of work. Thus, we aim at discovering this 'way of work' to deduce methods that novice workers can use to gain expertise while avoiding injuries and early retirement.

We are seeking to recruit trainees in construction apprenticeship programs to participate in this study. The study will recruit 150 trainees or more from four of experience levels in the program (no experience, first year, second year, and third year trainees). We will also recruit 50 expert workers, with 5 or more years of experience, in construction trades and no apparent health challenges.

Procedures Involved in this Study

The project will collect data about how you move during your daily work tasks. Two types of sensors will be used in this study. 1) Whole-body motion data: Wearable commercial motion-tracking suit that will be mounted on each body segment of upper and lower body. Specifically, upper arms, forearms, trunk, thighs, and legs. These are commercially available sensors that measure the joint angles. More information on the suit is available at (http://perceptionmocap.com/). 2) Real-time streaming acceleration data: Wearable and mountable wireless IMUs will be attached at the lower back and each of the thighs. The sensor information is available at (https://mbientlab.com/).

The motion tracking suit units, also known as suit, and the Mbient IMUs will be strapped to body segments using Velcro tape. No adhesive material will be used. The suit and Mbient IMUs send the measured motions wirelessly to a nearby computer and smartphone, respectively.

The placement of all types of sensors will not need removing of clothing articles. However, you will need to lift your shirt sleeve to expose your upper shoulder for the placement of the sensor on the skin of your shoulder area. After the placement of the sensor your sleeve can be lowered down again.

The suit will be placed on both sides of your body to provide full motion tracking. In addition, one or two video cameras will record how you complete the task.

Prior to the task, you will be asked about your height, age, and weight. You will be asked to participate in one of the described tasks below. The tasks involved are:

- Complete a wall starting from a lead wall. Mortar and blocks will be brought to the site of building. The wall is 6 blocks high and 12 blocks wide.
- Lay one or two courses of blocks in an existing wall.
- Complete tool and material handling tasks, such as rebar tying of reinforcement walls, drilling of reinforcement walls, and grinding or welds. Material will be laid out before hand for your task.
- A regular eight-hour construction work shift. We will only use IMU data for the working hours and will exclude data for break times and lunch time. In addition, the collected data will only be used for the analysis of physical exertion.

As token of our appreciation, a $10 Tim Card will be given for each participant. The amount received is taxable. It is your responsibility to report this amount for income tax purposes.

Risks to Participation and Associated Safeguards

- There is always a risk of muscle, joint or other injury in any physical work. However, the risks in this study are not anticipated to be greater than those required for your daily work tasks.
- If you are allergic to alcohol swabs used to sanitize the equipment and/or adhesive material used in double-sided tapes you are not be eligible to participate in this study as both materials will be used in this study.
- Sensors are not disposable and will be used for all participants in this study. The sensors will be sanitized using alcohol swabs between uses. The double-sided tape is disposable. Redness or a rash may occur when removing the tape from your skin. This should be temporary and disappear in one or two days.

Time Commitment

Participation in this study will require approximately 1 hour of your time. All sessions will be scheduled outside of class time.

Changing Your Mind about Participation

You may withdraw from this study at any time without penalty. To do so, indicate this to the researcher or one of the research assistants by saying, "I no longer wish to participate in this study".

Personal Benefits of Participation

There are no direct benefits for participating in the study. However, this study will provide researchers with knowledge about how workers move in their daily tasks thus allowing researchers to design work tasks safer and more efficient.

Confidentiality

To ensure the confidentiality of individuals' data, each participant will be identified by a participant identification code known only to the principal investigators and student investigators. Videotapes will be stored for 7 years, from the day of study anticipated completion (Aug 2021), in a secure area for further research purposes in the future e.g. alerting the worker using video data. No face blurring will be used as the video recording will not be facing the participant, hence, mostly no face recording is done. A separate consent will be requested in order to use the videotapes and/or photographs for teaching, for scientific presentations, or in publications of this work.

Data related to your participation will be submitted to an online data repository. It will be completely anonymized/de-identified by removing names and video recordings before submission. This process is integral to the research process as it allows other researchers to verify results and avoid duplicating research. Other individuals may access this data by downloading data spreadsheets. Should you choose, you may review all data that will be submitted before it is entered into data repository.

Participant Feedback

After the study is completed, you will be provided with an appreciation letter from the research team.

Concerns about Your Participation

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#30382). If you have questions for the Committee contact the Chief Ethics Officer, Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

For all other questions contact Eihab Abdel-Rahman, Carl Haas, JuHyeong Ryu at 519-888-4567 Ext. 37737, 35492, and 33929 respectively.

Questions about the Study

If you have additional questions later or want any other information regarding this study, please contact (Eihab Abdel-Rahman, Carl Haas, JuHyeong Ryu) at 519-888-4567 Ext. 37737, 35492, and 33929 respectively.

CONSENT TO PARTICIPATE

By signing this consent form, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities.

I agree to take part in a research study being conducted by Dr. Eihab Abdel-Rahman, Dr. Carl Haas, and Juhyeong Ryu of the Department of Systems Design Engineering and Civil and Environmental Engineering, University of Waterloo.

I have made this decision based on the information I have read in the Information letter. All the procedures, any risks and benefits have been explained to me. I have had the opportunity to ask any questions and to receive any additional details I wanted about the study. If I have questions later about the study, I can ask one of the researchers (Eihab Abdel-Rahman, Department of Systems Design Engineering, Carl Haas, JuHyeong Ryu, Department of Civil and Environmental Engineering at 519-888-4567 exts. 33737, 35492, 33929 respectively).

I understand that I may withdraw from the study at any time without penalty by telling the researcher.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#20023). If you have questions for the Committee contact the Chief Ethics Officer, Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

Do you want to review data before it is stored in data repository?

Yes ☐ No ☐

Printed Name of Participant	Signature of Participant
Dated at Waterloo, Ontario	Witnessed

Consent to Use Video and/or Photographs

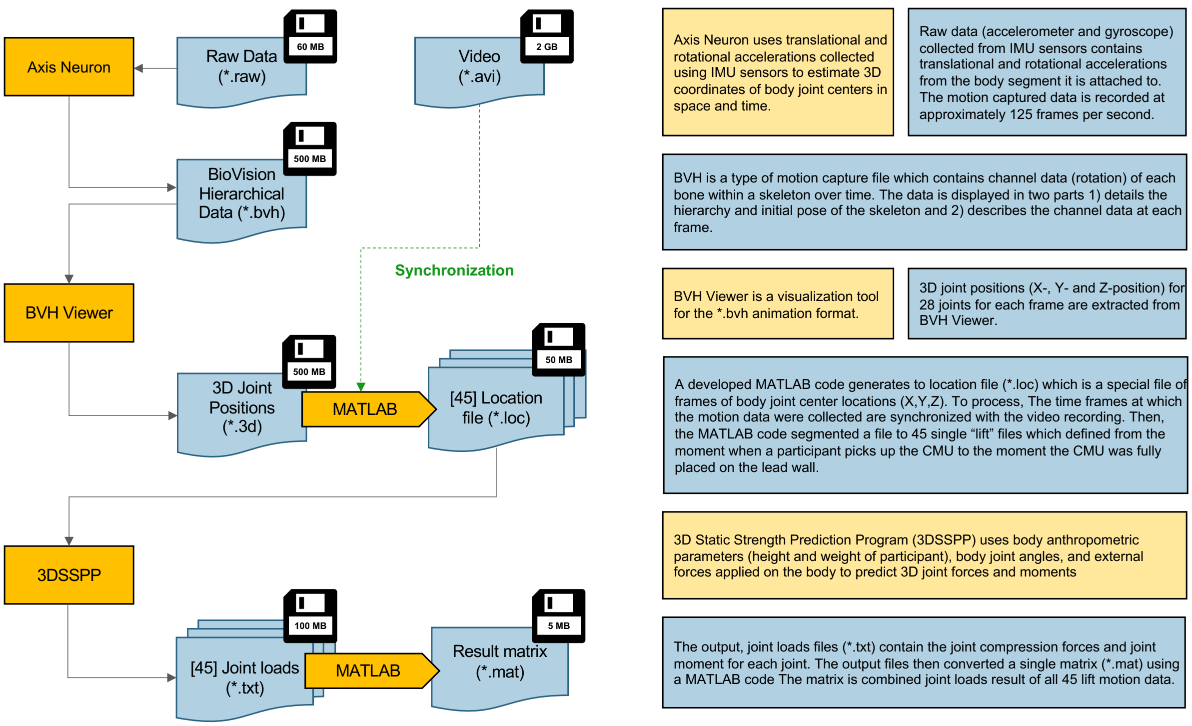
Sometimes a certain photograph and/or part of a video-tape clearly shows a particular feature or detail that would be helpful in teaching or when presenting the study results in a scientific presentation or publication. If you grant permission for photographs or videotapes in which you appear to be used in this manner, please complete the following section.

I agree to allow video and/or photographs to be used in teaching or scientific presentations, or published in scientific journals or professional publications of this work without identifying me by name.

______________________________	___________________________
Printed Name of Participant	Signature of Participant
______________________________	____________________________
Dated at Waterloo, Ontario	Witnessed

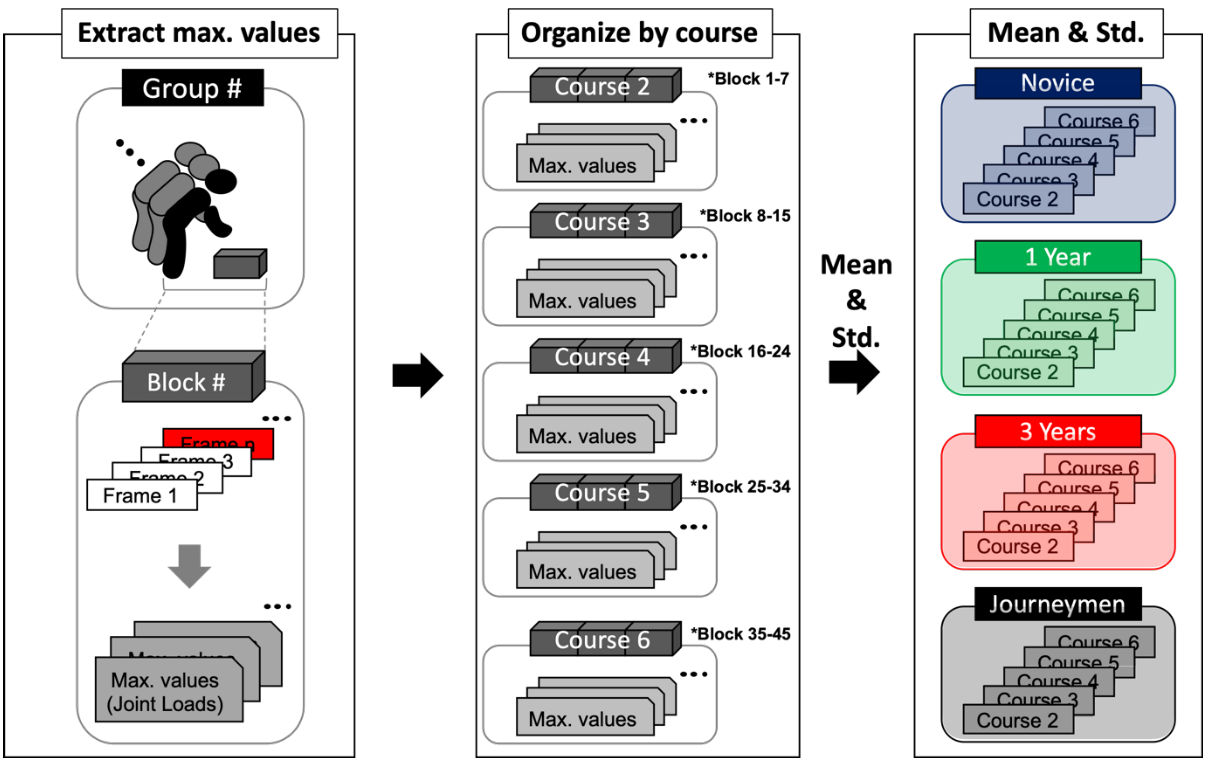
APPENDIX B

Data Processing Chart


Axis Neuron
Raw Data (*.raw)
60 MB
Video (*.avi)
2 GB
BioVision Hierarchical Data (*.bvh)
500 MB
Synchronization
BVH Viewer
3D Joint Positions (*.3d)
500 MB
MATLAB
[45] Location file (*.loc)
50 MB
3DSSPP
[45] Joint loads (*.txt)
100 MB
MATLAB
Result matrix (*.mat)
5 MB
Axis Neuron uses translational and rotational accelerations collected using IMU sensors to estimate 3D coordinates of body joint centers in space and time.
Raw data (accelerometer and gyroscope) collected from IMU sensors contains translational and rotational accelerations from the body segment it is attached to. The motion captured data is recorded at approximately 125 frames per second.
BVH is a type of motion capture file which contains channel data (rotation) of each bone within a skeleton over time. The data is displayed in two parts 1) details the hierarchy and initial pose of the skeleton and 2) describes the channel data at each frame.
BVH Viewer is a visualization tool for the *.bvh animation format.
3D joint positions (X-, Y- and Z-position) for 28 joints for each frame are extracted from BVH Viewer.
A developed MATLAB code generates to location file (*.loc) which is a special file of frames of body joint center locations (X,Y,Z). To process, The time frames at which the motion data were collected are synchronized with the video recording. Then, the MATLAB code segmented a file to 45 single "lift" files which defined from the moment when a participant picks up the CMU to the moment the CMU was fully placed on the lead wall.
3D Static Strength Prediction Program (3DSSPP) uses body anthropometric parameters (height and weight of participant), body joint angles, and external forces applied on the body to predict 3D joint forces and moments
The output, joint loads files (*.txt) contain the joint compression forces and joint moment for each joint. The output files then converted a single matrix (*.mat) using a MATLAB code The matrix is combined joint loads result of all 45 lift motion data.

APPENDIX C

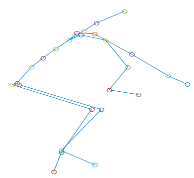
Framework for Biomechanical Analysis


Extract max. values
Group #
Block #
Frame n
Frame 3
Frame 2
Frame 1
Max. values
Max. values
(Joint Loads)
Organize by course
Course 2
*Block 1-7
Max. values
Course 3
*Block 8-15
Max. values
Course 4
*Block 16-24
Max. values
Course 5
*Block 25-34
Max. values
Course 6
*Block 35-45
Max. values
Mean
&
Std.
Mean & Std.
Novice
Course 6
Course 5
Course 4
Course 3
Course 2
1 Year
Course 6
Course 5
Course 4
Course 3
Course 2
3 Years
Course 6
Course 5
Course 4
Course 3
Course 2
Journeymen
Course 6
Course 5
Course 4
Course 3
Course 2

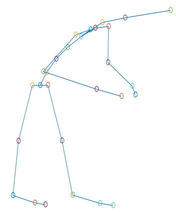
APPENDIX D

Representative Examples of Postures Classified using *k*-mean Clustering

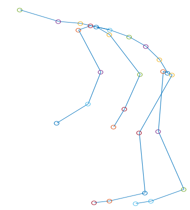
Expert Dominant Postures



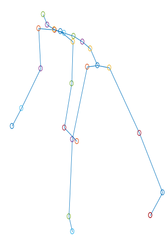
Bin 5– Expert Dominated
G5P4: Lift 10 (Frame 462)



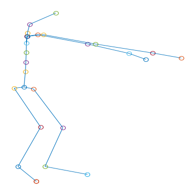
Bin 8– Expert Dominated
G5P1: Lift 23 (Frame 257)



Bin 9– Expert Dominated
G5P2: Lift 10 (Frame 125)

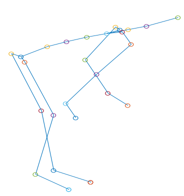


Bin 23– Expert Dominated
G5P6: Lift 16 (Frame 135)

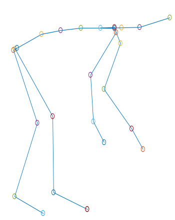


Bin 46– Expert Dominated
G5P4: Lift 39 (Frame 500)

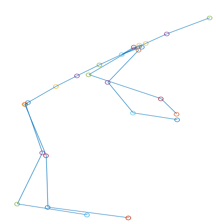
Apprentice dominant postures



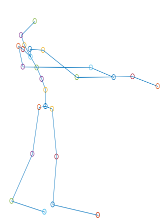
Bin 3– Apprentice Dominated
G1P6: Lift 31 (Frame 391)



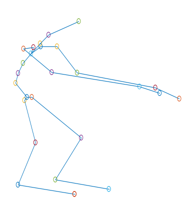
Bin 10– Apprentice Dominated
G2P6: Lift 4 (Frame 397)



Bin 15– Apprentice Dominated
G1P6: Lift 31 (Frame 278)

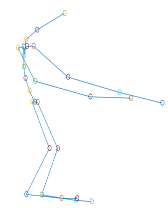


Bin 26– Apprentice Dominated
G1P6: Lift 43 (Frame 391)

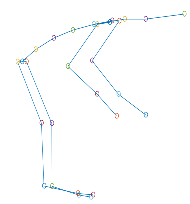


Bin 34– Apprentice Dominated
G1P7: Lift 29 (Frame 427)

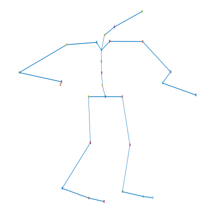
Equal representation



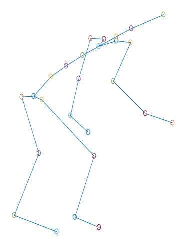
Bin 1– Equally Represented
G4P2: Lift 27 (Frame 277)



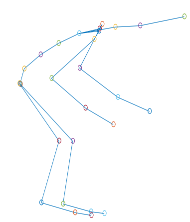
Bin 11– Equally Represented
G2P2: Lift 7 (Frame 432)



Bin 21– Equally Represented
G1P5: Lift 11 (Frame 100)



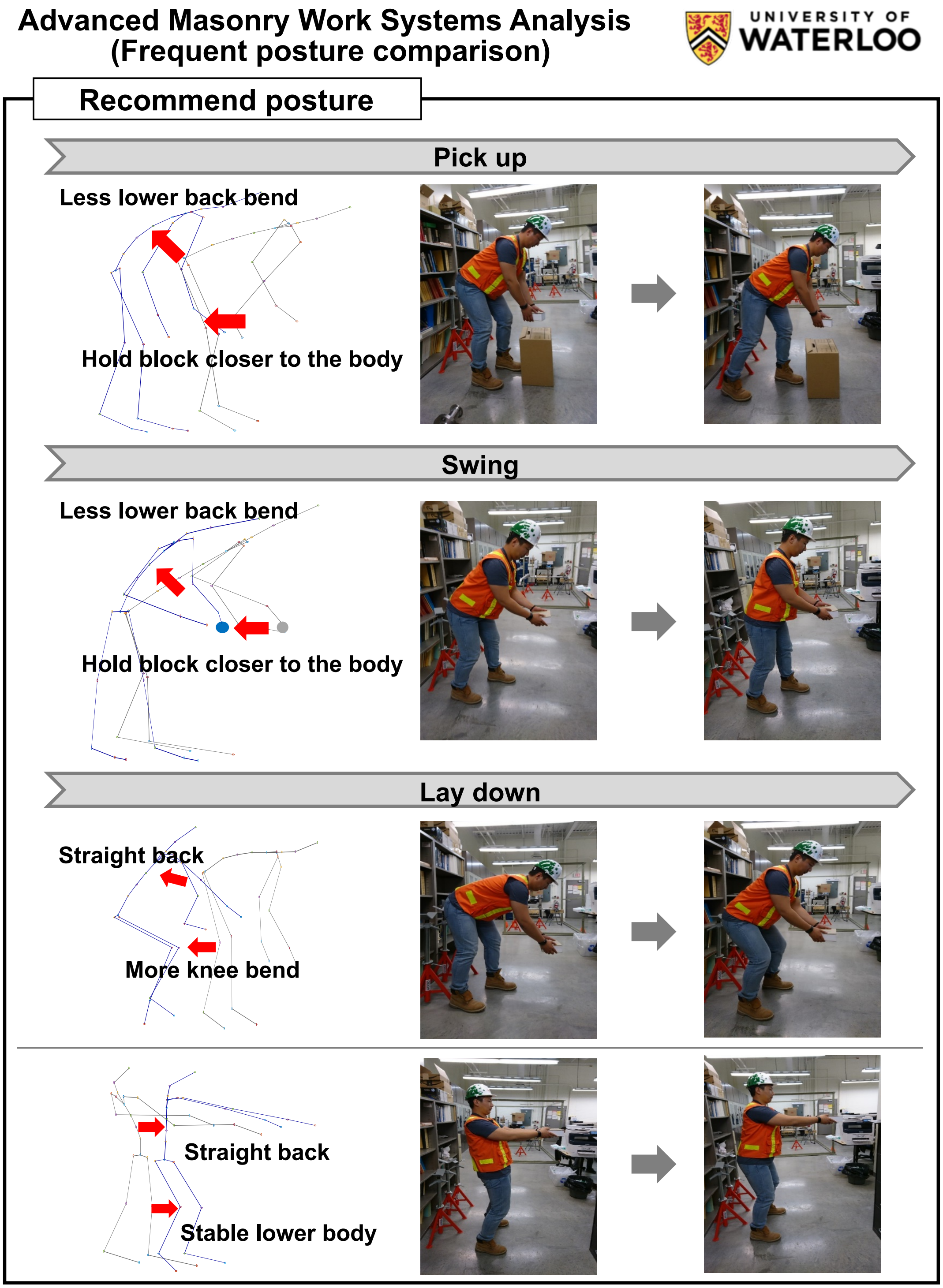
Bin 23– Equally Represented
G5P6: Lift 17 (Frame 422)



Bin 33– Equally Represented
G4P7: Lift 7 (Frame 318)

APPENDIX E

Safety Training Literature for Apprenticeship Programs


Advanced Masonry Work Systems Analysis
(Frequent posture comparison)
UNIVERSITY OF WATERLOO
Recommend posture
Pick up
Less lower back bend
Hold block closer to the body
Swing
Less lower back bend
Hold block closer to the body
Lay down
Straight back
More knee bend
Straight back
Stable lower body