EVALUATION OF BIOMECHANICAL RISK FACTORS FOR WORK-RELATED MUSCULOSKELETAL DISORDERS AND FALL INJURIES AMONG CONSTRUCTION WORKERS

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Evaluation of Biomechanical Risk Factors for Work-Related Musculoskeletal Disorders and Fall Injuries among Construction Workers

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

____ (Signed)

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DEDICATION

To the ALMIGHTY GOD and most especially to my parents Mr. ANTWI-AFARI ATTA AUGUSTINE and MRS. ANTWI-AFARI COMFORT POKUAAH for their unconditional love, immense support, guidance, motivation and encouragement for making this PhD study a success.

ABSTRACT

Work-related musculoskeletal disorders (WMSDs) represent major health issues for construction workers (e.g., rebar workers), yet biomechanical risk factors associated with repetitive lifting tasks, which have detrimental effects on loss of balance and may contribute towards non-fatal fall injuries, remain unexplored. While wearable sensor-based systems have shown promising potentials in risk assessment for WMSDs, scant research has been conducted on using direct measurement sensors such as surface electromyography (sEMG), inertial measurement units (IMUs), and wearable insole pressure sensors to avoid and minimize the exposure of construction workers biomechanical risks. Moreover, the current risk assessment methods of WMSDs (e.g., self-reports and observational-based methods) are subjective and require complicated analysis to identify risk factors for WMSDs. Consequently, there is a crucial need to introduce effective and practical solutions for identifying potential biomechanical risk factors which may lead to WMSDs and non-fatal fall injuries among construction workers.

The present study aims to evaluate biomechanical risk factors for WMSDs and non-fatal fall injuries among construction workers. The main objectives of this research study are set to: summarize musculoskeletal symptoms (MSS) prevalence in different construction trades, gender and age groups, which may help develop specific ergonomic interventions; examine the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving occupational health and safety (OHS) through the analysis of articles published between 1996 and 2017 (years inclusive); evaluate the effects of lifting weights, and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment; examine the self-reported discomfort and spinal biomechanics (muscle activity and spinal

kinematics) experienced by rebar workers; propose a novel approach and efficient method to automatically detect and classify construction workers' awkward working postures based on foot plantar pressure distribution measured by wearable insole pressure system; evaluate the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks; and develop a method to detect and classify loss of balance events based on foot plantar pressure distributions data captured using wearable insole pressure sensors.

Based on well-established research methods, participants performed simulated repetitive lifting tasks, awkward working postures and loss of balance events in a controlled laboratory setting. During the experiments, trunk muscle activity, spinal kinematics, and foot plantar pressure distribution data were recorded using sEMG, IMUs, and wearable insole pressure sensors, respectively. The key findings of this research indicate that (1) workers frequently involved in risk factors such as lifting weights, lifting durations, and lifting postures during repetitive lifting tasks may increase their risk of developing WMSDs; (2) lifting different weights causes disproportional loading upon muscles, which shortens the time to reach working endurance and increases the risk of developing low back disorders (LBDs) among rebar workers; (3) developing an automated wearable insole pressure system could assist researchers and construction managers in understanding the contributing role of workers' awkward working postures as an informative source of data for WMSDs prevention in construction; (4) repetitive lifting of heavier weights would significantly jeopardize individuals' balance control on unstable supporting surfaces, which may heighten the risk of non-fatal fall injuries; and (5) foot plantar pressure distribution data contain valuable information relating to specific loss of balance events, which can be used to understand the causes of falls on the same level in a timely manner.

This current study presents the first laboratory-based simulated testing conducted to investigate the risk factors for WMSDs primarily caused by repetitive lifting tasks and manual handling. As such, it contributes to an identified need to study laboratory-based simulated tasks conducted to investigate the risk of developing LBDs among rebar workers primarily caused by repetitive rebar lifting. In addition, this study substantiated the feasibility of using a wearable insole pressure system to identify risk factors for developing WMSDs and could help safety managers eliminate workers' exposure to awkward working postures on construction sites. Furthermore, it provides preliminary and invaluable information to researchers and practitioners seeking to develop practical interventions to reduce the developing WMSDs among construction workers (e.g., masons, rebar workers) involved in repetitive lifting tasks. Collectively, the proposed approach can serve as an automated risk assessment tool that allows practitioners to take proactive actions to eliminate the fundamental causes of WMSDs and non-fatal fall injuries among construction workers.

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Journal Papers (Published & Accepted)

1. **Antwi-Afari, M. F**., and Li, H. (2018g) Fall risk assessment of construction workers based on biomechanical gait stability parameters using wearable insole pressure system. *Advanced Engineering Informatics*, Vol. 38, pp. 683-694. DOI: https://doi.org/10.1016/j.aei.2018.10.002.

2. **Antwi-Afari, M. F**., Li, H., Yu, Y., and Kong, L. (2018f) Wearable insole pressure system for automated detection and classification of awkward working postures in construction workers. *Automation in Construction*, Vol. 96, pp. 433-441. DOI: https://doi.org/10.1016/j.autcon.2018.10.004.

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2. **Antwi-Afari, M. F**., Li, H., Seo, J., Lee, S., Edwards, D. J., and Wong, A. Y. L. (2018c). Wearable insole pressure sensors for automated detection and classification of slip-trip-loss-of-balance events in construction workers. *Construction Research Congress,* New Orleans, Louisiana, USA, April 2-5, 2018. DOI: https://doi.org/10.1061/9780784481288.008.

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1. Owusu-Manu, D., Edwards, D. J., Pärn, E. A., **<u>Antwi-Afari, M. F.</u>,** and Aigbavboa, C. (2018). The knowledge enablers of knowledge transfer: a study in construction industries in Ghana. *Journal of Engineering, Design and Technology*, Vol. 16, No. 2, pp. 194-210. DOI: https://doi.org/10.1108/JEDT-02-2017-0015.

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Honors and Awards

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5. **Gibrine Adam Promising Young Scholar Award** at the 7th West Africa Built Environment Research (WABER) Conference, Accra, Ghana, 16-18 August 2017. Paper title: *Effects of quadriceps muscle fatigue on balance control and fall injuries following repetitive squat lifting task in construction workers.*

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LIST OF GLOSSARY AND VARIABLES

A/D	Analog to Digital
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ART	Assessment of Repetitive Task
AT	Assistant Tag
BB	Biceps Brachii
BIM	Building Information Modelling
BLS	Bureau of Labor Statistics
BMI	Body Mass Index
Borg CR	Borg categorical rating scale
bpm	Beats Per Minute
BR	Breathing Rate
BR	Brachioradialis
CART	Classification and Regression Tree
CBR	Case-Based Reasoning
CI	Confident Interval
CoP	Center of Pressure
CPWR	Center to Protect Workers' Right
CSS	Chirp Spread Spectrum
CSV	Comma-Separated Values
DT	Decision Tree
DTMC	Discrete-Time Markov Chain
ECF	Eyes Closed on a Foam Placed on a Force Plate
ECG	Electrocardiogram
ECS	Eyes Closed on a Force Plate
EEG	Electroencephalogram
FF	Frequency-Domain Features
FFT	fast Fourier transforms
FOSs	Fiber Optic Sensors
GIS	Geographical Information Systems
GPS	Global Positioning System
GSM	Global System Mobile
HKOSH	Hong Kong Occupational Safety and Health
HKSAR	Hong Kong Special Administrative Region
HR	Heart Rate
HSA	Health and Safety Authority
IMUs	Inertial Measurement Units
ISO	International Organization for Standardization
JRPDS	Job Requirements and Physical Demands Survey
KNN	K-Nearest Neighbor
LAN	Local Area Network
LBDs	Low back disorders
LES	Lumbar Erector Spinae

LMM	Lumbar Motion Monitor
MAC	Manual Handling Assessment
MAPE-K	Monitor–Analyze–Plan–Execute and Knowledge
MEMS	Micro-Electromechanical Sensors and Systems
MF	Median Frequency
MG	Medial Gastrocnemius
M/L	Medial/Lateral
MLS	Maximum Lifting Strength
MSS	Musculoskeletal Symptoms
MV	Mean Velocity
MVC	Maximum Voluntary Contraction
NIOSH	National Institute for Occupational Safety and Health
N/S	No Significant Difference
OBR	Optical Backscatter Reflectometry
ODI	Oswestry Disability Index
OHS	Occupational Health and Safety
OSHA	Occupational Safety and Health Administration
OWAS	Ovako Working Analysis System
PAR-Q	Physical Activity Readiness Questionnaire
PATH	Posture, Activity, Tools, and Handling
PCMS	Proactive Construction Management Systems
PolyU	Hong Kong Polytechnic University
PPG	Photoplethysmograph
PROSPERO	Prospective Register of Systematic Reviews
PtD	Prevention through Design
PTI	Pressure Time Integral
QEC	Quick Exposure Check
RAMIRES	Risk-Adaptive Management in Resilient Environments with Security
RBF	Radial Basis Function
REBA	Rapid Entire Body Assessment
RF	Rectus Femoris
RFID	Radio-Frequency Identification
RIP	Respiratory Inductance Plethysmograph
RT	Random Forest
RTLS	Real-Time Location System
RULA	Rapid Upper Limb Assessment
SAA	Standard Amplitude Analysis
SD	Standard Deviation
sEMG	Surface Electromyography
SHM	Structural Health Monitoring
SPSS	Statistical Package for the Social Science
SVM	Support Vector Machine
SWEs	Smart Work Environments
TF	Time-Domain Features
TRC	Rectal Temperature

TSK	Multipoint Skin Temperature
UHF	Ultra-High Frequency
USB	Universal Serial Bus
UWB	Ultra-Wide Band
VR	Virtual Reality
WMSDs	Work-related musculoskeletal disorders
3D	Three-dimensional
3DSSPP	3D Static Strength Prediction Program
4D CAD	Four-dimensional Computer Aided Design

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

This chapter sets the background, states the research problem, states the aim and research objectives, outlines the research approaches and contribution to knowledge, and presents the structure of the thesis.

1.2 BACKGROUND

1.2.1 Work-related musculoskeletal disorders in the construction industry

The construction industry is a labor-intensive and hazardous occupation as compared with other industries. Consequently, construction workers are frequently exposed to physically demanding tasks that require manual handling, heavy lifting, force exertions, sustained and awkward working postures (Spielholz et al., 2006). These workplace activities associated with the physical demand on workers' bodies may lead to health issues and bodily injuries known as work-related musculoskeletal disorders (WMSDs) (Health and Safety Executive, 2016). According to the Bureau of Labor Statistics (BLS) in the United States, 32 construction workers in every 10,000 get injured from a WMSD and take leaves from work (BLS, 2014). In Germany, WMSDs were the largest causes of occupational disabilities among construction workers during a 10-year follow-up study (Arndt et al., 2005). Similarly, several studies conducted in the United Kingdom and Taiwan have demonstrated that workers in the construction industry are highly prevalent to WMSDs (Guo et al., 2004; Lee et al., 2005). In addition to their adverse physical implications, WMSDs can also lead to increased cost of insurance premium, loss of productivity, schedule delays, early retirement and psychological issues in the construction industry (Inyang and Al-Hussein, 2011).

According to the Occupational Health and Safety Administration (OSHA), laborers have the highest prevalent rate (45 workers in every 10,000) of WMSDs, followed by helpers, plumbers, carpenters, and other trades (OSHA, 2012). Symptoms of WMSDs are numerous; including pains in body regions such as lower back, neck/shoulder, wrist, elbow, knee, and ankle (Bernard and Putz-Anderson, 1997; Occupational Health Clinics for Ontario Workers Inc, 2017; Umer et al., 2017a). Notably, low back disorders (LBDs) are reported as the commonest MSDs that involve pain, discomfort or malfunction of spinal muscles, nerves, bones, discs or tendons in the low back region (Burdorf and Sorock, 1997; Boschman et al., 2012; McGill, 2015). Compared to workers in different construction trades, rebar workers are at a higher risk of developing LBDs (Albers and Hudock, 2007). Given the above, there is a crucial need for researchers to explore ways to ergonomically prevent WMSD-related risks among construction workers.

1.2.2 Fall injuries in the construction industry

Falls are the second most common causes of non-fatal workplace injuries and the leading cause of fatal injuries in the construction industry (Center to Protect Workers' Right (CPWR), 2007). In the USA, 36% of fatalities (1231 of 3419) were related to fall injuries in the construction industry from 2011 to 2014 (BLS, 2016). In Hong Kong, fall injuries contributed to more than 47% of the total fatal incidents (Chan et al., 2008). Moreover, the Hong Kong Occupational Safety and Health (HKOSH) reported that there were 3,332 fall injuries and 37 fatalities that occurred in the construction industry in 2013, accounting for 19.68% of fatalities across all the industries (HKOSH, 2014). According to the Health and Safety Authority (HSA) in the United Kingdom, fatal injuries in the construction industry account for 31% of fatal injuries to workers in 2013 (HSA, 2015). Fall accidents cause the majority of fatalities in the European construction industry and they account for 52% of all accidents (Carbonari et al., 2011). Approximately 40% of fatal accidents in the Japanese construction industry are caused by falls (Ohdo et al., 2011). Fall accidents also represent the largest proportion of work-related fatalities (181 of 606) in the Korean construction industry (Min et al., 2012).

In addition, non-fatal injuries caused by falls have been reported in the construction industry. In 2005, the construction industry experienced almost twice the rate of non-fatal falls experienced in all other industries (BLS, 2006b). Non-fatal injuries due to falls on the same level accounted for 34% in the construction industry (BLS, 2006b). Slips, trips, and loss of balance events which often precede non-fatal fall injuries are reported as the most common sources of injury to workers on construction sites (Kemmlert and Lundholm, 2001; Lipscomb et al., 2006; Omale and Oriye, 2013). Loss of balance or postural instability is often a contributing factor in injuries resulting from falls (Hsiao and Simeonov, 2001). While the risks of non-fatal fall injuries can be mitigated by the ergonomic design of the working environment, balance control is inherently far more complex and relies upon the coordination of multiple sensory systems (visual, vestibular, and proprioception/somatosensory), the motor system and the central nervous system (Horak, 2006). A good understanding of this complexity of loss of balance can help develop relevant fall prevention interventions for the construction industry.

1.3 RESEARCH PROBLEM

The most frequent non-fatal occupational health issues, especially in the labor-intensive and manually demanding construction industry are WMSDs (Eaves et al., 2016). According to a report by BLS in 2015, WMSDs accounted for 31% (356,910 cases) of the total non-fatal occupational injury cases of the construction industry in the U.S. (BLS, 2015). In addition to non-fatal occupational injuries among construction workers, WMSDs may lead to chronic health problems, permanent disabilities, early retirement, loss of productivity and high economic costs (BLS, 2015). Therefore, risk factors associated with WMSDs should be identified in order to develop effective ergonomic interventions to prevent WMSDs in construction workers.

Although WMSDs can be attributed to numerous risk factors (e.g., physical, psychosocial, individual), the majority of these health problems are caused by awkward working postures (da Costa and Vieira, 2010; McGaha et al., 2014). These postures are frequently observed in tasks that involve working overhead, kneeling, semi-squatting, back bending, squatting, neck bending, and reaching (Chen et al., 2017). Construction workers (e.g., rebar workers) frequently adopt awkward postures by virtue of their occupation (Antwi-Afari et al., 2017a, b; Antwi-Afari et al., 2018a). A typical rebar work tasks include i) preparing rebars (e.g., pulling rebars from the stack, cutting or bending rebars) and ii) assembling rebars (e.g., lifting, placing and tying rebars) (Saari and Wickström, 1978). Chan et al. (2012) have reported that rebar workers in Hong Kong spend 30% of their work time preparing rebars and 70% assembling them. These repetitive lifting tasks require rebar workers to spend most of their time in manual handling of heavyweight in awkward postures. A worker's performance in a construction task is associated with the type of working postures, the duration of each posture and the recovery time between postures (Lavender et al., 1999). Knowing this information, safety managers can reduce the hazard of WMSDs through interventions such as training and redesigning of site layout to minimize workers' exposure to awkward postures (Chen et al., 2017). Unfortunately, there is no continuous monitoring and warning system that allows the recognition and quantification of awkward working postures among construction workers so that timely warnings can be given to workers they are exposed to posture-related hazards.

The extant literature reports that there are four assessment techniques that have been developed to examine WMSDs risk factors of construction workers. These are (1) self-reported methods; (2) observational methods; (3) vision-based methods; and (4) direct measurements. Self-reported methods assess physical workloads and stresses through rating scales, questionnaires or checklists (Li and Yu, 2011). However, the reliability of self-reported methods has been questioned because they relied on subjective assessment, and are subjected to imprecise recall (Thanathornwong et al., 2014). Over the past decades, observational methods that have been developed include the following: *Assessment of Repetitive Task (ART)* (The Health and Safety Executive, 2009); *Manual Handling Assessment (MAC*) (The Health and Safety Executive, 2002); *Ovako Working Analysis System (OWAS)* (Karhu et al., 1977); *Posture, Activity, Tools, and Handling (PATH)* (Forde and Buchholz, 2004); *Rapid Upper Limb Assessment (RULA)* (McAtamney and Corlett, 1993); and *Rapid Entire Body Assessment (REBA)* (Hignett and McAtameny, 2000). However, these methods require well-trained observers to review the postures correctly and require a significant amount of time for the analysis of data (Li and Buckle, 1999a). Recently, various vision-based measuring devices have been used for biomechanical analysis of workers in construction. Amongst these modern devices, marker-based optical motion tracking systems (Hwang et al., 2009) have been widely used given their precision. Alternatively, markerless optical motion tracking systems with video cameras have also been adopted (Ray and Teizer, 2012). These systems have also been used to classify different postures and movements. However, a major pragmatic limitation of these vision-based systems is that a direct line of sight is required to register the movements (Valero et al., 2017). In the field of construction, researchers have developed direct measurements (e.g., inertial measurement units (IMUs)) to conduct biomechanical analysis of workers during some construction tasks (Umer et al., 2016; Antwi-Afari et al., 2017b; Umer et al., 2017b; Antwi-Afari et al., 2018a). By using surface electromyography (sEMG) and IMUs, Antwi-Afari et al. (2017b; 2018a) correlated the self-reported discomfort with spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers. However, attaching direct measurements to the various body parts are uncomfortable and inconvenient for participants during task execution.

In addition to WMSDs, fall injuries are also widespread in the construction industry. In 2015, of the total of 25 industrial fatalities that occurred in Hong Kong, 19 were in the construction industry (Labor Department, 2016). Conversely, a fall on the same level is a frequent occupational health problem, which accounts for 19% of all non-fatal injuries in the construction industry (HSA, 2015). It was estimated that non-fatal falls in the USA construction industry caused an average of 10 days of sick leave between the period of 1992 and 2000 (Bobick, 2004). Likewise, the highest number of compensation claims filed for non-fatal injuries in the Hong Kong construction industry from 2004 to 2008 were associated with falls (Li and Poon, 2009). Such incidents are usually associated with slips, trips or loss of balance events caused by a disruption of normal walking or gait (Lipscomb et al., 2006). For example, in the USA, UK, and Sweden, occupational injuries related to slips, trips or loss of balance events were between 20% and 40% of all occupational injuries (Kemmlert and Lundholm, 2001; Yoon and Lockhart, 2006). Generally, these events are caused by multiple interactions of environmental, individual, and task-related factors (Bentley and Haslam, 2001; Redfern et al., 2001). Given that falls on the same level due to slips, trips or loss of balance events can delay/disrupt the construction schedule, decrease productivity, increase economic burden and deprive the supply of skilled workers (Earnest and Branche, 2016), there is a pressing need to control the risk of falls among construction workers.

Generally, fall risk identification has been performed through qualitative measures (such as questionnaires or surveys) on injured workers in practice, which is subjective, reactive and time-consuming (Howcroft et al., 2013). For a real-time proactive fall risk monitoring and warning feedbacks, the use of wearable sensors such as IMUs provides a pragmatic, light-weight and low-cost means to collect real-time data. For instance, acceleration signals from IMUs can: i) be used to identify accidental falls and provide a useful data for on-site safety management in construction (Tsai, 2014) and ii) detect near-miss fall incidents in ironworkers' movements and postures (Yang et al., 2014). Whilst the IMU-based approach detects imbalance caused by fall or near-miss fall events by attaching sensors on a torso, they may not be able to detect loss of balance events that have been caused by foot disruption for the restoration of balance during normal gait. Taken together, reducing the occurrences of WMSDs and non-fatal fall injuries has become a concern of critical importance for both researchers and practitioners.

1.4 RESEARCH AIM AND OBJECTIVES

1.4.1 Aim

The present study aims to evaluate biomechanical risk factors for WMSDs and non-fatal fall injuries among construction workers.

1.4.2 Research objectives

In order to achieve the overall aim, the following specific research objectives are derived:

1. To summarize musculoskeletal symptoms (MSS) prevalence in different construction trades, gender and age groups, which may help develop specific ergonomic interventions.

2. To examine the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving occupational health and safety (OHS) through the analysis of articles published between 1996 and 2017 (years inclusive).
3. To evaluate the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment.
4. To examine the self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers.
5. To propose a novel approach and efficient method to automatically detect and classify construction workers' awkward working postures based on foot plantar pressure distribution measured by wearable insole pressure system.
6. To evaluate the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks.
7. To develop a method to detect and classify loss of balance events based on foot plantar pressure distributions data captured using wearable insole pressure sensors.

As depicted in Figure 1.1, the study begins with a systematic review of literature on musculoskeletal symptoms (Objective 1). Although individual studies have reported high prevalence of MSS among construction workers, no systematic review has summarized their prevalence rates. Similarly, a comprehensive review was conducted on sensing and warning-based technology for improving OHS in construction (Objective 2). Sensing and warning-based technologies are widely used in the construction industry for OHS monitoring and management. A comprehensive understanding of the different types and specific research topics related to the application of sensing and warning-based technologies is essential to improve OHS in the construction industry. Next, a series of simulated laboratory experiments were conducted for evaluating biomechanical risk factors for WMSDs (Objective 3 to 5) and non-fatal fall-related injuries in construction sites (Objective 6 and 7). WMSDs represent major health issues among construction workers; yet, risk factors associated with repetitive lifting tasks remain unexplored. This study evaluates the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment (Objective 3). LBDs are prevalent among rebar workers although their causes remain uncertain. This study examines the self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers (Objective 4). Awkward working postures are the main risk factor for work-related musculoskeletal disorders (WMSDs) causing non-fatal occupational injuries among construction workers. However, it remains a challenge to use existing risk assessment methods for detecting and classifying awkward working postures because these methods are either intrusive or rely on subjective judgment. Therefore, this study developed a novel and non-invasive method to automatically detect and classify awkward working postures based on foot plantar pressure distribution data measured by a wearable insole pressure system (Objective 5). Repetitive lifting tasks have detrimental effects on balance control and may contribute to fall injuries. Despite this causal link, risk factors involved remain elusive. This study evaluates the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks (Objective 6). Fall on the same level is the leading cause of non-fatal injuries in construction workers; however, identifying loss of balance events associated with specific unsafe surface conditions in a timely manner remain challenging. The objective of the current study was to develop a novel method to detect and classify loss of balance events that could lead to falls on the same level by using foot plantar pressure distributions data captured from wearable insole pressure sensors. (Objective 7).

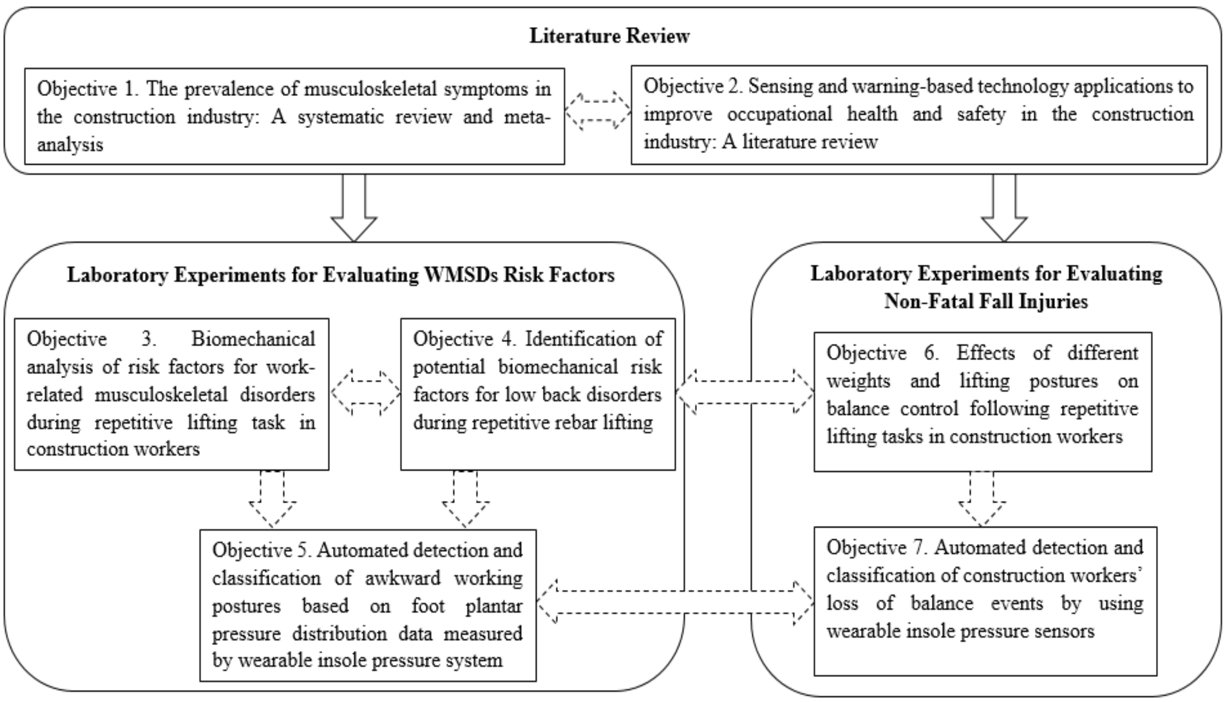


Figure 1.1 Relationship between research objectives

1.5 RESEARCH APPROACHES AND CONTRIBUTION TO KNOWLEDGE

In order to achieve these research objectives, inter-disciplinary approaches were employed to assemble research data and generate relevant information. Figure 1.2 illustrates the flow diagram of the research approach.

The first approach in this research was a systematic literature review and meta-analyses on the prevalence of MSS among construction workers (Objective 1). Nine databases were searched for articles related to the research objective. Two reviewers independently screened citations, extracted information and conducted a quality assessment of the included studies. Meta-analyses were conducted on clinical and statistical homogenous data. This review has strong implications for construction managers, ergonomists, policy makers and researchers. The results signify that more than half of the construction workforce face lumbar MSS, of which nearly one-third of them face knee, shoulder and wrist MSS annually. These figures underscore the necessity of deriving relevant policies as well as developing and implementing effective prevention strategies to attenuate the prevalence of work-related MSS in the construction industry.

Similarly, a comprehensive literature review was conducted on sensing and warning-based technology for improving OHS through the analysis of articles published between 1996 and 2017 (years inclusive) (Objective 2). The review methods comprise three major steps: (1) literature search; (2) literature selection; and (3) literature coding. The three-step method was adopted from a similar review (Zhou et al., 2013) of applying advanced technology to improve safety management in the construction industry. A total of 87 articles met the inclusion criteria. The annual publication trends and relative contributions of individual journals were discussed. Additionally, this review discussed the trend of ten different types of sensing and warning-based technology applications for improving OHS in the industry, six relevant research topics, four major research gaps and future research directions. Overall, this review may serve as a spur for researchers and practitioners to extend sensing and warning-based technology applications to improve OHS in the construction industry.

Conversely, a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment was conducted to evaluate the effects of lifting weights and postures on spinal biomechanics (Objective 3). Twenty healthy male participants performed simulated repetitive lifting tasks with three different lifting weights using either a stoop (*n* =10) or a squat (*n* =10) lifting posture until subjective fatigue (a point in time at which the participant cannot continue lifting further) was reached. Spinal biomechanics during repetitive lifting tasks were measured by sEMG. These findings suggest that risk factors such as lifting weights, repetitions and lifting postures may alleviate the risk of developing WMSDs. This work represents the first laboratory-based simulated testing conducted to investigate WMSDs, which are primarily caused by repetitive lifting tasks and manual handling. Cumulatively, the results and ensuing discussion offer insight into how these risks can be measured and mitigated.

Likewise, a simulated repetitive rebar lifting task undertaken within a strictly controlled laboratory experimental environment was conducted to examine the self-reported discomfort and spinal biomechanics (Objective 4). Twenty healthy male participants performed simulated repetitive rebar lifting tasks with three different lifting weights, using either a stoop (*n* =10) or a squat (*n* =10) lifting posture until subjective fatigue was reached. During these tasks, trunk muscle activity and spinal kinematics were recorded using surface electromyography and motion sensors respectively. A mixed-model, repeated measures analysis of variance revealed that an increase in lifting weight significantly increased lower back muscle activity at the L3 level but decreased fatigue and time to fatigue (endurance time) ($p < 0.05$). Lifting postures had no significant effect on spinal biomechanics ($p < 0.05$). Test results revealed that lifting different weights causes disproportional loading upon muscles, which shortens the time to reach working endurance and increases the risk of developing LBDs among rebar workers. This research fulfils an identified need to study laboratory-based simulated task conducted to investigate the risk of developing LBDs among rebar workers primarily caused by repetitive rebar lifting.

Another approach used in this research was a simulated laboratory experiment to automatically and continuously detect and classify awkward working postures based on foot plantar pressure distributions captured by using a wearable insole pressure system (Objective 5). Ten asymptomatic participants performed five different types of awkward working postures (i.e., overhead working, squatting, stooping, semi-squatting, and one-legged kneeling) in a laboratory setting. Four supervised machine learning classifiers (i.e., artificial neural network (ANN), decision tree (DT), K-nearest neighbor (KNN), and support vector machine (SVM)) were used for classification performance using a 0.32s window size. The main contributions of this research were to: (1) propose a wearable insole pressure system for detecting, classifying and continuous monitoring of awkward working postures based on foot plantar pressure distribution data; and (2) automatically evaluate awkward working postures to identify potential risk factors for WMSDs in construction. Specifically, our novel approach examined combined features (e.g., time-domain, frequency-domain, spatial-temporal features) of foot plantar pressure distribution patterns for WMSDs' risk prevention. The findings substantiated that it is feasible to use a wearable insole pressure system to identify risk factors for developing WMSDs, and could help safety managers to minimize workers' exposure to awkward working postures.

Furthermore, a simulated repetitive lifting task was conducted to evaluate the effects of different weights and lifting postures on balance control (Objective 6). Twenty healthy male participants underwent balance control assessments before and immediately after a fatiguing repetitive lifting task, using three different weights in a stoop (n = 10 participants) or a squat (n = 10 participants) lifting posture. Balance control assessments required participants to stand still on a force plate with or without a foam (which simulated an unstable surface) while the center of pressure (CoP) displacement parameters on the force plate was measured. Findings suggest that repetitive lifting of heavier weights would significantly jeopardize individuals' balance control on unstable supporting surfaces, which may heighten the risk of falls. This research offers an entirely new and novel approach to measuring the impact that different lifting weights and postures may have upon worker stability and consequential fall incidents that may arise.

Lastly, a simulated laboratory experiment was conducted to detect and classify loss of balance events based on foot plantar pressure distributions data captured using wearable insole pressure sensors. Ten healthy volunteers participated in experimental trials, simulating four major loss of balance events (e.g., slip, trip, unexpected step-down, and twisted ankle) to collect foot plantar pressure distributions data. Supervised machine learning algorithms (i.e., DT, ANN, KNN, random forest (RT) and SVM) were used to learn the unique foot plantar pressure patterns, and then to automatically detect loss of balance events. We compared classification performance by varying window sizes, feature groups and types of classifiers, and the best classification accuracy (97.1%) was achieved when using the Random Forest classifier with all feature groups and a window size of 0.32s. This study is important to researchers and site managers because it uses foot plantar pressure distribution data to objectively distinguish various potential loss of balance events associated with specific unsafe surface conditions. The proposed approach can allow practitioners to proactively conduct automated fall risk monitoring to minimize the risk of falls on the same level on sites.

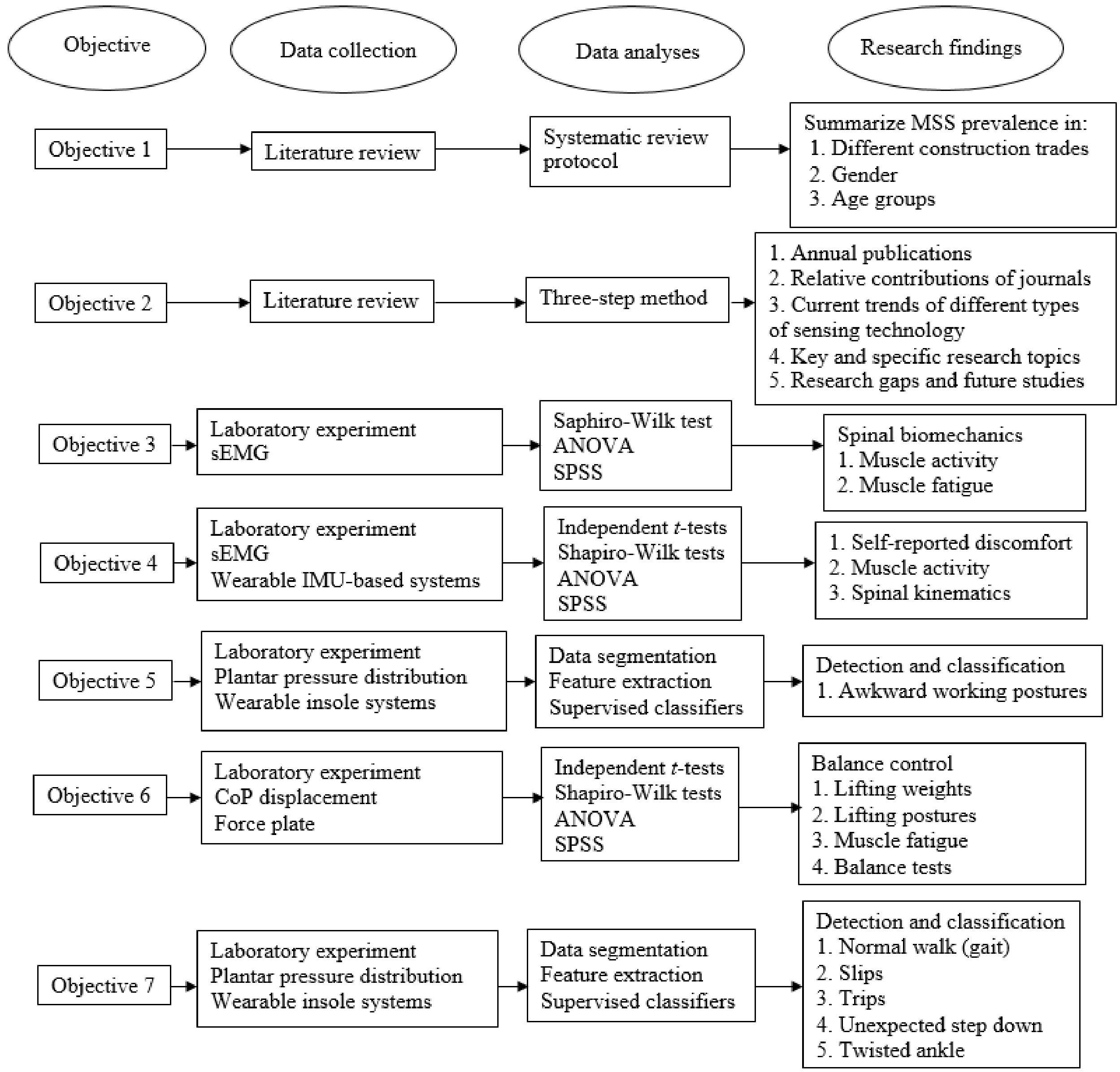


Figure 1.2 Flow diagram of the research approach

1.6 STRUCTURE OF THESIS

This thesis is a compilation of the published studies used to achieve the proposed research objectives. This thesis is composed of nine Chapters. Chapters 2 to 8 introduce each of the studies that correspond to a research objective. Figure 1.3 presents the sequence of chapters in the thesis. Following is the list of the Chapters. The list of Chapters is presented below:

Chapter 1: Introduction. This chapter covers the background, research problem, aim and research objectives, research approaches and contribution to knowledge and structure of the thesis.

Chapter 2: The Prevalence of Musculoskeletal Symptoms in the Construction Industry: A Systematic Review and Meta-Analysis. This chapter discusses a systematic review/meta-analysis aimed to summarize MSS prevalence in different construction trades, gender and age groups, which may help develop specific ergonomic interventions. In addition, this chapter compares the prevalence of MSS: (1) among different construction trades (2) between male and female workers, and (3) among different age groups in the industry.

Chapter 3: Sensing and Warning-Based Technology Applications to Improve Occupational Health and Safety in the Construction Industry: A Literature Review. This chapter discusses the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving OHS through the analysis of articles published between 1996 and 2017 (years inclusive). The chapter: (1) reports a three-step method to identify and summarize relevant article; (2) presents results on the annual publication trends and contributions of journal publications; (3) discusses the current trends of different types of sensing and warning-based technology applications for OHS, and the key research topics covered; (4) summarizes the research gaps and directions for future studies; and (5) presents the conclusions of this review.

Chapter 4: Biomechanical Analysis of Risk Factors for Work-Related Musculoskeletal Disorders during Repetitive Lifting Task in Construction Workers. This chapter discusses the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment. A laboratory controlled repetitive lifting tests are undertaken using sensors. Also, the impact of lifting/manual handling upon spinal biomechanics is assessed. Finally, key interventions to mitigate injury and ill-health are elucidated.

Chapter 5: Identification of Potential Biomechanical Risk Factors for Low Back Disorders during Repetitive Rebar Lifting. This chapter discusses the self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers. In addition, it provides pragmatic and ergonomic guidance to practitioners in optimizing lifting postures for rebar workers.

Chapter 6: Wearable Insole Pressure Sensors for Automated Detection and Classification of Awkward Working Postures in Construction Workers. This chapter proposes a novel approach and efficient method to automatically detect and classify construction workers' awkward working postures based on foot plantar pressure distribution measured by a wearable insole pressure system. It also discusses research and practical implications of this approach to both researchers and practitioners.

Chapter 7: Effects of Different Weights and Lifting Postures on Balance Control following Repetitive Lifting Tasks in Construction Workers. This chapter discusses the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks. Moreover, it provides preliminary and invaluable information to researchers and practitioners seeking to develop practical interventions to reduce the risk of falls among construction workers (e.g., masons, rebar workers) involved in repetitive lifting tasks.

Chapter 8: Automated Detection and Classification of Construction Workers' Loss of Balance Events by using Wearable Insole Pressure Sensors. This chapter discusses a method to detect and classify loss of balance events based on foot plantar pressure distributions data captured using wearable insole pressure sensors. A laboratory controlled falls on the same level tests are undertaken using wearable insole pressure sensors. The chapter also discusses the research and practical implications of this method to both researchers and practitioners.

Chapter 9: Conclusions and Recommendations. This chapter provides a summary of the conclusions that can be drawn from the research. Some recommendations for directions for future studies are also provided.

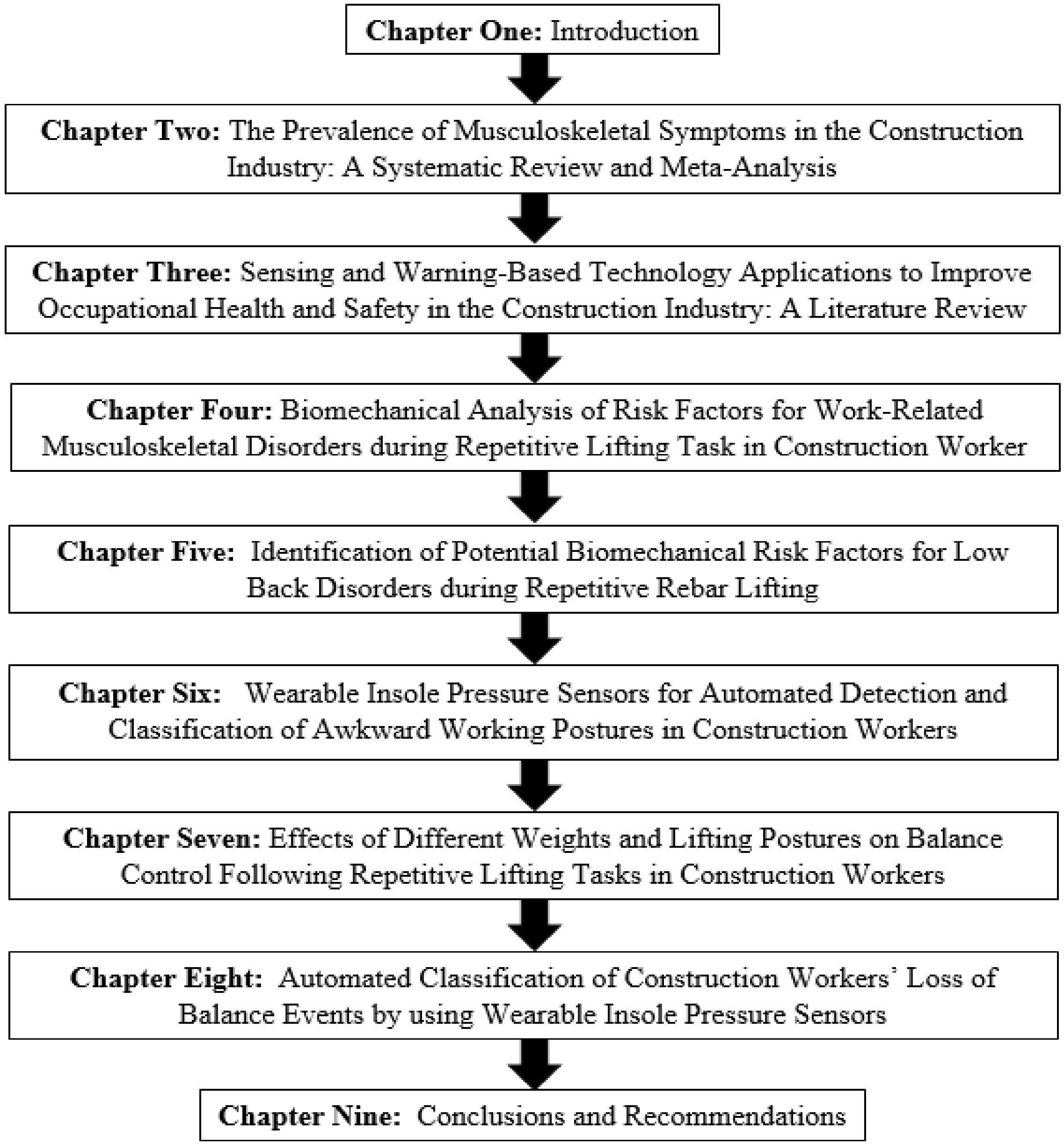


Figure 1.3 Sequence of chapters in the thesis

1.7 CHAPTER SUMMARY

This chapter has presented a general introduction of the research, including the background of the study and the research problem. It has also highlighted the research aim and objectives, the research approaches and contribution to knowledge. Finally, the structure of the thesis was presented.

CHAPTER 2

THE PREVALENCE OF MUSCULOSKELETAL SYMPTOMS IN THE CONSTRUCTION INDUSTRY: A SYSTEMATIC REVIEW AND META-ANALYSIS[1]

2.1 BACKGROUND

Musculoskeletal symptoms (MSS) are one of the most prevalent occupational health problems among construction workers (Inyang et al., 2012). Given the high physical work demand, prolonged awkward static/repetitive postures, whole-body vibrations, long working hours, and unfavorable work environment (Buchholz et al., 1996; Forde and Buchholz, 2004; Haslam et al., 2005; Umer et al., 2017a, b), construction workers are constantly exposed to multiple ergonomic risk factors. Consequently, work-related musculoskeletal symptoms are the main cause of non-fatal injuries in the construction industry (Wang et al., 2015a).

The high prevalence of work-related MSS not only causes work absenteeism, schedule delays and compensation claims but also heightens the recruitment/training costs of the construction industry (Inyang et al., 2012). Approximately 33.0% of the total absenteeism in the USA construction industry in 2012 were attributed to MSS (BLS, 2013). Similarly, The Alberta Construction Safety Association reported that 41.9% of all accepted lost time claims in 2008 were related to MSS (Inyang et al., 2012). In Germany, MSS is the major cause of occupational disabilities among construction workers (Arndt et al., 2005).

[1] Presented in a published paper: Umer, W., **Antwi-Afari, M. F.,** Li, H., Szeto, G. P., & Wong, A. Y. L. (2017a). The prevalence of musculoskeletal symptoms in the construction industry: A systematic review and meta-analysis. *International Archives of Occupational and Environmental Health*, 1-20. DOI: https://doi.org/10.1007/s00420-017-1273-4.

Although individual studies have reported prevalence rates of various MSS in numerous construction trades, no systematic review has summarized these findings. Without such information, it is difficult for relevant stakeholders (e.g. policymakers, project managers, and healthcare providers) to comprehend the scope of the problem and to allocate resources to develop/evaluate prevention or treatment strategies for musculoskeletal symptoms in various trades of the construction industry. Importantly, given the increased employments of females (Kinoshita and Guo, 2015) and older workers (Samorodov, 1999; Schwatka et al., 2011) in the construction industry, it is essential to summarize the evidence regarding the prevalence of MSS in construction workers of different genders or ages. This information can help develop specific management strategies (e.g. job modification) to reduce the risk of work-related MSS in vulnerable subgroups.

Given the above, the primary objective of this systematic review was to summarize the prevalence of various MSS in the construction industry. The secondary objectives were to compare the prevalence of MSS: (1) among different construction trades (2) between male and female workers, and (3) among different age groups in the industry.

2.2 METHODS

This systematic review protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO, registration ID: CRD42016036051). The current review was reported according to the Preferred Reporting Items for Systematic Reviews and Meta-analyses guidelines (Moher et al., 2009).

2.2.1 Literature search and study selection

Candidate publications were searched from nine databases from their inception to August 2016: Academic Premier (1990+), CINAHL (1937+), Health and Safety Science Abstract (1981+), Medline (1965+), PsycINFO (1806+), Science Direct (1823+), Scopus (1996+), SportDiscus (1830+) and Web of Science (1970+) (Figure 2.1). The search string included keywords, MeSH terms, and free-text words and consisted of three parts. The first part was related to prevalence or incidence. The second part encompassed the topic of MSS, while the third-one covered construction trades. Since there were no universal list/definitions of the construction trades around the globe, the search string utilized both distinct trade names and general terms to amass all potential articles. Appendix A illustrates the exact search strategy employed. The corresponding authors of the included articles were contacted via email to identify additional articles.

Articles were included if they were primary studies published in peer-reviewed journals regarding the prevalence rates of MSS in one or more construction trades. There was no language restriction. Studies were excluded had they solely reported MSS related to infections, or accidents occurred at or outside worksites. Additionally, publications that did not directly or indirectly provide the prevalence rate of MSS (e.g. proportion of affected workers) were excluded. For multiple articles presenting the same data from a single cohort, only the one with the largest relevant data set was included.

Citations identified from the systematic searches were stored in EndNote X7 (Thomson Reuters, New York, USA) and duplicated citations were removed. Two reviewers (WU and MA) independently screened the titles and abstracts and selected the potential citations based on the selection criteria. Any disagreement was resolved by consensus. Those potential citations were then retrieved for full-text reading. The same screening procedures were adopted for full-text screening. Disagreements between the two reviewers were discussed to achieve consensus. Persistent disagreements were resolved by the third reviewer (AW). The reference lists of the included articles were searched for relevant citations. Forward citation tracking of the included articles was conducted using Scopus to identify relevant articles that were missed at the initial database searches.

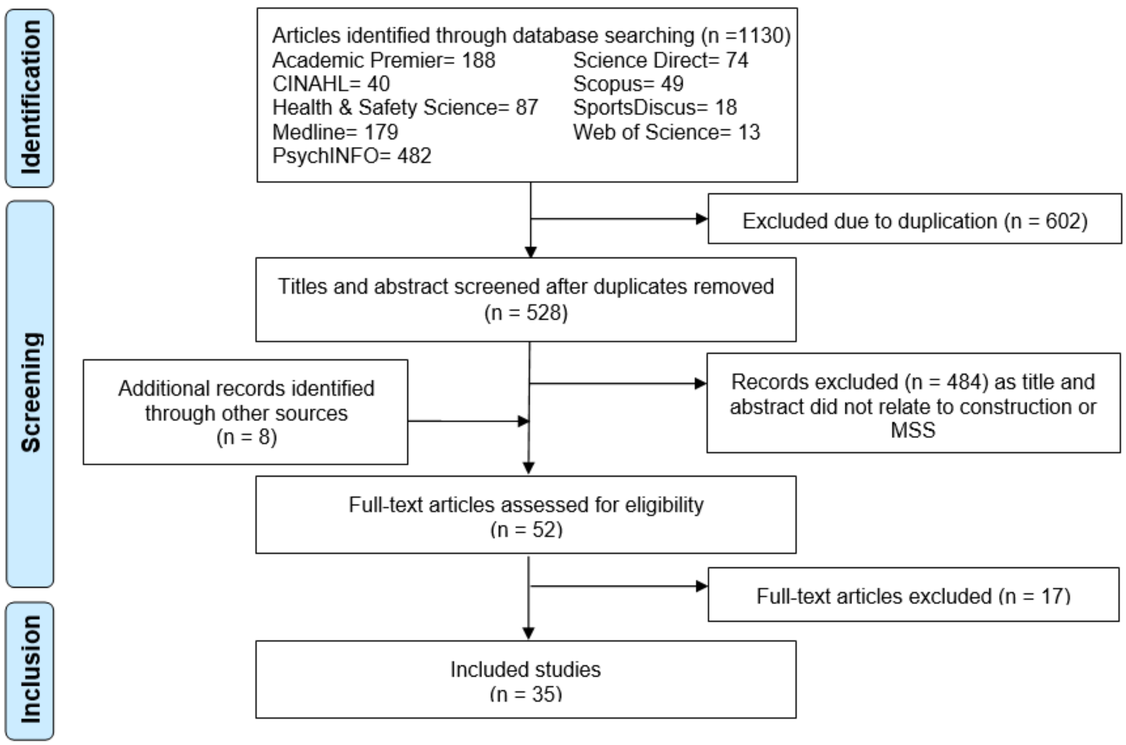


Figure 2.1 A flowchart depicting the systematic search

2.2.2 Data extraction

The two reviewers independently extracted relevant data from the included articles. The extracted data included year of the publication, duration and location(s) of data collection, study design, involved trade(s), sample size, response rate, age and gender of the participants, case definition, types of period prevalence (e.g. point or 1-week), and data pertaining to the prevalence or frequencies of different MSS in the sample. Consensus meetings were held to resolve any discrepancies arising from data extraction.

2.2.3 Quality assessment

Both reviewers independently evaluated the quality of each included study using a tool developed by *Loney et al.* (1998). The tool (Appendix B) has been used in many systematic reviews to evaluate the quality of primary incidence/prevalence studies (Graham et al., 2003; Fejer et al., 2006; Peppas et al., 2008; King et al., 2011; Kok et al., 2016). The tool consists of eight questions in three domains. The first six questions appraised the study methodology (i.e., study design and method, sampling frame, adequacy of the sample size, validity of the measurement tools, potential biases of the outcome measurement, and response rate and descriptions of non-respondents). The last two questions evaluated domains related to the results reporting quality and sociodemographic description of participants. Six of the eight questions in the tool score either 0 or 1 point each, while another two questions comprise two sub-questions. Each sub-question may score a maximum of 0.5 points. Accordingly, each study might score between 0 and 8. Studies with scores ≤ 4 were labeled as low-quality whereas studies with scores > 4 were considered as high-quality (Wong et al., 2013; Kok et al., 2016). Discrepancies between reviewers were resolved by discussion.

2.2.4 Data synthesis

The 95% confidence interval of the prevalence rate in a given included study was estimated using Wald's formula had it not been reported (Agresti and Coull, 1998). Meta-analysis was planned for each type of period prevalence rate of a given MSS if the studies had an identical case definition. I-squared (I^2) statistic was used to quantify the extent of statistical heterogeneity among the prevalence estimates. A random-effect model was used to estimate the period prevalence. Outliers were subjectively identified through scatterplots and were discarded from meta-analysis if the study quality was low (Hoy et al., 2012). RevMan 5.3 (The Cochrane Collaboration, Oxford, UK) was used for the meta-analysis. To minimize publication bias, comprehensive literature searches were conducted to ensure that relevant studies were included (Hoy et al., 2012).

2.3 RESULTS

The searches identified 1,130 citations (Figure 2.1). Five hundred and twenty-eight citations were screened for titles and abstracts after duplicates' removal. Among them, 484 were excluded as the titles and abstracts were unrelated to construction or MSS. Fifty-two articles were selected for full-text screening (including eight articles identified from forward citation tracking and reference lists of the included studies). Seventeen articles were excluded after reviewing the full text because they did not report prevalence data or had insufficient data for the prevalence estimation (e.g. injury/claim data without healthy workers' statistics or hospital reports). Therefore, 35 articles were included in this review (Table 2.1).

Table 2.1 Characteristics of the included studies (arranged according to the year of publication)

Study name	Country	Study population	Mode of data collection	Sample size, response rate	Age (years)	Gender	Case definition	Types of MSS	Type of period prevalence	Quality score
Arndt et al. (1996)	Germany	Architects, Carpenters, Engineers, Laborers, Office employees, Painters, Plasterers, Plumbers	Physical examination	N= 4,958 R= 78.0%	Range: 40.0 to 64.0	100.0% male	Pain, tenderness or symptoms at the spine, arms and legs	Spine, arms and legs	Point	7.5
Rothenbacher et al. (1997)	Germany	Carpenters, Laborers, Painters, Plasterers, Plumbers	Q	N= 4,958 R= 78.0%	Mean= 50.0, SD= 5.4	Unknown	Any type of back pain or sciatica experienced	Spinal	Point	6
Lemasters et al. (1998)	USA	Carpenters	Phone interview	N= 489 R= 83.0%	Mean= 42.3, SD= 10.6	97.8% male	Any recurring symptoms such as pain, aching, numbness	8 anatomical parts	1-year	8
de Zwart et al. (1999)	The Netherlands	Bricklayers, Carpenters, Laborers, Painters	Q	N= 3,827 R= unknown	Young workers: mean= 25.9 Older workers: mean= 50.1	100.0% male	Complaints	Neck, spinal, upper and lower extremities MSS	Point	5
Ueno et al. (1999)	Japan	Carpenters, Electricians, Interior finish workers, Iron-workers, Laborers, Painters,	Q	N= 2,205 R= 81.0%	Mean= 44.7, SD= 12.0	100.0% male	Have hand and arm pain, shoulder pain, or low back pain	Shoulders, hand and arm, and low back	Point	5

		Plasterers, Plumbers								
Jensen et al. (2000)	Denmark	Carpenters, Floor layers	Q	Floor layers: N= 133, R= 85.0% Carpenters: N= 506, R= 79.0%	Floor layers: mean= 47.0 Carpenters: mean= 45.0	Unknown	Ache, pain, or discomfort (for 1-week and 1-year) Knee complaints >30 days (1-year)	Knee	1-week, 1-year	6.5
Molano et al. (2001)	The Netherlands	Scaffolders	Q	N=323, R= 86.0%	Mean= 37.0, SD= 9.1	Unknown	Pain, which had continued for at least a few hours	Neck, shoulder, back and knee	1-year	5
Rosecrance et al. (2001)	Hungary	Apprentices (Electricians, Plumbers, Sheet metal workers)	Q	N= 193, R= 96.0%	Mean= 17.0, SD= 1.2	100.0% male	Job-related ache, pain, discomfort	As per NMQ	1-year	4
Goldsheyder et al. (2002)	USA	Demolition workers, Laborers, Masons	Q	N= 312, R= 70.2%	Mean= 39.9, SD= 9.2	85.0% mason male, 94.0% labor male	Musculoskeletal symptoms experienced	As per NMQ	Point, 1-year	5
Merlino et al. (2003)	USA	Electricians, Plumbers, Sheet metal workers	Q	N= 996, R= 84.8%	Mean= 27.7, SD= 6.2	93.9% male	Job-related ache, pain, discomfort	As per NMQ	1-year	5.5
Elders et al. (2004)	The Netherlands	Scaffolders	Q	At baseline: N= 288 R= 85.0% At 1-year FU: N= 209 R= 73.0%	Range: 35.0 to 44.0	Unknown	One episode of low back pain, stiffness or discomfort	Lower back	1-year	4.5

				At 2-year FU: N= 182 R= 78.0% At 3-year FU: N= 144 R= 78.0%						
Guo et al. (2004)	Taiwan	Nation-wide study stratified for construction industry	Q	N= 588* R= unknown	unknown	Unknown	Soreness or pain in any body part	As per NMQ	1-year	6.5
Engholm and Holmström (2005)	Sweden	Construction workers from multiple trades	Q	N= 85,191 R= unknown	Range: 25.0 to 60.0+	Unknown	Pain, ache	As per NMQ	1-year	7.5
Forde et al. (2005)	USA	Iron-workers	Phone interview	N= 981 R= 72.0%	Mean= 48.8, SD= 13.7	97.9% male	Chronic or recurring musculoskeletal symptoms (pain, aching, discomfort, or numbness)	As per NMQ	Over the entire working career	6.5
Lee et al. (2005)	Taiwan	Nation-wide study stratified for construction industry	I	N= 2021 R= 85.0%	unknown	90.0% male	Soreness or pain	Neck, shoulder, upper back, elbow, wrist and hand	1-year	5.5

Gilkey et al. (2007)	USA	Carpenters	Q	N= 91 R= unknown	Mean= 37.0	Unknown	Low back pain which resulted in lost time from work and/or altered some aspects of the normal activities of daily living and/or caused the sufferer to seek medical care	Lower back	2-week, 1-year, lifetime	2.5
Welch et al. (2008)	USA	Roofers	Phone interview	N= 979 R= 62.0%	Range: 40.0 to 59.0	Unknown	In the past 2 years, did you take medication for or need to regularly see a doctor for musculoskeletal problems?	8 anatomical parts	2-year	4.5
Gheibi et al. (2009)	Iran	Laborers, Machine operators, Truck drivers	Q	N= 110 R= unknown	Mean= 34.9, SD= 9.4	100.0% male	Ache, pain, or discomfort	As per NMQ	1-year	3
van der Molen et al. (2009)	The Netherlands	Carpenters, Pavers	Q	Carpenters At baseline: N= 401 R= 61.0%, At 5-year FU N= 361 carpenters, R= 78.0%,	Carpenters: At baseline, mean= 42.0, SD= 10.0 At 5-year FU, mean= 47.0, SD= 10.0	Unknown	Musculoskeletal lower back or shoulder complaints	Shoulders, lower back	1-year	5

				Pavers: At baseline: N= 177 R= 53.0% At 5-year FU N= 163 R= 64.0%	Pavers At baseline, mean= 39.0, SD= 9.7 At 5-year FU, mean= 43.0, SD= 9.6					
Caban-Martinez et al. (2010)	USA	Hispanic construction workers in the USA	Q	N=49 R= 98.0%	Mean= 41.9, SE=1.8	100.0% male	Any symptoms of pain, aching, or stiffness in or around a joint. During the past 3 months, did you have low back pain that lasted a whole day?	7 anatomical parts	1-month for other parts, 3-month for LBP	3.5
Hoonakker and van Duivenbooden (2010)	The Netherlands	Carpenters, Concrete workers, Masons and others	Q	From 1993 to 94: N= 53,500 R= unknown From 1995 to 96: N= 50,300 R= unknown From 1997 to 98: N= 58,340 R= unknown From 1999-	unknown	Unknown	Regular pain or stiffness	Spinal, upper and lower extremities MSS	Point	5

				2000: N= 50,500 R= unknown From 2002 to 03: N= 75,500 R= unknown						
Bodhare et al. (2011)	India	Bricklayers, Carpenters, Electricians, Laborers, Painters, Plumbers, Welders	Q	N= 211 R= unknown	Range: 15.0 to 65.0	85.0% male	Pain, numbness, tingling, aching, stiffness or burning in the past year that lasted at least a week or more or occurred at least monthly with a pain scale rating of moderate on a 5-point scale.	As per NMQ	1-week, 1-year	3
Boschman et al. (2012)	The Netherlands	Bricklayers	Postal questionnaire	At baseline: N= 292 R= 39.0% At 1-year FU: N= 256 R= 34.0%	At baseline: Median age 50 At 1-year FU: Median age 51	100.0% male	Regular or long-lasting complaints during the last six months	11 anatomical parts	6-month	6
Dong et al. (2012)	USA	Unknown	Q	At baseline: N= 616 R= unknown	Mean= 55.46, SE= 0.15	90.3% male	Back pain	Back	Point	4.5

				At 16-year FU: N= 364 R= unknown	Mean= 70.91, SE= 0.18	90.4% male				
Pandey et al. (2012)	India	Managers	Q	N= 22, R= unknown	Mean= 34.4, SD= 9.5	Unknown	Musculoskeletal problem	As per NMQ	1-year	3
Burstrom et al. (2013)	Sweden	Construction workers from multiple trades	I	N= 118,258 R= 80.0%	Mean= 40.6, SD= 13.5	100.0% male	Pain in the upper back and neck that hindered your work	Neck, lower back	1-year	4.5
Meo et al. (2013)	Saudi Arabia	Concrete workers, Electricians, Iron-workers, Laborers, Machine operators, Masons, Plumbers, Supervisors	Q	N= 389 R= 72.0%	Mean= 34.6, SD= 8.3	100.0% male	Complaints of the musculoskeletal system	Neck, shoulder, upper back, lower back, leg, ankle	Point	6.5
Telaprolu et al. (2013)	India	Laborers	I	N= 118 R= 94.4%	Mean= 36.4, SD= 7.8	100.0% female	Musculoskeletal symptoms	As per NMQ	1-year	4
Visser et al. (2013)	The Netherlands	Floor-layers	Postal questionnaire	N= 409 R= 53.0%	Mean= 41.0, SD= 12.0 and mean= 42.0, SD= 13.0 for two types of floor layers	Unknown	Regular/recurring musculoskeletal complaints	As per NMQ	6-month	5
Deros et al. (2014)	Malaysia	Bricklayers, Housekeepers, Plasterers, Skimcoaters	Q	N= 60 R= unknown	Range: 17.0 to 50.0	Unknown	Trouble (ache, pain, discomfort, numbness)	As per NMQ	1-year	3

Ekpenyong et al. (2014)	Nigeria	Bricklayers, Carpenters, Earth-movement laborers, Electricians, Iron-workers	Q+I	N= 1,200 R= 56.0%	Mean= 26.4, SD= 0.4	100.0% male	Musculoskeletal problems that could have prevented their normal activities	Spinal, upper and lower extremities MSS	1-year	6
Hanklang et al. (2014)	Thailand	Iron-workers	Q	N= 272 R= unknown	Mean= 48.2, SD= 9.7	100.0% female	Musculoskeletal pain/symptoms	Neck, shoulders, wrist/hand, back and knee	1-year	3.5
Kim et al. (2014)	USA	Bricklayers, Electricians, Iron-workers, Painters, Pipefitters, Plumbers	Q	N= 1,817 R= 93.6%	Range: 18.0 to 45.0+	95.2% male	Pain, aching, burning, stiffness, cramping, or soreness in your neck more than 3 times or that lasted more than 1 week	Neck, shoulder, hand and back	Over the entire working career	5
Alghadir and Anwer (2015)	Saudi Arabia	Bricklayers, Carpenters, Crane operators, Electricians, Interior finish workers, Laborers, Painters, Plumbers, Scaffolders	I	N= 165 R= unknown	Mean= 34.8, SD= 8.3	100.0% male	Musculoskeletal pain	As per NMQ	1-year	2
Eaves et al. (2016)	UK	Bricklayers, Carpenters, Electricians, Iron-workers, Joiners, Laborers, Painters,	Q+I	N= 74 R = unknown	Range= under 25.0 to 50.0+	Unknown	Aches and pains in body areas	As per NMQ	1-year	3.5

	Plasterers, Plumbers, Scaffolders, Welders	

Note: FU, follow-up; I, face-to-face interview; MSS, musculoskeletal symptoms; N, number of participants; NMQ, Nordic musculoskeletal questionnaire; Q, questionnaire; R, response rate; SD, standard deviation; SE, standard error; *, it indicates data was calculated from the data provided in the included study

2.3.1 Study characteristics

Four types of study designs were observed in the included studies. Twenty-six studies were cross-sectional studies. One study was a repeated cross-sectional cohort study (Hoonakker and van Duivenbooden, 2010). Four studies were case-control studies (Arndt et al., 1996; Rothenbacher et al., 1997; Ueno et al., 1999; Burström et al., 2013), and four were prospective cohort studies (Elders and Burdorf, 2004; van der Molen et al., 2009; Boschman et al., 2012; Dong et al., 2012). The included studies comprised 303,384 construction workers in at least 19 different construction trades/specialities from 15 countries. Two cohorts were reported in four distinct included articles (Arndt et al., 1996; Rothenbacher et al., 1997; Molano et al., 2001; Elders and Burdorf, 2004). Since none of them reported duplicate data from the same cohort, all four studies were included for review. Most of the included studies were conducted in the USA (n = 9) followed by the Netherlands (n = 7) and India (n = 3) (Table 2.1). Other data were collected from Denmark, Hungary, Iran, Japan, Malaysia, Nigeria, Saudi Arabia, Sweden, Taiwan, Thailand, and the UK (Table 2.1).

The included studies had variable sample sizes, data collection methods, and response rates. The sample size of the included studies ranged from 22 to 118,258 (Pandey et al., 2012; Burström et al., 2013). Of them, 23 (66%) had a sample size of more than 300 participants. Twenty-three included studies used self- or researcher-administered questionnaires to collect prevalence data (Table 2.1). Four studies used face-to-face interviews, three used phone interviews, two used postal questionnaires, and two adopted semi-structured questionnaires for data collection (Table 2.1). Further, one study estimated the prevalence of MSS solely based on physical examination findings (Arndt et al., 1996). Thirteen studies did not report the response rate (Table 2.1). Five studies had a response rate of less than 70%, while 17 studies reported response rates ranging from 70.2% (Kim et al., 2014) to 98% (Caban-Martinez et al., 2010).

The included studies reported divergent types of period prevalence for work-related MSS (Table 2.1). Seven studies exclusively reported point prevalence, two described 6-month, 18 reported 1-year, and one described 2-year prevalence. Two studies revealed a prevalence over the entire working career. Only five studies reported two to three types of period prevalence. The case definitions employed by the included studies also varied markedly from subjective pain perception to symptoms that caused the sufferer to seek medical care (Table 2.1).

2.3.2 Study quality

The quality assessment scores varied from a minimum of two (Alghadir and Anwer, 2015) to a maximum of eight (Lemasters et al., 1998) with a mean value of 4.9 (1.5) (Table 2.2). Eleven out of 35 included studies (31%) were rated as low-quality (Table 2.2). Overall, the included studies scored well on items related to demographics and work setting description (86%), and the use of a validated questionnaire for data collection (77%). Only five included studies adopted physician examinations of sub-samples to validate the results of self-reported prevalence or used physical examinations as a primary tool for data collection (Arndt et al., 1996; Rothenbacher et al., 1997; Lemasters et al., 1998; Engholm and Holmström, 2005; Meo et al., 2013). However, the included studies scored poorly on the description of non-respondents' characteristics (refusers, n= 29) and on the confidence interval of prevalence rate (n= 22) (Table 2.2, Appendix C).

Table 2.2 The quality assessment results of the included studies

Included studies/ Quality assessment criteria	Study design	Sampling frame	Sample size	Suitable and standard criteria used	Biases possibility in outcome reporting	Adequate response rate & refusers described	95% CI given & sub-group analysis done	Participants demographics and work setting described	Total score
Low-quality studies									
Alghadir and Anwer (2015)	1	0	0	0	0	0	0	1	2
Gilkey et al. (2007)	1	1	0	0	0	0	0.5	0	2.5
Bodhare et al. (2011)	1	0	0	1	0	0	0	1	3
Deros et al. (2014)	1	1	0	1	0	0	0	0	3
Pandey et al. (2012)	1	0	0	1	0	0	0	1	3
Gheibi et al. (2009)	1	0	0	1	0	0	0	1	3
Hanklang et al. (2014)	1	1	0	0	0	0	0	1	3
Caban-Martinez et al. (2010)	1	0	0	1	0	0.5	0	1	3.5
Eaves et al. (2016)	1	0	0	1	0	0	0.5	1	3.5
Telaprolu et al. (2013)	1	0	0	1	0	0.5	0.5	1	4
Rosecrance et al. (2001)	1	0	0	1	0	1	0	1	4
High-quality studies									
Elders et al. (2004)	1	0	0	1	0	0.5	1	1	4.5
Welch et al. (2008)	1	1	1	1	0	0.5	0	0	4.5
Burstrom et al. (2013)	1	1	1	0	0	0.5	0	1	4.5
de Zwart et al. (1999)	1	1	1	1	0	0	1	0	5
Dong et al. (2012)	1	1	1	0	0	0	1	1	5
Goldsheyder et al. (2002)	1	0	1	1	0	0.5	0.5	1	5
Hoonakker and van Duivenbooden (2010)	1	1	1	1	0	0	0	1	5
Kim et al. (2014)	1	1	1	0	0	0.5	0.5	1	5
Molano et al. (2001)	1	0	1	1	0	0.5	0.5	1	5
Ueno et al. (1999)	1	1	1	0	0	0.5	0.5	1	5
van der Molen et al. (2000)	1	1	1	0	0	0.5	0.5	1	5
Visser et al. (2013)	1	1	1	1	0	0	0	1	5
Lee et al. (2005)	1	1	1	1	0	0.5	0	1	5.5

Merlino et al. (2003)	1	1	1	1	0	0.5	0	1	5.5
Ekpenyong et al. (2014)	1	1	1	1	0	0	1	1	6
Rothenbacher et al. (1997)	1	1	1	1	1	0.5	0.5	0	6
Boschman et al. (2012)	1	1	1	1	0	0	1	1	6
Guo et al. (2004)	1	1	1	1	0	0.5	1	1	6.5
Jensen et al. (2000)	1	1	1	1	0	1	0.5	1	6.5
Forde et al. (2005)	1	1	1	1	0	1	0.5	1	6.5
Meo et al. (2013)	1	0	1	1	1	0.5	1	1	6.5
Arndt et al. (1996)	1	1	1	1	1	0.5	1	1	7.5
Engholm and Holmström (2005)	1	1	1	1	1	1	0.5	1	7.5
Lemasters et al. (1998)	1	1	1	1	1	1	1	1	8

CI, confidence interval

2.3.3. Different types of estimated period prevalence of MSS

The included studies reported diverse types of period prevalence and case definitions of MSS (Table 2.2 and 2.3). Since, most studies reported 1-year prevalence using the case definition of having at least one episode of pain/MSS in the last 12 months, only 1-year prevalence of MSS at nine body regions (as described in the Nordic Musculoskeletal Questionnaire) were pooled to calculate the respective mean prevalence. The following section summarizes the most common MSS (two to three body regions) for each period of prevalence. The detailed period prevalence rates of MSS in different body regions are presented in Table 2.3.

Table 2.3 Summary of various types of the prevalence of musculoskeletal symptoms in the construction industry

	Prevalence (%)								
Region/case definition	**Point**	**1-week**	**2-week**	**1-month**	**6-month**	**1-year**	**2-year**	**Over the entire career**	**Lifetime**
Neck (symptoms)	5.5 to 22.0[1,2,3]	--	--	--	--	24.4* (10.0 to 38.9)	--	--	--
Chronic	--	17.0[7]	--	--	7.0 to 50.0[11,12]	9.2 to 48.0[7,13]	14.1[17]	30.3 to 39.5[18,19]	--
Activity-limiting	--	--	--	--	--	8.6 to 48.2[7,14,15,16]	--	--	--
Shoulder (symptoms)	10.5 to 28.7[1,3,4]	--	--	6.0 to 7.7[10]	--	32.4* (17.2 to 47.7)	--	--	--
Chronic	--	13.0[7]	--	--	13.0 to 54.0[11,12]	18.4 to 40.0[7,13]	10.7[17]	35.6 to 40.7[18,19]	--
Activity-limiting	--	--	--	--	--	18.0 to 34.0[7,15]	--	--	--
Elbow (symptoms)	12.0[1]	--	--	1.5[10]	--	20.3* (7.7 to 32.9)	--	--	--
Chronic	--	6.0[7]	--	--	9.0 to 28.0[11,12]	18.8 to 24.0[7,13]	9.7[17]	21.2[19]	--
Activity-limiting	--	--	--	--	--	11.0[7]	--	--	--
Wrist/hand (symptoms)	21 to 28.4[1,4]	--	--	1.5[10]	--	30.4* (19.1 to 41.7)	--	--	--
Chronic	--	6.0[7]	--	--	13.0 to 35.0[11,12]	18.8 to 28.0[7,13]	8.3[17]	28.5 to 40.4[18,19]	--
Activity-limiting	--	--	--	--	--	9.0[7]	--	--	--
Upper back (symptoms)	6.2 to 14.0[1,3]	--	--	--	--	19.8* (5.8 to 33.8)	--	--	--
Chronic	--	6.0[7]	--	--	10.0 to 14.0[12]	19.0[7]	14.1[17]	18.1[19]	--
Activity-limiting	--	--	--	--	--	9.0[7]	--	--	--
Lumbar (symptoms)	16.5 to 60.3[1,3,4,5,6,20]	--	--	--	--	51.1* (40.9 to 61.3)	--	--	--
Chronic	--	34.0[7]	--	--	26.0 to 53.0[11,12]	15.7 to 92.0[7,13]	28.7[17]	50.5 to 56.0[18,19]	--

Activity-limiting	--	--	14.0[9]	--	--	24.3 to 42.0[7,9,14]	--	--	54.0[9]
Hip/thigh (symptoms)	11.0[1]	--	--	1.5[10]	--	15.1* (0.5 to 29.7)	--	--	--
Chronic	--	9.0[7]	--	--	6.0 to 53.0[11,12]	7.0 to 23.0[7,13]	3.9[17]	19.6[19]	--
Activity-limiting	--	--	--	--	--	12.0[7]	--	--	--
Knee (symptoms)	22.0[1]	27.0 to 39.0[8]	--	33.8[10]	--	37.2* (22.4 to 52.0)	--	--	--
Chronic	--	15.0[7]	--	--	18.0 to 56.0[11,12]	15.3 to 68.0[7,8,13]	15.0[17]	39.4[19]	--
Activity-limiting	--	--	--	--	--	19.0 to 37.0[7,15]	--	--	--
Ankle/foot (symptoms)	13.4 to 19.0[1,3]	--	--	3.1 to 4.6[10]	--	24.0* (15.2 to 32.8)	--	--	--
Chronic	--	4.0[7]	--	--	0.0 to 48.0[11,12]	4.3 to 17.0[7,13]	8.9[17]	29.4[19]	--
Activity-limiting	--	--	--	--	--	8.0[7]	--	--	--

Note: In each cell, the range of prevalence rate is presented, if possible. * represents the estimated mean 1-year prevalence from meta-analysis. The numbers in the parenthesis represent the 95% confidence interval. 1= (Goldsheyder et al., 2002); 2= (de Zwart et al., 1999); 3= (Meo et al., 2013); 4= (Ueno et al., 1999); 5= (Arndt et al., 1996); 6= (Dong et al., 2012); 7= (Bodhare et al., 2011); 8= (Telaprolu et al., 2013); 9= (Gilkey et al., 2007); 10= (Caban-Martinez et al., 2010); 11= (Boschman et al., 2012); 12= (Visser et al., 2013); 13= (Lemasters et al., 1998); 14= (Burström et al., 2013); 15= (Molano et al., 2001); 16= (Ekpenyong and Inyang, 2014); 17= (Welch et al., 2008); 18= (Kim et al., 2014); 19= (Forde et al., 2005); 20= (Rothenbacher et al., 1997)

Seven studies reported point prevalence of MSS among construction workers (Table 2.2 and 2.3) with lumbar, neck and lower limb MSS being the most common ones. In the USA, the point prevalence of lumbar pain/MSS ranged from 33% to 39%, while neck and knee MSS were also common with a prevalence rate of 22% each (Goldsheyder et al., 2002; Dong et al., 2012). In Saudi Arabia, the most common MSS were legs, lumbar and foot with the estimated point prevalence rates of 23.9%, 16.5% and 13.4%, respectively (Meo et al., 2013). A Japanese study involving multiple construction trades reported that the point prevalence rates of lumbar and shoulder MSS were substantial with the respective estimated rates of 53.2% and 28.7% (Ueno et al., 1999). Likewise, the point prevalence of self-reported back pain ranged from 47.8% to 60.3% among German construction workers whereas another German study entailing physical examination/diagnosis revealed a slightly lower prevalence of back MSS (32.5%) (Arndt et al., 1996; Rothenbacher et al., 1997). Similarly, back MSS is the most noteworthy MSS among Dutch construction workers. The point prevalence rates of back MSS among young and older workers were 25.0% and 43.8%, respectively (de Zwart et al., 1999).

Two studies reported the 1-week prevalence of MSS while one reported the 2-week prevalence (Table 2.3). Two most prevalent recurring MSS were found at lumbar and neck regions among Indian construction workers with estimated 1-week prevalence rates of 34% and 17%, respectively (Bodhare et al., 2011). Conversely, knee pain MSS was the most common MSS among Danish floor layers and carpenters in the last 7 days. The 1-week prevalence rates of knee pain/MSS in Danish floor layers and carpenters were 39% and 27%, respectively (Jensen et al., 2000). Additionally, the 2-week prevalence of activity-limiting lumbar MSS was 14% among American carpenters (Gilkey et al., 2007).

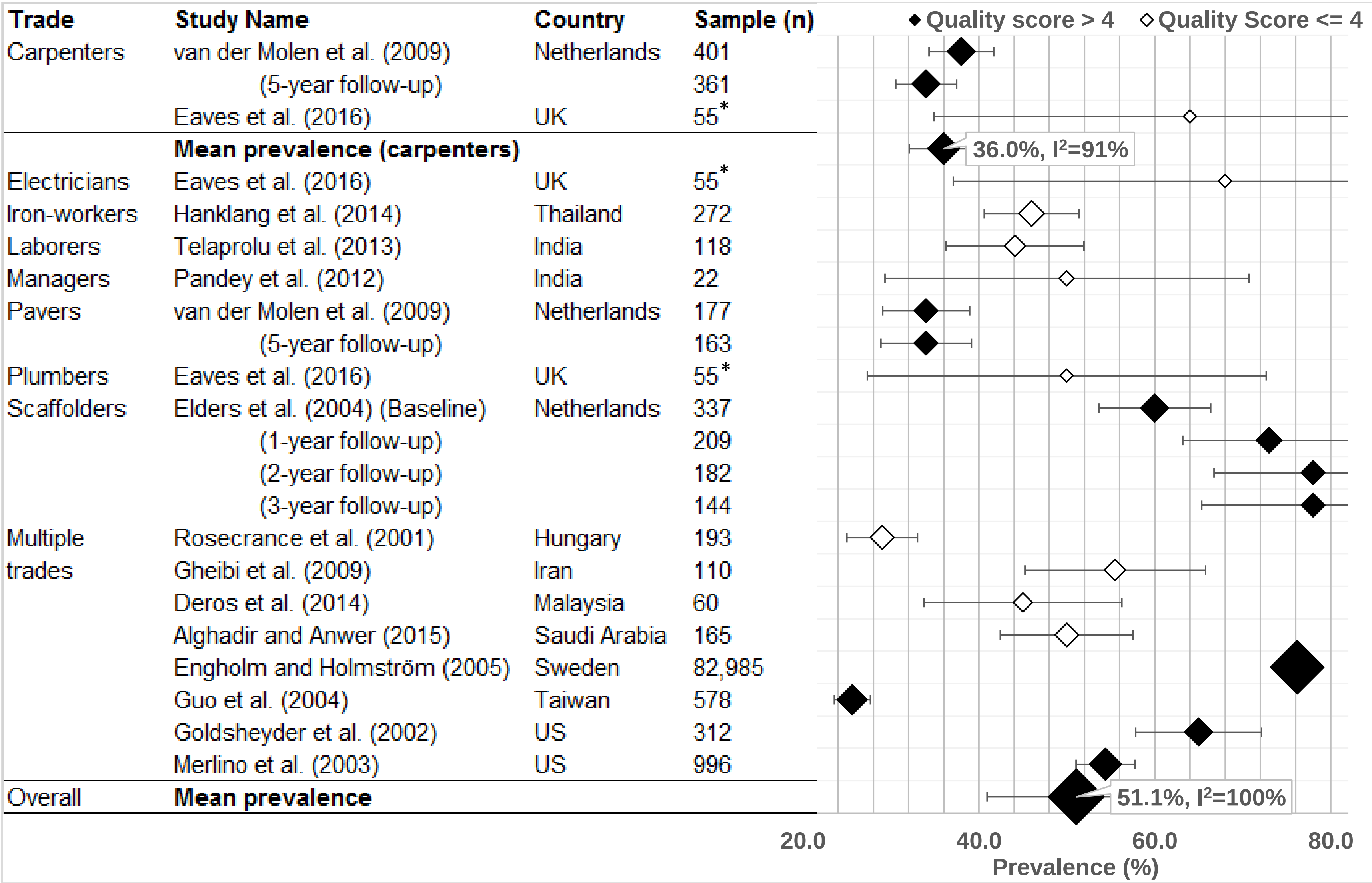
Only one study reported the 1-month and 3-month MSS prevalence while two reported 6-month MSS prevalence rates of different body regions (Table 2.3). Caban-Martinez et al. (2010) estimated the 1-month pain/MSS prevalence of knee (33.8%), shoulder (6.2% to 7.7%), and ankle (3.1% to 4.6%) among Hispanic-American construction workers. Additionally, their reported 3-month prevalence of all day lasting lumbar pain was 63%. The two most prominent regular/recurring MSS in sand-cement-bound and anhydrite-bound screed Dutch floor layers were lumbar and shoulder MSS with 6-month prevalence rates of 39% and 27%; and 26% and 13%, respectively (Visser et al., 2013). A prospective Dutch survey on bricklayers also revealed that the 6-month prevalence rates of recurring MSS were 42% for back and 27% for the knee at baseline, while the respective rates at 1-year follow-up were 53% and 56% (Boschman et al., 2012).

The pooled mean 1-year prevalence rates of MSS (defined as at least one episode of pain/MSS in the last 12 months) are shown in Figure 2.2 and Appendix C. The estimated mean 1-year prevalence rates were 51.1% for the lumbar region (95% confidence interval (CI): 40.9% to 61.3%, from 19 estimates, Figure 2.2), 37.2% for knee (95% CI: 22.4% to 52.0%, from 13 estimates), 32.4% for shoulder (95% CI: 17.2% to 47.7%, from 10 estimates), 30.4% for wrist (95% CI: 19.1% to 41.7%, from 9 estimates), 24.4% for neck (95% CI: 10.0% to 38.9%, from 12 estimates), 24.0% for ankle/foot (95% CI: 15.2% to 32.8%, from 7 estimates), 20.3% for elbow (95% CI: 7.7% to 32.9%, from 6 estimates), 19.8% for upper back MSS (95% CI: 5.8% to 33.8%, from 6 estimates) and 15.1% for hip/thigh (95% CI: 0.5% to 29.7%, from 5 estimates) (Table 2.3, Appendix C).

Three studies reported 1-year prevalence rates of various chronic MSS (Tables 2.1 and 2.3). Notably, chronic elbow and wrist MSS (18.8%), and chronic shoulder MSS (18.4%) were commonly found among American carpenters (Lemasters et al., 1998). For Indian construction workers, 1-year prevalence rates of chronic lumbar, neck and knee MSS were substantial with estimated rates of 92.0%, 48.0% and 47.0%, respectively (Bodhare et al., 2011). Additionally, 1-year prevalence rates of chronic knee MSS among Danish floor layers and carpenter were 56.4% and 68.0%, respectively (Jensen et al., 2000).

Five studies reported the 1-year prevalence of activity-limiting MSS, but the prevalence rates varied among populations (Tables 2.1 and 2.3). The estimated 1-year prevalence rate of activity-limiting lumbar MSS was 38.0% among American carpenters (Gilkey et al., 2007), while those of lumbar and neck MSS in Swedish construction workers were 24.3% and 8.6% respectively (Burström et al., 2013). Among Indian construction workers, 1-year prevalence rates of activity-limiting MSS in lumbar (42.0%) and neck (21.0%) regions were most notable (Bodhare et al., 2011). Similarly, the 1-year prevalence of activity-limiting MSS among Nigerian construction workers were 48.2%, 26.5% and 25.3% for neck and upper limb, lower limb, and trunk and waist, respectively (Ekpenyong and Inyang, 2014). Further, the two most common MSS that limited activity of Dutch scaffolders for several hours over the last 12 months were back (60.0%) and knee (37.0%) (Molano et al., 2001).

One study investigated two-year prevalence rates of MSS that required medical assistance in USA roofers (Welch et al., 2008). It showed that lumbar (28.7%) and knee (15.0%) were most affected (Table 2.3). Two studies investigated the prevalence of chronic MSS over the entire career of construction workers. Specifically, chronic lumbar (56.0%), wrist/hand/finger (40.4%), and knee (39.4%) MSS were most prevalent among USA iron-workers (Forde et al., 2005). Similarly, prevalence rates of chronic back (50.5%) and shoulder MSS (40.7%) were eminent in American construction apprentices throughout their entire career (Kim et al., 2014). Additionally, Gilkey et al. (2007) found that the lifetime prevalence of activity-limiting lumbar MSS in the USA carpenters was 54.0%.



Note: MSS = Musculoskeletal symptoms, The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval, * indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.

The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality. Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals. Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

Figure 2.2 The 1-year prevalence of lumbar MSS in different construction trades

2.3.4 Trade-specific analysis

Many included studies did not provide stratified prevalence data that hampered comparison among various trades. Only 16 studies reported trade-specific MSS prevalence (Arndt et al., 1996; Rothenbacher et al., 1997; Lemasters et al., 1998; Ueno et al., 1999; Jensen et al., 2000; Molano et al., 2001; Elders and Burdorf, 2004; Forde et al., 2005; Gilkey et al., 2007; Welch et al., 2008; van der Molen et al., 2009; Boschman et al., 2012; Visser et al., 2013; Ekpenyong and Inyang, 2014; Hanklang et al., 2014; Eaves et al., 2016). Unfortunately, given the divergent reports of period prevalence and inconsistent definitions of body parts and cases, no meta-analysis was conducted for each trade. Two studies found that lumbar pain was the most prevalent MSS among bricklayers (Rothenbacher et al., 1997; Boschman et al., 2012), although others reported that neck, upper limb, and legs MSS were predominant in bricklayers (Arndt et al., 1996; Ekpenyong and Inyang, 2014). Similarly, lumbar MSS were the most ubiquitous in carpenters (Arndt et al., 1996; Ueno et al., 1999; Gilkey et al., 2007; van der Molen et al., 2009; Eaves et al., 2016), while MSS of knee (Rothenbacher et al. 1997) and upper extremity (e.g. wrist and elbow) (Lemasters et al., 1998; Ekpenyong and Inyang, 2014) were also common. For electricians, MSS of lumbar (Ueno et al., 1999; Burström et al., 2013) and upper extremity (Ekpenyong and Inyang, 2014) were most common. Similarly, MSS of lumbar (Visser et al., 2013) and knees (Jensen et al., 2000) were most prevalent among floor layers. For iron-workers, lumbar (Ueno et al., 1999; Forde et al., 2005), wrist and shoulder (Ekpenyong and Inyang, 2014; Hanklang et al., 2014) MSS were mostly reported. Likewise, plumbers mostly suffered from back (Arndt et al., 1996; Rothenbacher et al., 1997; Ueno et al., 1999), wrist and knees (Eaves et al., 2016) MSS. Additionally, lumbar pain (Arndt et al., 1996; Rothenbacher et al., 1997; Ueno et al., 1999) was prominent in laborers, painters, plasterers, pavers (van der Molen et al., 2009), roofers (Welch et al., 2008) and scaffolders (Elders and Burdorf , 2004).

2.3.5 Gender analysis

There is a paucity of studies that reported gender-specific MSS prevalence. Thirteen out of the 35 included studies did not report the gender composition within the sample population (Table 2.1). Eight included studies recruited more than 85% of male participants. Two solely enrolled women construction workers (Telaprolu et al., 2013; Hanklang et al., 2014). Only two studies provided gender-segregated MSS prevalence data (Merlino et al., 2003; Guo et al., 2004). Both found that females had a significantly higher 1-year prevalence of MSS (difference ranging from 0.9% in the wrist to 30.1% in shoulder) as compared to their male counterparts.

2.3.6 Age-stratified analysis

Since the included studies used variable age group stratification methods, study designs and statistical analyses, no meta-analysis was conducted. The age range of construction workers in the included was large, ranging from a mean age of 17 (Rosecrance et al., 2001) to 71 years (Dong et al., 2012). Most studies reported both mean and standard deviation of participants' age, while only a few reported age ranges (Table 2.1).

Nine of the included studies provided age-stratified analysis on prevalence data of MSS in construction workers (Alghadir and Anwer, 2015; Bodhare et al., 2011; Eaves et al., 2016; Hoonakker and van Duivenbooden, 2010; Jensen et al., 2000; Telaprolu et al., 2013; Ueno et al., 1999; Welch et al., 2008; de Zwart et al., 1999). Five of them found no significant association between stratified age groups and MSS prevalence (Jensen et al., 2000; Welch et al., 2008; Telaprolu et al., 2013; Alghadir and Anwer, 2015; Eaves et al., 2016). Conversely, one study proclaimed a trend of increasing MSS prevalence with age although no detailed statistical result was reported (Hoonakker and van Duivenbooden, 2010). The remaining three studies found significant positive associations between age and point (Ueno et al., 1999; de Zwart et al., 1999) or 1-year (Bodhare et al., 2011) MSS prevalence.

Additionally, four studies investigated the relation between age and prevalence of MSS without using stratified age data. Three studies reported positive associations between age and MSS prevalence. Specifically, a longitudinal study reported a significant increase in the prevalence of low back pain over a 15-year period although the results were confounded by workers' job history and job exposures (Dong et al., 2012). Another study found that older Nigerian workers doubled the odds of suffering from work-related MSS than their younger counterparts (Ekpenyong and Inyang, 2014). An Iranian study also found a significant positive association between workers' age and MSS prevalence (Gheibi et al., 2009). However, a study on USA ironworkers found that older age was significantly associated with a lower risk of lumbar MSS after adjusting for prior injuries and work duration (Odds ratio: 0.97) (Forde et al., 2005).

2.4 DISCUSSION

This is the first systematic review to summarize the prevalence of MSS in the construction industry. Although 35 articles were included, their heterogeneous period prevalence rates and case definitions prevented the meta-analysis of each period prevalence except for 1-year prevalence (defined as at least one episode of pain/MSS in the last year). Nevertheless, our meta-analysis showed that lower back had the highest mean 1-year prevalence of MSS (51.1%) among construction workers while hip/thigh had the lowest one (15.1%). Collectively, findings from different types of period prevalence consistently suggested that construction workers most commonly suffer from lumbar, knee, shoulder and wrist MSS.

While subgroup analyses were planned for MSS prevalence of all available construction trades, the lack of relevant information prevented these analyses. Intuitively, the prevalence of MSS is related to work conditions, work-related risk factors, cultures, and personal characteristics. For example, Asian construction workers prefer to squat during work as compared to those in western countries (Chung et al., 2003; Jung and Jung, 2008), which may affect their body biomechanics (Umer et al., 2017b) and predispose them to task-specific MSS. Since certain work-related tasks (e.g. frequent bending and twisting, whole-body vibration and carrying load) may increase the risk of lumbar MSS, proper ergonomic interventions should be implemented to reduce the occurrence of lumbar MSS (Burdorf and Sorock, 2016). Imperatively, the current review only identified a few studies reporting MSS prevalence in individual construction trades. Therefore, there is an urgent need to investigate MSS prevalence in different trades so that trade-specific prevention/treatment strategies can be developed and implemented.

While only two studies reported MSS prevalence of both genders in the construction industry (Merlino et al., 2003; Guo et al., 2004), both indicate that female workers are more susceptible to MSS. Although speculative, this phenomenon may be attributed to differences in between-gender physique (e.g. lower muscle strength in females) (Miller et al., 1993), genetic pain coping (Bartley and Fillingim, 2013), or the higher reliance on male anthropometric data for designing workspace/tools (Pheasant, 1996). Importantly, with the increasing global trend of female participation in the labor force (Kinoshita and Guo, 2015), it is crucial for stakeholders to investigate causes underlying differential MSS prevalence, and adopt preventive measures to minimize the risk of work-related MSS in both genders.

The current review highlights an age-related MSS trend that deserves further investigation. Thirteen included studies examined the relation between ages of construction workers and MSS prevalence with or without providing age-stratified prevalence data. Six of them concluded a non-significant association between the two variables (Jensen et al., 2000; Forde et al., 2005; Welch et al., 2008; Telaprolu et al., 2013; Alghadir and Anwer, 2015; Eaves et al., 2016), while seven found a significant association between them (Bodhare et al., 2011; Dong et al., 2012; Ekpenyong and Inyang, 2014; Gheibi et al., 2009; Hoonakker and van Duivenbooden, 2010; Ueno et al., 1999; de Zwart et al., 1999). Despite the inconsistent findings, it cannot downplay the importance of clarifying the association between age and work-related MSS in construction workers. It is known that the proportion of the older workforce is increasing in many industrialized countries (Samorodov, 1999). Older workers commonly experience a decline in physical work capacity (Kenny et al., 2008), cardiac output (Fitzgerald et al., 1997), muscle strength and mass (Thomas, 2010). Physical decline alongside the presence of MSS will increase the risk of work injury in older workers who usually have higher rehabilitation demands (Schwatka et al., 2011). Importantly, the literature suggests that previous occupational biomechanical exposures (e.g. twisting and bending) can increase the risk of future episodes of low back pain in older/retired workers (Plouvier et al., 2015). Accordingly, future studies should clarify the relation between age and work-related MSS, and develop strategies to minimize the propensity of MSS in older workers.

2.4.1 Implications

Despite the limitations, our review has strong implications for construction managers, ergonomists, policy makers and researchers. The results signify that more than half of the construction workforce face lumbar MSS, nearly one-third of them face knee, shoulder and wrist MSS annually. These figures underscore the necessity of deriving relevant policies and developing/implementing effective prevention strategies to attenuate the prevalence of work-related MSS in the construction industry.

2.5 CHAPTER SUMMARY

This chapter has provided a systematic review/meta-analysis to summarize the MSS prevalence in different construction trades, gender and age-groups, which may help to develop specific ergonomic interventions for workers in the construction industry.

CHAPTER 3

SENSING AND WARNING-BASED TECHNOLOGY APPLICATIONS TO IMPROVE OCCUPATIONAL HEALTH AND SAFETY IN THE CONSTRUCTION INDUSTRY: A LITERATURE REVIEW[2]

3.1 INTRODUCTION

Enhancing occupational health and safety (OHS) is a major issue across global construction industries (Zhou et al., 2012). The construction industry is one of the industry sectors with severe occupational injuries and fatality risks, making it both a unique and challenging sector (Umer et al., 2017a). For example, in Hong Kong Special Administrative Region (HKSAR), there were 3,332 injuries and 37 fatalities in the construction industry in 2013, which accounted for 19.68% of fatalities across all industries (HKOSH, 2014). In the USA, 36% of fatalities (1231 of 3419) were related to fall injuries in the construction industry from 2011 to 2014 (Bureau of Labor Statistics, 2016a). In Australia, there were 35 out of 182 fatalities in the construction industry in 2016, which accounted for 3.3 fatality rate (fatalities per 100,000 workers) across all industries (Safety Work Australia, 2017). In addition, occupational injuries can lead to project delays, increased project costs, medical burden and disabilities (Umer et al., 2017a). In order to improve OHS in the construction industry, there is a need to develop and provide pragmatic solutions to prevent occupational injuries and fatalities.

With the development of sensing and warning-based technology, a growing number of researchers and practitioners have realized that their applications could provide effective solutions to improve

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OHS in the construction industry. Heng et al. (2016) developed a behavior-based safety (BBS) with a proactive construction management system (PCMS) for intrusion warning and assessment method in reducing incidents and enhancing workplace site safety. Yi et al. (2016) developed a global system mobile communication (GSM) based on environmental sensors for warning site worker in hot and humid environments. These findings indicate that the applications of sensing and warning-based technology can be a feasible way to eventually avoid fatal and non-fatal occupational injuries in the construction industry. Antwi-Afari et al. (2017b) and Umer et al. (2017b) evaluated the effect of biomechanical risk factors such as awkward working postures based on self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) by using surface electromyography (sEMG) and inertial measurement units (IMUs) sensors. Based on the proposed methods of using sensing and warning-based technologies, the findings of these studies demonstrated that the suggested interventions (e.g., team lifting, adjustable lift equipment, and domestic stool) have a great potential in reducing work-related musculoskeletal disorders (WMSDs) risks in construction workers. Therefore, there is a need for innovative sensing and warning-based technology applications to improve OHS in the construction industry globally.

Generally, advanced information-based technologies (e.g., Video Range Imaging, Virtual Reality (VR), 4D Computer Aided Design (4D CAD), Building Information Modelling (BIM), sensing and warning-based technology) have received significant attention and have been widely applied to detect, model and track moving construction resources like workforce, equipment or materials within the construction workplace (Bai et al., 2015; Yi et al., 2016; Zhou and Ding, 2017). The applications of sensing and warning-based technology offer many advantages and have been used in various civil engineering applications such as structural health monitoring (SHM) (Wang and

Yim, 2010; Bai et al., 2015; Song et al., 2017). While these applications can effectively collect, identify and process information from workers during the construction phase, they can also be used in the operation phase of a project to monitor the safety of users. Specifically, the quality of a structure, as well as the safety issues, are related to the livelihood of users, which may be important OHS issues during the operation phase. Undoubtedly, structural failures/damages can result in severe injuries of workers during the construction and fatalities of users during operation (Acikgoz et al., 2017; Song et al., 2017). For instance, Lee et al. (2014) developed and validated a curing temperature management system based on wireless sensor network (WSN) that enabled direct, real-time and continuous monitoring of the internal temperature of concrete and curing process at real construction sites. Similarly, fiber optic sensors (FOSs) used in SHM of OHS research not only improve workers' safety during construction phase but also help users to take corrective steps to avoid further damages (e.g., cracks, deformation) of concrete structures (e.g., bridges, dams) during the operation phase (Afzal et al., 2012). Continuous monitoring of temperature, deformation, and displacement should be considered in the total life cycle approach of a construction project. As such, SHM can be considered as an important part of OHS in construction.

Within the construction industry, key stakeholders including construction managers, safety officers, and researchers, could benefit from an overall understanding of the current types and applications of sensing and warning-based technology for improving OHS. In order to share innovative research findings, access future research directions, suggest potential safety interventions, and prevent occupational injuries and fatalities, construction safety practitioners and researchers need a critical review of previous studies on sensing and warning-based technology.

Such a review can summarize various types of sensing and warning-based technology, and their key applications areas to improve OHS. The results can allow researchers and practitioners to recognize the research gaps and opportunities between construction safety research and construction safety practice. Taken together, there is an essential need to conduct a comprehensive literature review on the applications of sensing and warning-based technology to improve OHS in the construction industry.

With the goal of fostering and directing further research on the application of sensing and warning-based technology for OHS in construction, this review article focuses on several streams. First, this review summarized the current trend of sensing and warning-based technology in leading peer-reviewed journal publications from different database sources. Second, various state-of-the-art sensing and warning-based technology and key research areas of OHS were discussed to provide directions for researchers in planning their future studies and in introducing new sensing and warning-based technology to improve construction workplace safety performance. In short, the current review study aimed to summarize existing sensing and warning-based technology, identify research gap, and discuss future directions through answering the following research questions:

1. What were the annual publication trends of sensing and warning-based technology applications for OHS in the construction industry from 1996 to 2017 (years inclusive)?
2. What were the relative contributions of different journals to the field of sensing and warning-based technology applications during that period?
3. What are the current trends of different types of sensing and warning-based technology applications for OHS in the construction industry?

4. What are the key and specific research topics/areas related to the application of sensing and warning-based technology for OHS in the construction industry?
5. What are the research gaps and future research directions in using sensing and warning-based technology for OHS in the construction industry?

The remaining part of this review is structured as follows. Section 2 reports a three-step method to identify and summarize relevant articles. Section 3 presents results and discussion on the annual publication trends, contributions of journal publications, and the current trends of different types of sensing and warning-based technology applications for OHS. In the fourth section, the key research topics covered were discussed. Section 5 summarizes the research gaps and directions for future studies. Finally, the conclusions of this review are presented in section six.

3.2 METHODS

The current review methods comprise three major steps: (1) literature search; (2) literature selection; and (3) literature coding. The three-step method was adopted from a similar review (Zhou et al., 2013) of applying advanced technology to improve safety management in the construction industry.

3.2.1 Step 1: Literature search

With regards to the diversity of the aforementioned research questions on this research topic, the literature search was conducted across disciplines and included several databases. As a result, a systematic search was conducted to obtain relevant articles on sensing and warning-based technology applications for OHS in the construction industry through searching eleven electronic databases: Academic Search Premier, ASCE Library, CINAHL Complete, Emerald Management e-Journals, Health and Safety Abstract, Medline, PsycINFO, Science Direct, Scopus, Web of Science, and Wiley Online Library. In addition, other relevant information sources were identified by manually checking references to include seven relevant articles.

In this review, keywords search, and free-text words were adopted to select relevant articles on sensing and warning-based technology applications for OHS. A systematic and extensive search was conducted under the 'article title/abstract/keyword' field in the databases. Although there are different codes among the eleven selected databases, the search string consisted of three parts. The first part comprised keywords related to 'wearable sensors' or 'sensing technology' or 'warning technology'. The second part comprised 'occupational' or 'health' or 'safety' or 'accident' or 'incident' or 'work-related musculoskeletal disorders' (WMSDs). The final part covered 'construction industry' or 'construction sector' or 'construction workers'. As such, these three components of keyword searches were used in this review article to retrieve relevant articles on the topic of sensing and warning-based technology applications to improve OHS in the construction industry.

The total search terms and results (number of included relevant articles) are shown in Figure 3.1. For instance, the full search code for Science Direct database was: TITTLE-ABS-KEY (("wearable sensors" OR "sensing technology" OR "warning technology") AND ("occupational" OR "health" OR "safety" OR "accident" OR "incident" OR work-related musculoskeletal disorders") AND ("construction" OR construction industry" OR "construction sector" OR "construction workers")). All citations identified from the systematic searches from the selected databases were exported into EndNote X7 (Thompson Reuters, New York, USA). A total of 1,608 references were identified through the 11 databases.

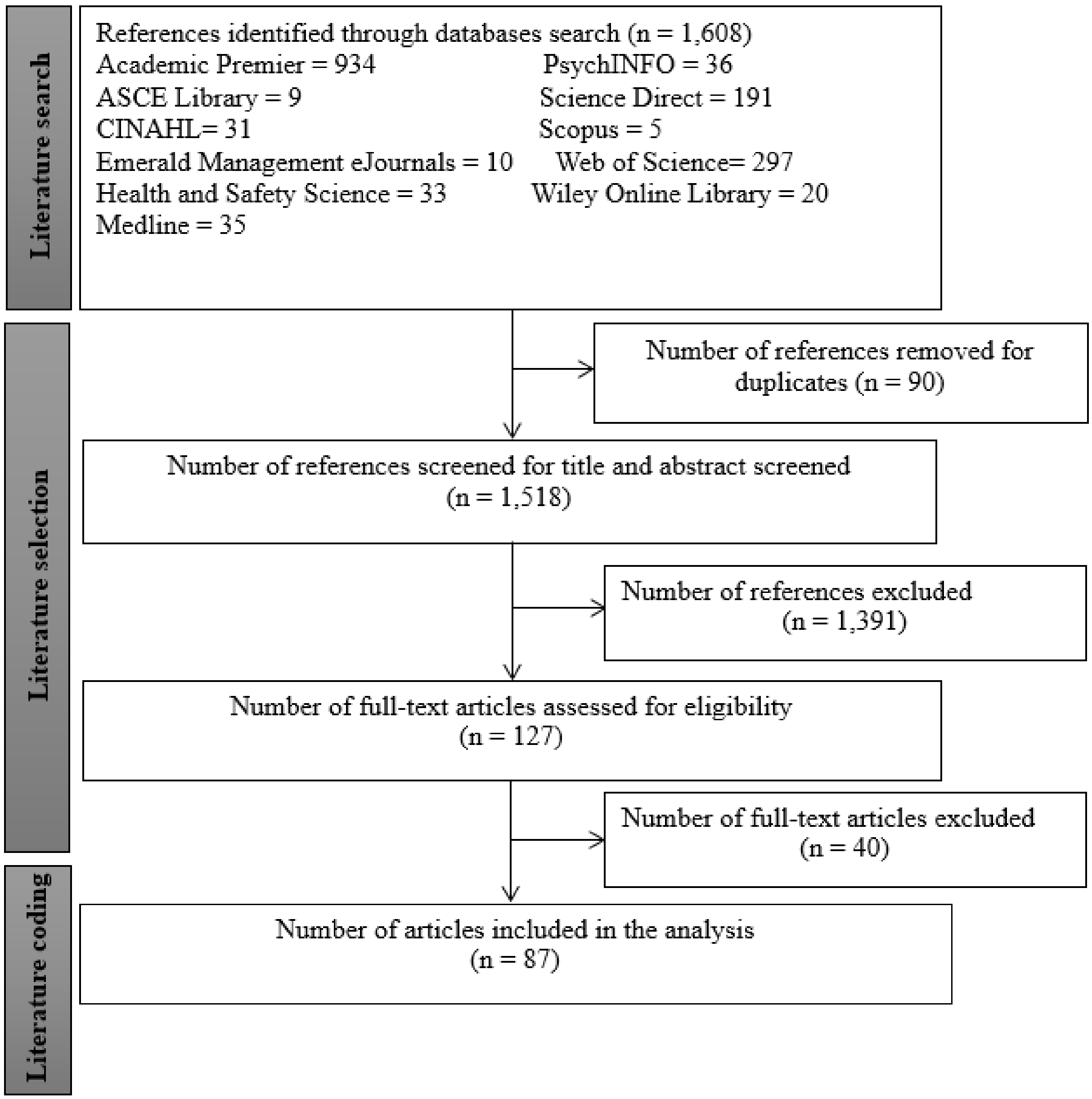


Figure 3.1 Flowchart depicting a three-step method to identify relevant included articles

3.2.2 Step 2: Literature selection

A total of 1,518 articles were identified after removing the duplicates. A two-stage screening process was then conducted. At the first stage, titles and abstracts were screened by two independent authors (MA and TO). Citations related to book reviews, company directory, editorials, editor's notes, generics, letters to editors, news items, and patents were excluded. Any disagreements between the two reviewers were resolved by consensus among all authors. For instance, articles that just mentioned some keywords in their titles or abstracts, but irrelevant to the research topic were excluded by consensus. Potential citations were then retrieved for full-text screening. The number of included full-text articles was 127. The second stage screening involved the selection of relevant full-text articles that met the following inclusion criteria:

1. The article was empirical with a substantive focus on sensing and warning-based technology for OHS.
2. The contents involved construction related resources (i.e., personnel/worker, equipment, and material), construction-related OHS (e.g., building, tunnel, bridge etc.), and different types of OHS fatalities, unsafe behaviors, and injuries (e.g., crane collapse, cracks, scaffold collapse, slips, trips, falls, WMSDs etc.). For example, Zhou and Ding (2017) established a hazard energy monitoring system and the use of Internet-of-Things (IoTs) technologies to provide safety barrier strategies and scenarios for avoiding unsafe behaviors and unsafe status of construction equipment and workers' environment on underground construction sites such as Yangtze River-crossing Metro Tunnel.
3. The article was published in a refereed journal.
4. The article was published between January 1996 to December 2017 (years inclusive).
5. The article was written in English.

6. The article was available online.
7. The article focused on using sensing and warning-based technology for OHS applications as well as other applications for construction management research. For example, based on case-based reasoning, Liu et al. (2013) provided solutions to three key issues such as index selection, accident cause association analysis, and warning degree forecast implementation, through the use of association rule mining, support vector machine classifiers, and variable fuzzy qualitative and quantitative change criterion modes, which also penetrate the whole process of safety management.

A total number of 87 articles met the selection criteria and were included for analyses. A full list of the 87 articles is presented in a reference database.

3.2.3 Step 3: Literature coding

In this review, title, keywords, and abstract were the main sources for coding an article. Moreover, the full-text article reading was used for further coding and data extraction. The literature coding was mainly focused on the sections of the research method and conclusions. In order to provide data analysis to discuss the aforementioned research questions, each of the included articles was coded. In the process of coding an article, the following key data were extracted from each article and formatted in our database (see an example in Table 3.1):

1. Title of the article
2. Researcher/Author name
3. Research institution of each author
4. Country or origin of where the study was conducted
5. Publication year

6. Published journal
7. Type of sensing and warning-based technology adopted
8. Key research topic or application area

Following the literature coding and data extraction from the included studies (i.e., 87 articles), data analysis was carried out to summarize and discuss the applications of different types of sensing and warning-based technology in improving OHS in the construction industry. Further, various research gaps and future research direction were discussed. To identify the annual publication trend and the relative contributions of various journals of the included articles, the publication year and names of journals were analyzed, respectively.

Table 3.1 An example of article literature coding in a reference database

Item	Title of the article	Researcher/ Author name	Research institution	Country or origin	Publication year	Journal publication	Type of sensing and warning-based technology	Key research topic or application area
1.	Range Imaging as Emerging Optical Three-Dimension Measurement Technology	Jochen Teizer Timo Kahlmann	Georgia Institute of Technology Swiss Federal Institute of Technology	USA Switzerland	2007	Transportation Research Record: Journal of the Transportation Research Board	Remote-Sensing techniques (3D video range imaging camera)	Construction site safety management and monitoring

Note: The order of researcher/author names, research institutions and countries were maintained according to each article. A complete list of included studies (i.e., 87) is available upon request from the corresponding for our interested readers.

3.3 RESULTS AND DISCUSSION

3.3.1 Annual publication trend on sensing and warning-based technology articles

Figure 3.2 presents the annual publication trend of the included articles on sensing and warning-based technology during the studied period. There was no published article on sensing and warning-based technology between 1996 and 2006 (Figure 3.2). The first 2 relevant articles were published in 2007 (Figure 3.2). Since then the numbers of relevant articles published annually increased from 2 articles in 2008 to 9 articles in 2013. Following the decline in research outputs to 6 articles in both 2014 and 2015, 23 relevant articles were published in 2016 (Figure 3.2). Similarly, 24 articles were published in 2017 (i.e., peak year) (Figure 3.2). The current review revealed that sensing and warning-based technology did not play a significant role in OHS until 2007. The exponential increases in number of relevant articles showed that researchers and practitioners had recognized sensing and warning-based technologies as effective measures to provide potential OHS interventions in the construction industry in recent years.

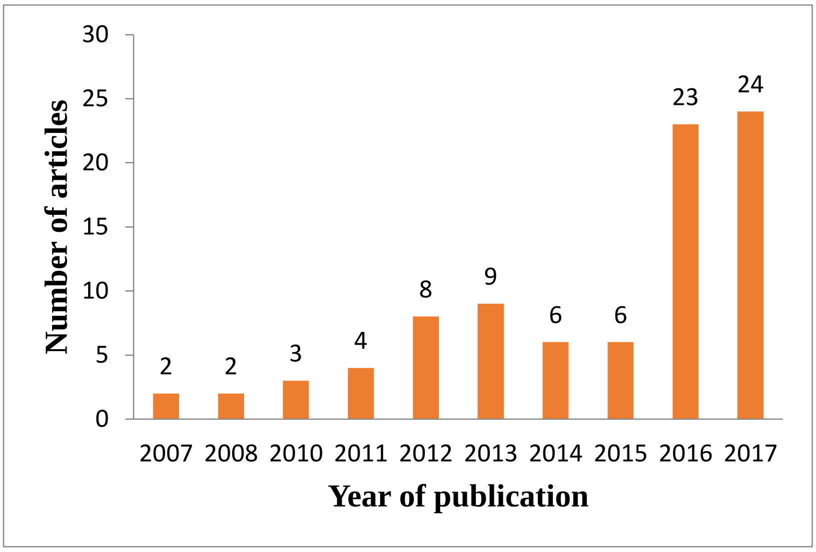


Figure 3.2 Annual trend of sensing and warning-based technology research articles from 1996 to 2017 (years inclusive)

3.3.2 Contribution of journal publications

Table 3.2 presents the contribution of journal publications with the corresponding number of relevant articles during the studied period. In this review article, a total of 34 peer-reviewed journal publications were included for the analysis during 1996 to 2017 (years inclusive) (Table 3.2). A majority of the journals only published a single article, representing 27.6% of all included studies (Table 3.2). Each of the 3 journals, namely: *Structural Control and Health Monitoring*, *Journal of Civil Engineering and Management*, and *Construction Innovation: Information, Process, Management* had published 2 relevant articles during the studied period (Table 3.2). In addition, a total of 3 relevant articles were published in either *Transportation Research Record: Journal of the Transportation Research Board* or *Applied Ergonomics* during the studied period (Table 3.2). Four relevant articles were found in *Advanced Engineering Informatics* (Table 3.2). Whilst 5 relevant articles were published in either *Safety Science* or *Journal of Construction Engineering and Management*, a total of 7 relevant articles were found published in *Journal of Computing in Civil Engineering*, representing 8% of all included articles (Table 3.2). Ultimately, there were 30 relevant articles published in *Automation in Construction*, representing 34% of all articles (Table 3.2). The finding of this result indicates the significant contribution of *Automation in Construction* in the domain of applying sensing and warning-based technology to improve OHS in the construction industry.

Table 3.2 Names of journal publication with the corresponding number of relevant articles during 1996 to 2017 (years inclusive).

Item	Journal publication	Number of articles
1.	Automation in Construction	30
2.	Journal of Computing in Civil Engineering	7
3.	Journal of Construction Engineering and Management	5
4.	Safety Science	5
5.	Advanced Engineering Informatics	4
6.	Applied Ergonomics	3
7.	Transportation Research Record: Journal of the Transportation Research Board	3
8.	Construction Innovation: Information, Process, Management	2
9.	Journal of Civil Engineering and Management	2
10.	Structural Control and Health Monitoring	2
11.	Annals of Work Exposures and Health	1
12.	Applied Mechanics and Materials	1
13.	BMC Musculoskeletal Disorders	1
14.	Computer-Aided Civil and Infrastructure Engineering	1
15.	Computer Vision and Image Understanding	1
16.	Engineering Geology	1
17.	Future Generation Computer Systems	1
18.	Information Fusion	1
19.	Instrumentation Science & Technology	1
20.	International Journal of Building Pathology and Adaption	1
21.	Journal of Architectural Engineering	1
22.	Journal of Information Technology in Construction	1
23.	Journal of Occupational and Environmental Hygiene	1
24.	Journal of Rehabilitation Research and Development	1
25.	Mechanical Systems and Signal Processing	1
26.	Optik-International Journal for Light and Electron Optics	1
27.	Practice Periodical on Structural Design and Construction	1
28.	Professional Safety	1
29.	Shock and Vibration	1
30.	Smart Structures and Systems	1
31.	Sustainability	1
32.	The Computer Journal	1
33.	The Egyptian Journal of Remote Sensing and Space Sciences	1
34.	The Scientific World Journal	1
	Total	**87**

3.3.3 Current trend of different types of sensing and warning-based technology

Table 3.3 presents the different types of sensing and warning-based technologies covered for OHS in the included studies. As shown in Table 3.3, there are 10 different types of sensing and warning-based technologies. It should be noted that about 11 articles integrated different types of sensing and warning-based technology. As such, the corresponding total number of articles of the different types of sensing and warning-based technologies was more than the total number of included articles. It was revealed that direct measurement sensors such as sEMG, force sensors, IMUs, and physiological status monitors (PSMs) were mostly applied in 44 included articles (Table 3.3). Other included sensing and warning-based technologies were remote-sensing techniques (14 articles), real-time location system (RTLS) based radio-frequency identification (RFID) (12 articles), global positioning system/geographical information systems (GPS/GIS) (6 articles), and RTLS based on ultra-wideband (UWB) (6 articles) (Table 3.3). The application of the other sensing and warning-based technologies was below 6 articles during the studied period (Table 3.3). Generally, sensing and warning-based technology applications are constantly changing with the development and integration of new sensors to improve OHS in the construction industry.

Table 3.3 Types of sensing and warning-based technologies covered by the included articles

Item	Sensing and warning-based technology	Number of articles
1.	Direct measurement sensors	44
2.	Remote-Sensing techniques	14
3.	RTLS based on Radio Frequency Identification (RFID)	12
4.	Global positioning system/Geographical information systems (GPS/GIS)	6
5.	RTLS based on Ultra-wide Band (UWB)	6
6.	Fiber Optic Sensors (FOSs)	5
7.	RTLS based on Bluetooth Sensing Technology	4
8.	Wireless Sensor Networks/Wireless Local Area Network/ Internet of things (WSN/WLAN/IoT)	4
9.	Behavior-Based Safety (BBS) with Proactive Construction Management Systems (PCMS)	2
10.	Safety Early Warnings based on Case-Based Reasoning and Variable Fuzzy Sets	1

Note: RTLS = Real-time location system

Figure 3.3 provides the trends of different types of sensing and warning-based technology applications of the included studies during the studied period. In order to depict the trend more clearly and comprehensively, the time span from 1996 to 2017 (years inclusive) was divided into 3 periods. Since no published articles were found in the first decade (i.e., 1996 to 2006), the included studies started from the second decade (i.e., 2007 to 2017). Each division contains 4 years except the last period, which spans from 2015 to 2017 (years inclusive).

From Figure 3.3, sensing and warning-based technology applications were distributed as discrete and individualized (i.e., using only one type of sensing and warning-based technology), because there were not many different types of sensing and warning-based technology used to improve OHS during 2007 to 2010 (years inclusive). Some of the individualized studies on the types of sensing and warning-based technologies used within these periods were: direct measurement sensor (Wang and Yim, 2010); RFID technology (Domdouzis et al., 2007; Ko, 2010; Teizer et al., 2010); remote-sensing techniques (Teizer and Kahlmann, 2007); UWB (Teizer et al., 2008). Only a single study (Behzadan et al., 2008) integrated two different types of sensing and warning-based technology (wireless local area network (WLAN) and GPS) during 2007 to 2010 (years inclusive).

During the period from 2011 to 2014 (years inclusive) (Figure 3.3), the trend of applying sensing and warning-based technology had gradually become more complicated. Despite the fact that some studies only applied a single type of sensing and warning-based technology, other included studies were more diversified and integrated sensing and warning-based technologies for OHS in the construction industry, particularly in the year 2013. The number of included articles that applied a single type of sensing and warning-based technology during 2011 to 2014 (years inclusive) was: direct measurement sensors (11 articles); RFID (4 articles); remote-sensing techniques (3 articles); UWB (4 articles); FOSs (1 article); and case-based reasoning and variable fuzzy sets (1 article). Conversely, the majority of the included articles integrated two or more sensing and warning-based technologies during this same period. For instance, the integration of RFID and micro-electromechanical sensors and systems (MEMS) based temperature and humidity sensors from a laboratory study as well as a small-scale field study (Ceylan et al., 2013). The integration of FOSs and RFID based labor tracking system was used to prevent accidents and to improve safety management in underground construction (Ding et al., 2013). Taken together, publications during this period focused on the integration of different types of sensing and warning-based technology to complement each other in improving OHS in the construction industry.

Interestingly, during the period from 2015 to 2017 (years inclusive), the trend of integrating different types of sensing and warning-based technologies to improve OHS increased (Figure 3.3). The number of articles that integrated two or more different types of sensing and warning-based technologies during this period were: direct measurement sensors and remote-sensing techniques (2 articles), direct measurement sensors and GPS (3 articles), RFID and remote-sensing techniques (1 article), and RFID and IoTs (1 article). On the other hand, many included studies only investigated the use of a single sensing and warning-based technology. These include: direct measurement techniques (25 articles); remote-sensing techniques (7 articles); RTLS based on Bluetooth sensing technology (4 articles); FOSs (3 articles); BBS with PCMS (2 articles); GPS/GIS (2 articles); WSN, WLAN, IoTs (2 articles); and RFID (1 article). One potential explanation for this massive increase was that more attention had been given to the use of sensing and warning based technologies as essential tools and pragmatic methods to improve OHS in recent years.

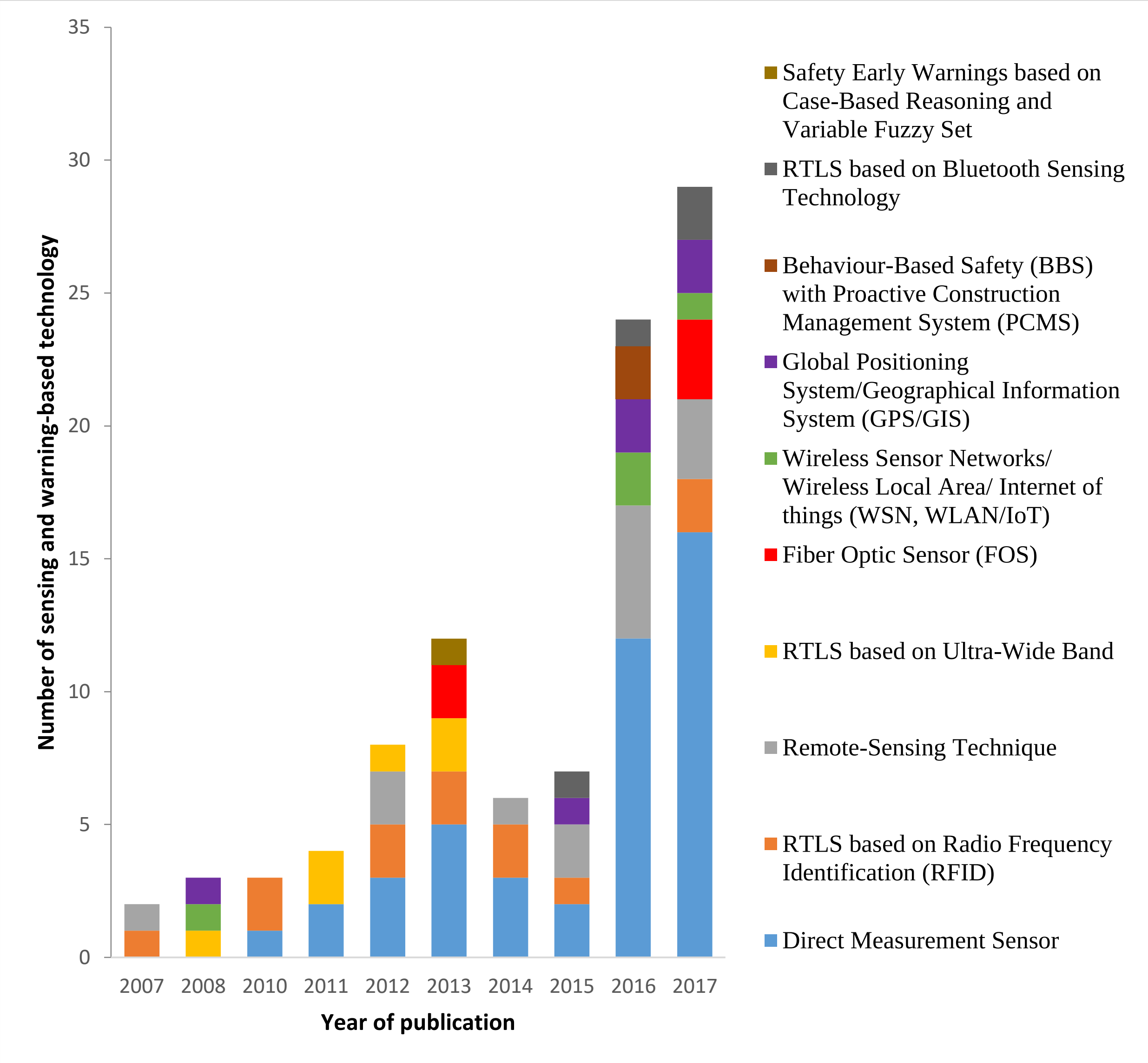


Figure 3.3 Current trend of sensing and warning-based technology applications

3.4 KEY AND SPECIFIC OHS RESEARCH TOPICS COVERED

In this review article, each included article was categorized according to the main research topic, although some articles may contain more than one research topic. Table 3.4 summarizes the key research topics covered by sensing and warning-based technology applications for OHS during the studied period. Our results found six main research topics (Table 3.4). As depicted in Table 3.4, the first research topic covered was construction site safety management and monitoring. This key research topic had a total number of 21 articles, representing 24.1% of the included articles during the studied period (Table 3.4). The second and third relevant research topics covered were safety risk identification and assessment (18 articles) and intrusion warnings and proximity detection (16 articles), respectively (Table 3.4). The awareness percentage of the first three research topics was 63.2% of the included articles during the studied period. The remaining three research topics covered had not more than 15 included articles in each area (Table 3.4).

Table 3.4 Key and specific occupational health and safety (OHS) research topics covered

Item	Research topic	Number of articles	Percentage of articles
1.	Construction site safety management and monitoring	21	24.1%
2.	Safety risk identification and assessment	18	20.7%
3.	Intrusion warnings and proximity detection	16	18.4%
4.	Physiological status monitoring	14	16.1%
5.	Activity recognition and classification accuracy	9	10.3%
6.	Structural health monitoring	9	10.3%
	Total	**87**	**100%**

3.4.1 Construction site safety management and monitoring

In the research application of construction site safety management and monitoring, different types of sensing and warning-based technology such as RTLS based on RFID, UWB, GPS/GIS, Bluetooth technology, and WLAN were most prominent. Unlike intrusion warnings and proximity detection, the focus of the included studies related to construction site safety management and monitoring applications was only based on using sensing and warning-based technologies such as RTLS tracking technologies to identify the location and tracking of resources (e.g., worker, material and equipment) for safety management and monitoring during the planning, designing, and execution phases of a construction project. By using a UWB technology, Cheng et al. (2011) showed that real-time location tracking has potential construction applications in assisting the safety management of job sites and other areas requiring monitoring and control. In particular, safety and efficient site resource allocation would be of help to any site manager in charge of planning and control work activities (Cheng et al., 2012). Several sub-topics applications of GPS/GIS technology were applied (1) to improve the management level and safety quality in different project phases; (2) in the studies of urban rail transit safety management and information integration; (3) to shield construction schedule information; (4) for construction safety risk information; (5) for construction site video information (Bai et al., 2015). Taken together, the included articles of construction site safety management and monitoring showed that real-time location tracking has potential construction applications in assisting the safety management of job sites and other areas requiring monitoring and control.

3.4.2 Safety risk identification and assessment

In the current review article, sensing and warning-based technology applications were predominantly covered in areas of safety risk identification and assessment. Even though the included articles which focused on safety risk identification and assessment used similar types of sensing and warning-based technology, their research provided evidence-based prevention of WMSDs and fall injuries about the level of physical exposure of the human body (e.g., back, shoulders) during specific work tasks in the construction (Seo et al., 2015; Jebelli et al., 2016; Antwi-Afari et al., 2017a; 2017b). Other included articles also suggested potential information on how to implement participatory interventions aiming at reducing excessive physical workload (Brandt et al., 2015; Umer et al., 2017b). Jebelli et al. (2016) demonstrated the feasibility of utilizing IMU sensor data for workers' posture and motion analysis to provide insights into understanding and characterizing the levels of fall risks of construction workers. Umer et al. (2017b) developed a simple ergonomic solution by attaching a low height domestic stool to the pants of rebar workers, which has a great potential in reducing WMSDs among Asian rebar workers. Ultimately, the included articles covered for safety risk identification and assessment provided the real-time monitoring of for workers' posture and motion analysis during construction tasks to enhance the understanding of the gap between physical work demands and workers' capability, and offer a firm foundation for the improvement of workers' safety and health in construction.

3.4.3 Intrusion warnings and proximity detection

Another relevant category of research topic covered from the application of using sensing and warning-based technology for OHS was intrusion warnings and proximity detection. In this category, the identified sensing and warning-based technologies were capable of detecting and providing warning alerts to construction workers, equipment operators, and pedestrians in real-time during hazardous proximity situations. For instance, Yi et al. (2016) developed a GSM based on environmental sensors to warn site workers in a hot and humid environment. The early-warning system involves: (1) collecting timely information and undertaking risk assessments of heat stress; (2) generating an accurate and timely warning to trigger prompt health and safety intervention; and (3) disseminating heat strain assessments and symptoms of heat illness to site supervisor/foreman. These authors also reported that the GSM system has other functions to support risk analysis, warning sign, and response capability. Heng et al. (2016) developed a BBS with PCMS for intrusion warning and assessment method in reducing incidents, enhancing site safety, and improving personal behavior. Although their study was exploratory on safety behavior in construction works, the reported research could inspire further research in safety behavior studies at petroleum, manufacturing, traffic management, and nuclear power industries. Based on IoTs technologies such as meter-level of RFID-based location and tracking technology, centimeter-level of ultrasonic detection technology, and infrared access technology, Zhou and Ding (2017) established a hazard energy monitoring system to provide safety barrier strategies and scenarios for avoiding unsafe behaviors and unsafe status of construction equipment and workers' environment on underground construction sites such as Yangtze River-crossing Metro Tunnel. Overall, the included articles covered for intrusion warnings and proximity detection in hazardous zones may not only provide supervisory staff and safety professionals with a surveillance method to safeguard the health and safety of frontline workers when working on construction sites but can also indirectly lower investment costs by guiding safety input benefit maximization.

3.4.4 Physiological status monitoring

The fourth research topic covered on OHS based on sensing and warning-based technology applications was physiological status monitoring. In this research application category, the included studies mostly used innovative direct measurement sensors called PSMs that can simultaneously monitor heart rate, breathing rate and other physiological parameters. Yan et al. (2013) developed an equivital life monitor (EQ02) which was a multi-parameter body-worn system capable of logging and transmitting physiological data describing a wearer's cardiorespiratory and thermal status. Another study combined UWB technology with PSM to automatically identify and localize the ergonomic-related unsafe working behaviors (Cheng et al., 2013). This study reported a new approach for automating remote monitoring of construction workers safety performance by fusing data on their location and physical strain. Zhao et al. (2017) developed a cooling vest to alleviate physiological and perceptual strain in hot and humid environment during two experimental conditions (i.e., cooling vest vs. no cooling vest). Their results indicated that the designed cooling vest can significantly alleviate heat strain and improve thermal comfort, based on the decrease in body temperature, heart rate, and subjective perceptions of the participants. Overall, the included studies covered for physiological status monitoring demonstrated that PSMs can have a positive impact on workers' safety, productivity, and long-term well-being.

3.4.5 Activity recognition and classification accuracy

The fifth key research topics covered on the application of sensing and warning-based technology for OHS was activity recognition and classification accuracy. Generally, this category of research application mostly used direct measurement sensors such as IMUs (Joshua and Varghese, 2013; Akhavian and Behzadan, 2016; Lim et al., 2016) and remote-sensing techniques such as Kinect (Khosrowpour et al., 2014; Ho et al., 2016) to provide insight into the accuracy of recognizing construction workers' activities by analyzing collected data using different machine learning algorithms (e.g., decision tree, artificial neural networks (ANN), support vector machine, etc.). Lim et al. (2016) demonstrated the feasibility of using triaxial accelerometer embedded in a smartphone for ANN-based near-miss classifiers to detect the type of near-miss event (slip or trip) and identification of the worker involved in real time. They concluded that information on a worker's motion was reliable and could be used for corrective and injury preventive measures. Alternatively, Ho et al. (2016) used Kinect data-driven framework to classify workers postures and differentiate between correctly and incorrectly performed the movement in the same context. By integrating R-GBD camera with IMUs sensors, Chen et al. (2017) proposed an efficient motion tensor decomposition approach to compress and reorganize two sample activities composed of sequential awkward postures in construction activities. The results revealed that the proposed approach is able to provide sufficient recognition accuracy with less computation power and memory. Ultimately, sensing and warning-based technology applications for activity recognition and classification accuracy help to measure and control safety, productivity, and quality in construction sites.

3.4.6 Structural health monitoring (SHM)

The final key research application area of OHS based on sensing and warning-based technology applications was SHM. SHM is an all-inclusive comprehensive process of monitoring the various types of damages and problems in different fields and areas of engineering (Afzal et al., 2012). Concrete structures are one of the most important filed in civil engineering and currently being widely used application in construction works. Generally, SHM as an application area of OHS is important to observe, monitor, and evaluate the conditions of mainly concrete structures (e.g., bridge, road highways, dams) in real-time to avoid any kind of occupational accidents (e.g., construction, mining) and tasks that may lead to structural failure (e.g., extension of existing bridges or buildings) (Wang and Yim, 2010; Ceylan et al., 2013; Acikgoz et al., 2017; Song et al., 2017). For example, FOSs in SHM of concrete structures are used to detect deflections in the embankment dams, and to detect cracks in roller-compacted concrete dams (Afzal et al., 2012). Song et al. (2017) integrated FOSs such as Raman optical time-domain reflectometry (ROTDR), Brillouin optical time-domain analysis (BOTDA) and fiber Bragg grating (FBG) to monitor the temperature and the stress/stain variations of a reinforced concrete pound lock structure during the construction process. The findings indicated that the proposed approach has a great potential in the performance monitoring of hydraulic structures.

3.5 RESEARCH GAPS AND FUTURE STUDIES

In this review article, different types of sensing and warning-based technologies were applied for OHS in the construction industry. This section highlights four main research gaps that are worth for directions in future studies.

3.5.1 Application of sensing and warning-based technologies in the total life cycle of a construction project

The applications of sensing and warning-based technologies need to cover pre-construction, construction, and post-construction phases of a construction project. Until recently, the use of FOSs for SHM mostly focused on the post-construction phase (i.e., operation and maintenance phases) to monitor concrete structures in order to prevent cracks and collapse of existing structures. However, many fatalities during the construction phase were due to falls from the height of temporary structures such as scaffolds, ladders, hoists and tower cranes. According to the Bureau of Labor Statistics (BLS) in the USA, fatal injuries caused by falls from heights remain to be the leading cause of fatalities on construction sites (Bureau of Labor Statistics, 2016b). Future studies should investigate the effectiveness of using FOSs and other sensing and warning-based technologies to detect the failure of temporary structures during the construction phase. Further, future research is warranted to develop a decision support tool to assist practitioners to incorporate construction risks monitoring and site safety management during the pre-construction phase. In short, more attention should be paid to the total life cycle of construction projects so that researchers and industry practitioners can explore the collective use of the identified sensing and warning-based technologies to optimize productivity and safety.

3.5.2 Hardware and software design of sensing and warning-based technologies

The size, weight, and data processing and transmission are examples of important attributes that need to be considered when designing sensing and warning-based technologies. The size and weight of sensing and warning-based technologies, particularly for direct measurement sensors, can cause workers' discomfort and interference of monitored activities due to the attached sensors on skin (Antwi-Afari et al., 2018a). In order to achieve non-invasive and unobtrusive monitoring of workers' activities on site, future research should develop small and lightweight wireless sensors. Such new sensors may improve workers' acceptance of using wearable sensing technologies. However, it is noteworthy that data transmission procedures of direct measurement sensors are often influenced by motion artefacts (i.e., noise), which affect measurement accuracy. Also, depending on the type of sensing and warning-based technologies, the collected data may need to be processed in multiple stages, which may delay the time to alert workers regarding hazardous zones, to detect unsafe behaviors or to identify specific hazard on construction sites. Future studies should also develop sensing and warning-based technologies that are less sensitive to motion artefacts and provide non-localized processing of output data.

3.5.3 Application of sensing and warning-based technologies from research to practice

In this review article, the research topics or the application areas of the identified sensing and warning-based technologies were mostly limited to academic research of simulated activities in a laboratory setting. Moreover, most of the laboratory experiments were conducted by novice volunteers. As a result, the identified sensing and warning-based technologies and the proposed methods have not been validated in real construction environments. Researchers and practitioners should focus more on sensing and warning-based technologies transition from construction safety research to construction safety practice (i.e., using real construction workers on sites). In addition, a robust cost-benefit analysis and validation of the identified sensing and warning-based technologies will be significant to both researcher and construction practitioners. Future research should give more attention to address these areas, in order to provide a holistic view.

3.5.4 Integration of sensing and warning-based technologies and other advanced information technologies

In this review article, different types of sensing and warning-based technologies used in OHS of the construction industry is listed in Table 3.3. First, there is a crucial need for future research to introduce and explore the use of other types of direct measurement sensors such as wearable insole pressure sensors for improving OHS in the construction industry. Wearable insole pressure sensors could be used to detect and classify construction workers' awkward working postures and loss of balance events in order to reduce the risks of developing WMSDs and non-fatal fall injuries, respectively. Second, there is a great potential for future research to evaluate the strengths and weaknesses of each sensing and warning-based technology in order to integrate different types of sensing and warning-based technologies for multi-sensor platforms and multi-parameter monitoring. For instance, remote-sensing techniques would complement the limited number of attachable tracking devices by providing clear site and object information regarding the size of heavy equipment and the boundary information of dangerous areas. Also, the integration of GPS and UWB tracking technologies and remote-sensing techniques could address the research gap on the performance of object identification and tracking with more accurate 3D spatial information. While the focus of this review article was on sensing and warning-based technologies, other advanced information technologies can be incorporated in future. Future research studies could integrate sensing and warning-based technologies with visualization and other information technologies such as 4D CAD, VR, and BIM to: (1) automatically identify and recognize potential safety hazards on construction sites; (2) collect and analyze the trajectories of workers with respect to potential hazards; and (3) enable safety managers or construction managers to continuously monitor construction resources against identified potential hazards in order to mitigate site accidents.

3.6 CHAPTER SUMMARY

This chapter has provided a review aimed to examine the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving OHS through the analysis of articles published between 1996 and 2017 (years inclusive). This review may serve as a spur for researchers and practitioners to extend sensing and warning-based technology applications to improve OHS in the construction industry.

CHAPTER 4

BIOMECHANICAL ANALYSIS OF RISK FACTORS FOR WORK-RELATED MUSCULOSKELETAL DISORDERS DURING REPETITIVE LIFTING TASK IN CONSTRUCTION WORKERS[3]

4.1 INTRODUCTION

Extant literature reports that work-related musculoskeletal disorders (WMSDs) are amongst the most prevalent occupational health problems affecting manual workers (Stattin and Jarvholm, 2005). In the United States, WMSDs account for 32% of all injury and illness cases that lead to absence from work for all industries (Bureau of Labor Statistics, 2015). While in construction and civil engineering, Schneider (2001) reported that WMSDs account for over 37% of all injuries. Construction workers (e.g., rebar workers, bricklayers and roofers) are by virtue of their occupation frequently exposed to elevated physical risk factors such as repetitive motions (lifting/lowering), awkward postures and lifting weights, which represent the major causes of WMSDs (Jaffar et al., 2011). Symptoms of WMSDs are myriad but may include lower back pain, neck/shoulder pain, tendonitis and carpal tunnel syndrome (Bernard, 1997). Fung et al. (2008) found that musculoskeletal symptoms are particularly common in the upper extremities and lower back region of the human torso. Notably, WMSDs not only lead to

[3] Presented in a published paper: **Antwi-Afari, M. F**., Li, H., Edwards, D. J., Pärn, E. A., Seo, J., & Wong, A. Y. L. (2017b). Biomechanical analysis of risk factors for work-related musculoskeletal disorders during repetitive lifting task in construction workers. *Automation in Construction*, *83*, 41-47. DOI: https://doi.org/10.1016/j.autcon.2017.07.007.

worker ill-health but also to reduced productivity and concomitant financial loss (Chen et al., 2017). Therefore, risk factors associated with WMSDs should be identified in order to develop effective ergonomic interventions to prevent WMSDs in construction workers.

Radwin et al. (2001) found that biomechanical and anthropometric parameters are significant determinants of the risk factors that instigate the development of WMSDs, but their true extent remains unclear. Other researchers such as de Looze et al. (1994a) and Norman et al. (1998) demonstrated a causal link between developing WMSDs and physical work exposure parameters. Specifically, Norman et al. (*ibid*) identified four risk factors for lower back disorders in automotive workers, namely: i) load moment; ii) hand forces; iii) peak shear force, and iv) peak trunk velocity. However, these studies only reported upon a specific body part (e.g., lower back and shoulder) and on an isolated risk factor (e.g., repetitions and lifting postures). In contrast, construction workers may sustain multiple injuries during repetitive lifting tasks (Albers and Hudock, 2007). The most important WMSDs risk factors relate to lifting weights and awkward postures because such requires maintaining muscle force over an extended period of time (Karwowski, 2001; Mcgaha et al., 2014; Grzywiński et al., 2016). Repetitive and prolonged lifting tasks cause muscle fatigue and discomfort for a worker, and invariably this activity increases the risk of developing WMSDs. Even though previous studies have widely advocated appropriate lifting postures (e.g., stoop and squat) (Van Dieen et al., 1999; Straker, 2003), their effect upon spinal biomechanics remains unclear. Therefore, laboratory-based simulated repetitive lifting tests are needed to gain a better understanding of spinal biomechanics and in turn, develop effective lifting procedures and processes which may elevate the risk of developing WMSDs. Given this contextual background, this study seeks to evaluate the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a laboratory-based simulated repetitive lifting task. To mitigate the risks of construction workers developing WMSDs, the research culminates by suggesting a number of potential pragmatic ergonomic interventions such as team lifting and adjustable lift equipment.

4.2 RESEARCH BACKGROUND

4.2.1 Current state of practice in WMSDs prevention

To reduce the risk of developing WMSDs among construction workers, general ergonomic practices have been promoted by safety and health organizations such as the Occupational Safety and Health Administration (OSHA) and the National Institute of Occupational Safety and Health (NIOSH). Instead of focusing on hazards to lower back disorders, general ergonomic practices typically focus on risk exposures associated with all WMSDs. For example, NIOSH published guidance which contains simple and inexpensive methods to help prevent injuries (Albers and Estill, 2007). In a similar vein, OSHA offers training materials and programs to help workers recognize, avoid and control safety and health hazards in their workplaces (OSHA, 2012). Despite these efforts, current ergonomic practices designed for general manual handling tasks still lack practicality for repetitive lifting tasks because i) most guidelines are presented in a brief and generic manner that is largely inappropriate to WMSDs prevention practices (Canadian Centre for Occupational Health and Safety, 2013); and ii) differences in work settings (e.g., repetitive lifting tasks, the weight being lifted and worker postures adopted during the lift) are often overlooked.

4.2.2 Risk assessment methods to identify potential risk factors of WMSDs

Within contemporary construction practice, techniques for assessing exposure to risk factors associated with WMSDs include self-reports, observations, direct measurement and remote sensing methods (Li and Buckle, 1999a). Despite the usefulness of these techniques, several limitations are apparent (David, 2005). For instance, self-reports (e.g., the Borg Scale) vary from the inter-rater difference of workers' perception and are consequently imprecise and unreliable (Wang et al., 2015a). An extensive array of observational tools for ergonomic and posture analysis have also been developed and include: Quick Exposure Check (QEC) (University of Surrey Health and Safety Executive, 1999), the Assessment of Repetitive Arts (ART) (Health and Safety Executive, 1999), the Manual Handling Assessment Chart (MAC) (Health and Safety Executive, 2014), the Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett, 1993; Stanton et al., 2004), the Rapid Entire Body Assessment (REBA) (Hignett and McAtamney, 2000), Washingston State's ergonomic rule (WAC 296-62-

051) (Washingston State Department of Labor and Industries, 2010), Posture, Activity, Tools and Handling (PATH) (Buchholz et al., 1996), Strain Index (Drinkaus et al., 2005), The Liberty Mutual Manual Material Handling Tables (SNOOK tables) (Liberty Mutual Research Institute, 2007), the NIOSH lifting equation (NIOSH, 1994; Vignais et al., 2013) and 3D Static Strength Prediction Program (3DSSPP) (The Center for Ergonomic at the University of Michigan, 2016).

The RULA observational tool is a postural targeting method for estimating the risks of work-related upper limb injuries based upon the positions of upper arms, wrists, neck and upper trunk; while the REBA estimates the entire body's risks according to the positions of arms, wrists neck, trunk and legs. All risk assessment methods provide an expeditious, systematic and quantitative assessment of the worker's postural risks with regard to major body joints and angles between joints (Chen et al., 2017). However, these posture assessment approaches usually collect data through observations, questionnaires or scorecards which are subject to the assessor's individual bias and judgement (Straker et al., 2010), as well as being inefficient and inaccurate (Levitt and Samelson, 1993; Laitinen et al., 1999). Remote sensing methods are potentially an attractive solution for assessing biomechanical risks and ill-health (Teizer and Vela, 2009; Weerasinghe and Ruwanpura, 2009; Seo et al., 2016). For example, Weerasinghe and Ruwanpura (2009) proposed infrared cameras for identifying worker activity status based upon heat emitted from the worker's body in conjunction with video images and acoustic data.

However, remote sensing methods use expensive cameras and have difficulties with moving backgrounds and varying light conditions as experienced within the dynamic and inclement construction environment (Wang et al., 2015a). Direct laboratory measurements provide accurate and reliable data by using relatively simple instruments such as surface electromyography (sEMG) sensors (Moeslund et al., 2006). Moreover, sEMG sensors are useful for biomechanical studies in laboratory settings (Hu et al., 2013). Hence, this study adopts sEMG sensors to supplement existing methods to identify risk factors of WMSDs.

4.2.3 Theories and models of WMSDs

There are several theories and models of WMSDs causation that have been discussed in the literature, however, based on the scope of the current study only biomechanical theories and models of risk factors for WMSDs causation were reviewed. During the 1970s, Chaffin and his colleagues (Chaffin and Baker, 1970; Martin and Chaffin, 1972; Chaffin and Park, 1973; Garg and Chaffin, 1975) and others developed simple, 2- and 3-D, static biomechanical models to estimate compressive and shear forces on lumbar spine as well as static strength requirements of jobs in occupational settings. These static biomechanical models generally tend to underestimate stresses on the low back predominately because they ignore the inertial loads (Jäger and Luttmann, 1992; de Looze et al., 1994a) as well as muscle contraction (McGill and Norman, 1986; Marras and Mirka, 1992). Using a multiple internal muscle model, Schultz and Andersson (1981) demonstrated that lifting of weights could generate large spinal forces due to the coactivation of trunk muscles. However, this modelling approach led to muscle contraction force calculations that were statistically indeterminate; therefore, optimisation techniques were used to make those calculations (Ladin et al., 1989; Hughes, 2000). Dynamic, 3-D, anatomically complex and sEMG driven models were also developed to predict individual lumbar tissue loads (McGill and Norman, 1987; Marras and Sommerich, 1991a, b; Granata and Marras, 1995a; Marras and Granata, 1997a; van Dieen and Kingma, 1999). Most of these models overcame limitations such as static or isokinetic mechanics, inaccurate prediction of muscle coactivity, static interpretation of myoelectric activity and physiologically unrealistic force per unit area. These models employ dynamic load in the hands, kinematic input, moment about the three orthopaedic axes of the low back normalised sEMG, muscle-cross section area, a gain factor to represent muscle force per unit area and modulation factors describing EMG and force behaviour as a function of muscle length and velocity to determine tensile load in each muscle. The model developed by McGill and colleagues (McGill and Norman, 1986; McGill, 1992; Cholewicki and McGill, 1996) also accounted for passive spinal and ligamentous forces. These theories and models represent significant improvements in biomechanical modelling to predict loads on the lumbar spine under different loading conditions.

Similarly, extant literature indicates that many factors with a biomechanical impact are strong risk factors for WMSDs to the upper extremities. Repetitiveness of the work activity has been shown to be a strong risk factor for cumulative trauma disorders (repetitive strain injury) (Armstrong, 1986; Stock, 1991; Waters et al., 1993; Hales and Bernard, 1996; Kumar, 1996; Malchaire et al., 1996; Latko et al., 1999). Repeated load application may result in cumulative fatigue, reducing the stress-bearing capacity of the upper extremities muscles. Besides, forcefulness/overexertion of job activities has similarly been strongly associated with these upper extremities injuries (Armstrong, 1986; Stock, 1991; Hales and Bernard, 1996; Malchaire et al., 1996; Sjogaard and Sogaard, 1998; Viikari-Juntura, 1998). In summary, Kumar (2001) reported that relatively recent and an epidemic increase of upper limb repetitive strain injury in many occupations has been largely attributed to the external loads, postural load levels, and repetition of posture and/or force application. Moreover, the duration of exposure was reported by Hales and Bernard (1996) and Spurgeon et al. (1997) as an important variable in precipitation of WMSDs of the upper extremities. Hales and Bernard stated that sustained activities with insufficient recovery time led to such afflictions. Overall, increased biomechanical loads whether due to posture (Armstrong, 1986; Malchaires et al., 1996; Hales and Bernard, 1996; Li and Buckle, 1999a) or to differential exposure due to handedness (Kucera and Robins, 1989) or to another combination of factors (Stock, 1991; Fransson-Hall et al., 1995; Grieco et al., 1998) is a significant risk factor in precipitation of WMSDs of the upper extremity. Hence, the current study supplements previously developed theories and models of WMSDs causation by evaluating the effects of lifting weights and postures on spinal biomechanics during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment. Taken together, these biomechanical models can provide a quantitative assessment of the musculoskeletal loads during occupational tasks, given spinal biomechanics information of different body parts (e.g., upper limbs, lower back and lower limbs muscles). They can also help to identify how hazardous loading conditions exceed a worker's physical capability. Although, it may be considered questionable to compare and contrast these models and theories due to different populations, and work settings; this was done to highlight the types of considerations that should be made when conducting ergonomic intervention research to alleviate WMSDs.

4.3 RESEARCH APPROACH

A laboratory simulated experiment was used to conduct the research. Twenty healthy participants (all males) were recruited from the student population of the Hong Kong Polytechnic University to participate in this study. The participants mean age was 27.9 ± 4.0 years, weight was 71.0 ± 8.97 kg, and height was 1.74 ± 0.09 m. All participants had no medical history of mechanical upper limbs and back pain or lower extremities injuries. Participants provided their informed consent as approved by the Human Subject Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20160719002).

Participants performed lifting of three different weights using either a stoop or squat lifting posture (see Figure 4.1); where these weights were 5%-, 10%-, and 15% of participant's maximum lifting strength (MLS). Lifting weights were randomized among participants, and they were allowed to practice each lifting posture for 10 seconds prior to undertaking the trial. During the first session, participants performed a stoop lifting posture in a sagittal plane. A specified location was demarcated on the floor for participants to place a wooden box (measuring 30 × 30 × 25 cm and containing dumbbell weights) with the target weight during lifting cycles. The lifting cycle started from the floor up to a bench at the waist level, rest for 3 seconds (without losing contact with the box) and then lowered the box down to the floor. The participants were instructed not to move their feet during the lifting cycle which was fixed at 10 cycles/min and controlled by a metronome. Participants performed each weight of repetitive lifting until subjective fatigue was reached (i.e., the participant could not complete a cycle of lifting after strong verbal encouragement). Another group of participants conducted a squat lifting posture in a sagittal plane using the same experimental procedures and set-up. A rest period of 20 minutes was allowed between each different weights to prevent accumulation of fatigue. To determine the MLS, participants performed a test using an isometric strength testing device (Chattecx Corporation, USA). Each participant was instructed to start in either a stoop or a squat position and then gradually brought the handle/lever of a dynamometer upward until the perceived MLS was achieved; where the dynamometer measures the strength of the whole body (Kg). This procedure was repeated after a 2-minute break. The highest value generated on the digital force monitor during the two trials was assumed to be the participant's MLS (Piezotronics, New York Inc., USA).

(a) (b)

Figure 4.1 Two lifting postures: (a) Stoop posture; and (b) Squat posture

4.3.1 Surface electromyography measurements

Two pairs of wireless bipolar Ag/AgCl surface electrodes (Noraxon TeleMyo sEMG System, Noraxon USA Inc., USA) were attached bilateral to the left and right muscle of the: biceps brachii (BB); brachioradialis (BR); lumbar erector spinae (LES); rectus femoris (RF) and medial gastrocnemius (MG) (Hermens et al., 1999; Wong et al., 2016). The diameter of the electrode was 15mm, and the inter-electrode distance was 20mm. A standardized skin preparation procedure was used to ensure the skin impedance was below 10 kΩ (cf. Xie et al., 2015). Raw electrocardiography signals were filtered for all sEMG channels (Konrad's guidelines, 2005). Prior to the lifting task, the participant was instructed to perform two trials of maximum voluntary contraction (MVC) against manual resistance of each muscle (Hermens et al., 1999). The participant maintained the MVC for 5 seconds with 2-minute rest between trials (Wong et al., 2016). The maximum root mean square (RMS) of the sEMG signal of each muscle was identified using a 1000ms moving window passing through the sEMG signals during the two MVCs. The highest RMS sEMG signal of each muscle was chosen to normalization.

All sEMG signals were processed with a band-pass filter of 20–500 Hz. A notch filter centered at 50 Hz was used to reduce power-line interference. Full-wave rectification and signal smoothing with a constant window of 100 ms RMS algorithm were also applied (Vezina and Hubley-Kozey, 2000). The left and right of each muscle were averaged because no significant difference was observed between the left and right side in sEMG signals. The sEMG signals recorded were expressed as mean RMS sEMG activity (mean EMG RMS). The sampled RMS sEMG data were normalized to the highest RMS sEMG during MVC and expressed as a percentage MVC (%MVC) sEMG. The signals from sEMG electrodes were recorded using the Noraxon MR 3.8 software (Noraxon USA Inc., USA). The sEMG activity levels during repetitive lifting were analyzed as average Standard Amplitude Analysis (SAA). The mean SAA was used to represent the average value during repetitive lifting to allow comparisons between different lifting weights and lifting postures to be made. The normalized RMS sEMG amplitude was used to predict the presence of muscle fatigue of each muscle. De Luca (1997) found that an observed increase in the RMS sEMG amplitude can be regarded as an indicator of localized muscle fatigue during repetitive lifting tasks. The muscle fatigue rate was determined as the average RMS sEMG activity over the endurance time.

4.3.2 Statistical analysis

The Shapiro-Wilk test was used to confirm that the data was normally distributed. A mixed-model repeated measures analysis of variance (ANOVA) was then adopted to evaluate the effect of different lifting weights (5%- vs. 10%- vs. 15% MLS) and lifting postures (stoop vs. squat) on spinal biomechanics. Post hoc pairwise comparisons were conducted with the Bonferroni adjustment. All statistical analyses were analyzed by the Statistical Package for the Social Science version 20.0 (IBM, USA). Statistical significance was set at $p < 0.05$.

4.4 RESULTS

4.4.1 Effects of lifting weights on spinal biomechanics

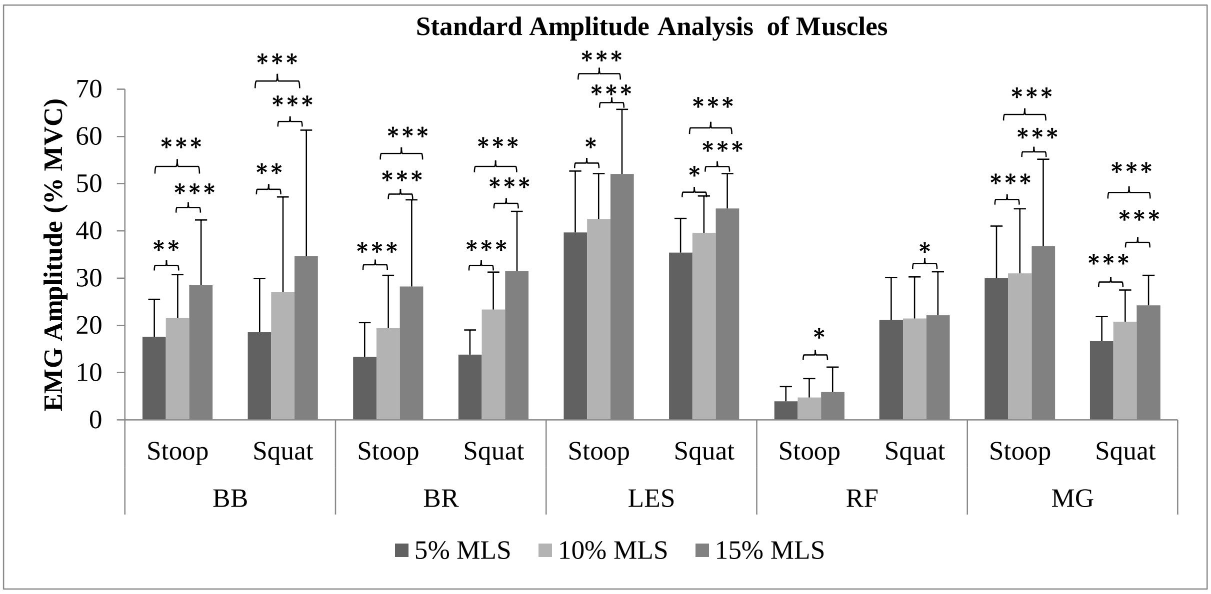
Table 4.1 presents the results of mean and standard deviation of the normalized sEMG activity for each muscle during repetitive lifting tasks. Figure 4.2 represents the comparison of normalized sEMG activity between all muscles at different lifting weights and postures. Muscle activity of all muscles (BB, BR, LES, RF, and MG) increased with lifting weight (see Figure 4.2). Heavier lifting weights (15% MLS) had the highest sEMG activity for all muscles (see Table 4.1). The LES muscle displayed the highest mean sEMG activity (i.e., 52.04% MVC).

Conversely, the RF muscle showed the lowest sEMG activity (see Table 4.1). Interestingly, the results revealed that increased lifting weights significantly increased sEMG activity of all muscles, except the RF muscles (see Table 4.1). The non-significant different sEMG activity of the RF muscle in the 5% MLS compared with 10% MLS and 15% MLS were [mean difference = -0.49% MVC (95% confident interval (CI) = -2.39% to 1.41% MVC), standard error = 0.72; eta-square = 0.16; p = 1.00] and [mean difference = -1.40% MVC (95% CI = -3.40% to 0.59% MVC), standard error = 0.76; eta-square = 0.61; p = 0.24], respectively.

Table 4.1 Mean (standard deviation) of normalized muscle activity of different muscles

Muscle	**Lifting posture**	**5% Maximum lifting strength**	**10% Maximum lifting strength**	**15% Maximum lifting strength**	**Lifting weight *p*-value**	**Lifting posture *p*-value**	**Lifting weight × Lifting posture *p*-value**
BB	Stoop	17.58 (7.97)	21.53 (9.18)	28.52(13.80)	0.00*	0.55	0.33
	Squat	18.55(11.39)	27.09(20.08)	34.66(26.67)			
BR	Stoop	13.32 (7.24)	19.41(11.21)	28.24(18.33)	0.00*	0.59	0.51
	Squat	13.82 (5.17)	23.36 (7.93)	31.46(12.65)			
LES	Stoop	39.64(12.99)	42.51 (9.61)	52.04(13.67)	0.00*	0.28	0.19
	Squat	35.41 (7.24)	39.61 (7.74)	44.71 (7.44)			
RF	Stoop	3.96 (3.08)	4.72 (4.02)	5.87 (5.27)	0.12	0.00#	0.65
	Squat	21.21 (8.94)	21.43 (8.85)	22.11 (9.21)			
MG	Stoop	26.97(11.04)	31.00(13.67)	36.73(18.41)	0.00*	0.04#	0.45
	Squat	16.62 (5.26)	20.77 (6.74)	24.23 (6.38)			

Note: Biceps brachii (BB); Brachioradialis (BR); Lumbar erector spinae (LES); Rectus femoris (RF); Medial gastrocnemius (MG). *Indicates that there was a significant difference between different lifting weights at $p < 0.05$. #Indicates that there was a significant difference between stoop and squat lifting postures at $p < 0.05$.



Note: EMG = Electromyography; MVC= maximum voluntary contraction. $*p < 0.05$, $**p < 0.01$; $***p < 0.001$; bars indicate standard deviation.

Figure 4.2 Comparison of muscle activity from the biceps brachii (BB), brachioradialis (BR), lumbar erector spinae (LES), rectus femoris (RF) and medial gastrocnemius (MG) among stoop lift posture group and squat lift posture group during 5%-, 10%-, and 15% maximum lifting strength (MLS).

Table 4.2 reveals that a significant difference in muscle fatigue of all muscles in lifting weights was apparent, except the RF muscle (Table 4.2). Moreover, the highest muscle fatigue rate occurred at the LES muscle. Based upon participants' subjective fatigue, it was found that muscle fatigue occurs earlier for 15% MLS and 10% MLS compared to 5% MLS. The average endurance time were 205.6 seconds, 131.6 seconds, and 87 seconds for 5% MLS, 10% MLS, and 15% MLS respectively.

Table 4.2 Muscle fatigue rate

Maximum lifting strength	Muscle fatigue rate				
	BB*	**BR***	**LES***	**RF**	**MG***
5%	0.176	0.132	0.365	0.122	0.212
10%	0.369	0.325	0.624	0.199	0.393
15%	0.726	0.686	1.112	0.321	0.701

Note: Biceps brachii (BB); Brachioradialis (BR); Lumbar erector spinae (LES); Rectus femoris (RF); Medial gastrocnemius (MG). *Indicates a significant difference between different lifting weights at $p < 0.05$

4.4.2 Effects of lifting postures on spinal biomechanics

Conversely, mixed design ANOVA revealed a significant difference in sEMG activity between lifting postures of RG and MG muscles (see Table 4.1). Squat lifting postures had consistent higher sEMG activity (mean difference = 16.73% MVC) compared to stoop lifting postures in RF muscles. Alternatively, the MG muscle resulted in a higher sEMG activity of stoop lifting posture (mean difference = 11.01% MVC) compared to squat lifting postures. However, no significant difference in sEMG activity between lifting postures of BB, BR and LES muscles was recorded. The two upper limb muscles (BB and BR) showed higher sEMG activity in squat lifting postures as compared to stoop lifting postures. The mean difference between the two lifting postures of BB and BR muscles were 4.23% MVC and 2.55% MVC, respectively. In the LES muscles, stoop lifting postures had higher sEMG activity than squat lifting postures with a mean difference of 4.82% MVC. No significant interaction was found between lifting weights and lifting postures on muscle activity, and lifting posture had no main effect and non-significant interaction on muscle fatigue ($p > 0.05$).

4.5 DISCUSSION

This study sought to quantify the effects of lifting weights and lifting postures on spinal biomechanics during a laboratory-based simulated repetitive lifting task. Results of the analysis revealed that increased lifting weights significantly increased sEMG activity and muscle fatigue of all muscles, except the RF muscle. The highest sEMG activity occurred at the LES muscles. Moreover, the results revealed a significant difference in sEMG activity of the RF and MG muscles between lifting postures. Mixed design ANOVA did not reveal any significant interactions between lifting weights and lifting postures on spinal biomechanics. Overall, the findings suggest that increased lifting weights increased muscle activity and muscle fatigue during repetitive lifting tasks and may elevate the risk of developing WMSDs.

4.5.1 Effects of lifting weights on spinal biomechanics

Muscle activity expressed as the RMS sEMG value (% MVC) was found to increase significantly with increased lifting weights. Moreover, the maximum muscle activity occurred at the LES muscle with a value of 52 % MVC. The average muscle activity of LES muscle increased by 10.9% MVC for heavier lifting weight (15% MLS) as compared relatively to the lower lifting weight (5% MLS). The LES muscle exhibited the highest muscle activity followed by BB, MG, BR and RF. These results concur with the findings of previous studies that focused upon repetitive lifting tasks during which the LES muscle activity increases with lifting weights (Dolan and Adams, 1998; Marras et al., 1999). In addition, lifting weight significantly increased the sEMG activity of the upper limb muscles (BB and BR), which concur with the findings of McBride et al. (2003). Cumulatively, this study's findings suggest that increased lifting weights increase sEMG activity and may increase the risk of developing WMSDs.

Analysis results also found that muscle fatigue (measured by RMS sEMG activity) increased over time for all muscles which indicate the development of muscle fatigue at different lifting weights. The LES muscle exhibited the highest muscle fatigue rate, which indicates the reference muscle in detecting muscle fatigue - that is, the muscle that indicates when an operator should stop performing the lifting task. The greater the motor unit recruitment and electric signals-firing rate (where the later is produced by muscle expansion and contraction), the greater is the generated muscle force (Merletti and Parker, 2004). During repetitive lifting tasks, the muscle force generated caused a gradual rise in sEMG activity, which results in muscle fatigue (Fallentin et al., 1993). As such, these findings explain the highest indication of muscle fatigue in the LES muscle and suggest that increased lifting weight increases sEMG activity with a corresponding increase in muscle fatigue rate. Overall, this research concurs with the findings of previous studies in which increased lifting weight resulted in an increase in muscle activity and muscle fatigue, to indicate an elevated risk of developing WMSDs (Lavender et al., 2003; Davis et al., 2010).

4.5.2 Effects of lifting postures on spinal biomechanics

The present study found inconsistent results of sEMG activity between lifting postures. The study revealed a significant difference in sEMG activity between lifting postures of the RF and MG muscles. Muscle activity of the RF muscle was higher during squat lifting posture compared to stoop lifting posture. Conversely, the stoop lifting posture had higher sEMG activity of the MG muscle compared to squat lifting posture. This result is consistent with the findings of previous biomechanical studies, which reported a significant effect of lifting postures on lower limbs sEMG activity (and thus elevated the risk of developing WMSDs in the lower extremities) (Trafimow et al., 1993). Alternatively, no significant difference of sEMG activity was found between lifting postures of the BB, BR and LES muscles and this may be due to differences in experimental protocols adopted. This research also found peak sEMG activity of the LES muscle at 7% less for squat lifting posture than stoop lifting posture – this compares to the research of Van Dieen et al. (1994), who reported significant peak sEMG activity of the LES muscle at 8% less for stoop lifting posture than squat lifting posture.

4.6 RECOMMENDATIONS FOR ALLEVIATING RISK FACTORS FOR WMSDs

The findings provide strong empirical implications that justify the industry's obligation to reduce the risk of developing WMSDs in construction workers; six key interventions are identified. First, a worker not only needs to reduce the weight of load being lifted but also avoid lifting below their knee height. Davis et al. (2010) found that a 50% reduction in the lifting weight decreased the peak loads to the lumbar back muscles by 22.5%, and noted that the negative impact of heavyweights on the lumbar region increased sagittal trunk loading by approximately 33% to 55% if the lifting weight was below knee height. Second, the research has also estimated the normative duration of repetitive lifting at different lifting weights prior to the worker experiencing subjective fatigue. Construction workers and health and safety managers should refer to these figures when attempting to mitigate the risks posed by repetitive lifting tasks. Third, team lifting (i.e., two or more rebar workers) or use of mechanical lifting equipment is recommended for lifting heavy rebar in order to minimize the risk of developing WMSDs (Edwards et al., 2003; Visser et al., 2014). Fourth, although the research found no statistically significant difference in spinal biomechanics between the two lifting postures (except muscle activity in lower limb muscles), it does not preclude the necessity of adopting proper ergonomic interventions. For example, adjustable lift tables (and other lifting equipment/ machinery) can be used to improve body posture during work (Karsh et al., 2001). Similarly, education on physical and psychosocial risk factors for WMSDs and proper lifting techniques can improve the awareness of WMSDs and cultivate proper work behavior

(Lagerstrom et al., 1998; Van Poppel et al., 1998; Karsh et al., 2001). Fifth, construction managers should also plan the work schedule of workers based on individual's physical capability to mitigate the risks posed by WMSDs during repetitive lifting tasks. For instance, rebar workers or masons can perform alternative tasks with different physical exposures, and use frequent breaks to minimize their back muscle fatigue (Seo et al., 2016). Sixth, assistive devices (e.g. cranes, exoskeletons, forklift, back belts or hoists) (Kraus et al., 1996) may be introduced to provide construction workers with better mechanical advantages during repetitive lifting tasks. For instance, knee pads can be worn to minimize the risk of knee inflammation and bursitis during kneeling postures (Lavender and Andersson, 1999). However, the cost-effectiveness of these devices should be further investigated and measured against the cost saving afforded by improved productivity and enhanced safety performance (Gallagher, 2005).

4.7 CHAPTER SUMMARY

This chapter discussed the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment. Overall, the results and ensuing discussion offer insight into how these risks can be measured and mitigated.

CHAPTER 5

IDENTIFICATION OF POTENTIAL BIOMECHANICAL RISK FACTORS FOR LOW BACK DISORDERS DURING REPETITIVE REBAR LIFTING[4]

5.1 INTRODUCTION

Work-related low back disorders (LBDs) involve excruciating pain and discomfort or malfunction of spinal muscles, nerves, bones, discs and/or tendons in the lower back region (McGill, 2015). Epidemiological studies provide causal evidence for associations between LBDs and workplace risk factors including heavy physical load, lifting and forceful movements, bending and twisting (awkward postures) and whole-body vibration (Bernard, 1997). Within the construction industry, LBDs are a prevalent health problem which accounts for over 37% of all absenteeism, 21.3% of claim costs and 25.5% of disability days among workers (Schneider, 2001; Courtney et al., 2002; Hoogendroom et al., 2002; Holmstrom and Engholm, 2003). The prevailing level of risk is not homogeneous throughout all trade disciplines, and rebar workers are particularly susceptible to LBDs (Albers and Hudock, 2007). Indeed, Forde et al. (2005) report that LBD is the most common work-related musculoskeletal disorder affecting rebar workers while Hunting et al. (1999) found that the level of LBDs experienced by rebar workers (11.8%) was higher than other construction workers (8.1%).

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Biomechanics provides a pragmatic and applied approach to evaluating the association between workplace risk factors and LBDs during repetitive rebar lifting tasks (c.f. de Looze et al., 1994a; van Dieen and Kingma, 1999). It is well known that an increase in height when lifting from the ground, fast lifting pace, and an increase in weight lifted will increase spinal loadings and elevate the risk of developing LBDs (Granata and Marras, 1999; Davis et al., 2010; Plamondon et al., 2012; Yoon et al., 2012). As such, it is not surprising to use these risk factors as inputs (usually height or pace) in designing lifting guidelines, especially for repetitive rebar lifting tasks. In addition, these aforementioned studies predict the associations between risk factors and LBDs; the approach adopted required complex data analytics augmented by video footage (to record joint motions) and electromyography (EMG) muscle activity. Such works are impractical in the workplace. In particular, reducing the incidence of LBDs among rebar workers requires endeavors to assess whether different weights of lift represent a LBD risk factor in the workplace.

Ergonomic safety convention states that a squat lifting posture is preferable to stoop lifting postures because it: reduces compression loading and ligamentous strain within the spine (Anderson and Chaffin, 1986; Davis et al., 2010); has inherently lower strength requirements (Anderson and Chaffin, 1986); and reduces perceived low back exertion (Hagen et al., 1993; Hagen and Harms-Ringdahl, 1994). Other studies contradict this established body of knowledge and report a higher perceived physical exertion for squat lifting (Garg and Moore, 1992; Straker and Duncan, 2000) and a higher rate of perceived discomfort (Straker and Duncan, 2000). Consequently, squat lifting postures engender more rapid development of physical fatigue (Hagen et al., 1993). Even though these contradictory studies have widely advocated lifting postures (e.g., stoop and squat) (Van Dieen et al., 1999; Straker, 2003), the effect of lifting various weights and postures on spinal biomechanics (i.e., spinal motion and trunk muscle activity) during repetitive rebar lifting tasks remains unclear. As such, the effect of different weights and lifting postures could be useful in designing repetitive lifting tasks guidelines, particularly for rebar workers. In addition, the effect of different weights and lifting postures on self-reported discomfort during repetitive rebar lifting remains elusive. To mitigate the risk of developing LBDs in rebar workers, there is a need to better understand the subjective and biomechanical demands incurred during repetitive rebar lifting so that pragmatic interventions and risk control measures can be successfully implemented. Therefore, this research seeks to better understand biomechanical risk factors that instigate the development of LBDs using laboratory controlled lifting trials encompassing quantifiable weights and predetermined body postures. Concomitant research objectives are to identify potential biomechanical risk factors and to provide pragmatic, ergonomic guidance to practitioners on optimizing lifting postures for rebar workers.

5.2 REBAR WORK AND ASSOCIATED RISK FACTORS

Rebar work is physically demanding, often requires awkward lifting postures and frequently involves heavy manual lifting of weights (Buchholz et al., 2003). Typical work tasks include i) preparing rebars (e.g. pulling rebars from the stack, cutting or bending rebars); and ii) assembling rebars (e.g. lifting, placing and tying rebars) (Saari and Wickström, 1978). Chan et al. (2012) report that rebar workers in Hong Kong spend 30% of their work time preparing rebars and 70% assembling them. Both tasks require repetitive rebar lifting, involving heavyweight handling with awkward postures. Saari and Wickström (1978) found that 15% of rebar assembly time was spent lifting and carrying rebars of heavyweight ≥ 30 kg and that a stoop lifting posture was commonly used. These physically demanding lifting tasks expose rebar workers to higher LBD risks and increase the mechanical loadings upon the spine structures (e.g. facet joints and intervertebral discs) (Granata and Marras, 1999; Umer et al., 2016; Antwi-Afari et al., 2017b). This assertion is validated by Marras et al. (1999d) and Davis et al. (2010) who report upon a similar increase in spinal loadings [~15% of maximum voluntary contraction (MVC)] when trial participants lifted heavy weights (27.3kg and 42.7 kg).

5.2.1 Risk assessment methods

Risk assessment methods for lifting tasks are categorized into four thematic groupings, namely: i) self-reports; ii) observational methods; iii) direct measurement techniques, and iv) camera-based techniques. Self-reports are widely used in epidemic and ergonomic studies (David, 2005; Inyang et al., 2012) and prominent exemplars adopted in practice include the: Nordic Musculoskeletal Questionnaire (Reme et al., 2012); Borg Scale (Li and Yu, 2011); and Job Requirements and Physical Demands Survey (JRPDS) (Dane et al., 2002). In a construction context, Riihimaki (1985) uses self-report survey questionnaires to investigate the effect of heavy physical work upon the backs of rebar workers and house painters. However, self-report assessment methods are subjective and prone to introducing recall bias (that is, a systematic error caused by differences in a participant's reporting accuracy or incompleteness of their recollections) (Spielholz et al., 2001; Jones and Kumar, 2010).

Observational methods developed are myriad and include the: *Assessment of Repetitive Task (ART)* (The Health and Safety Executive, 2009); *Manual Handling Assessment (MAC)* (The Health and Safety Executive, 2002); *Ovako Working Analysis System (OWAS)* (Karhu et al., 1977; and Kivi and Mattila, 1991); *Posture, Activity, Tools, and Handling (PATH)* (Forde and Buchholz, 2004); *Rapid Upper Limb Assessment (RULA)* (McAtamney and Corlett, 1993; and McGorry and Lin, 2007); *Rapid Entire Body Assessment (REBA)* (Kim et al., 2011; and Hignett and McAtameny, 2000); *Quick Exposure Check (QEC)* (University of Surrey Health and Safety Executive, 1999); *Washington State's ergonomic rule* (WAC 296-135 62-051) (Washington State Department of Labor and Industries, 2010); *Strain Index* (Drinkaus et al., 2005); and *3D*

Static Strength Prediction Program (3DSSPP) (The Center for Ergonomic at the University of Michigan, 2016). Although these observational methods are an improvement upon self-reports, they are subjective, lack precision and are less reproducible in work situations (Coenen et al., 2011).

Conventional direct measurement techniques include surface Electromyography (sEMG) recording of muscle action, video-based motion, inertial measurement unit (IMU) and lumbar motion monitor (LMM) (Merletti and Parker, 1999; Umer et al., 2016; Antwi-Afari et al., 2017b). sEMG recordings are ubiquitous within extant literature and typically report upon muscle exertions by attaching a group of sensors to the skin over the muscles being sampled (Ning et al., 2014; Umer et al., 2016; Antwi-Afari et al., 2017b). Recordings of muscle tension and computerized analysis of myoelectric signals evaluate spinal biomechanics (Nimbarte et al., 2014). sEMG sensors accurately measure physical exposure detection of manual handling activities (e.g. repetitive lifting tasks) and are applicable to both indoor and outdoor settings (Kim and Nussbaum, 2013). Equipment cost and data analysis time preclude their use on a large number of participants or for long-term data collection (Wang et al., 2015a).

Camera-based techniques utilise video/image sensors to capture human movements from indirect measurements (Han and Lee, 2013; Seo et al., 2015). Consequently, they allow remote analysis of work tasks without disturbing the work process. Accuracy however, relies upon the manual input of posture and joint angles and a direct line of sight (Han and Lee, 2013). Furthermore, this approach cannot: differentiate whether a person is stationary and stable or struggling to regain balance; or detect body postures under bright light conditions (Chen et al., 2014).

Although these four methods have been used in both field and laboratory-based studies, direct measurement methods under strict laboratory-controlled conditions (using a combination of sEMG and IMU sensors) provide an affordable and detailed solution to assessing LBDs risk factors during simulated repetitive rebar lifting tasks (Moeslund et al., 2006). Consequently, this research study examines and compares the effect of different lifting weights and lifting postures on spinal motion and trunk muscle activity during simulated repetitive rebar lifting tasks.

5.3 RESEARCH METHODS

A convenient sample of twenty (20 no.) healthy participants (all males) was recruited from the student population of the Hong Kong Polytechnic University to participate in this study (Table 5.1). Sample exclusion criteria included 'high risk' participants with a history of: low back pain (using the 10-item Oswestry Disability Index (ODI) > 20%) (c.f. Fairbank and Pynsent, 2000; Wong et al., 2016); and/or cardiac or other health problems (e.g. dizziness, chest pain, and heart pain) (using a 7-item Physical Activity Readiness Questionnaire (PAR-Q)) (c.f. Baecke et al., 1982). Participants provided their informed consent as approved by the Human Subject Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20160719002). No significant between-group difference in demographic data and ODI scores was observed.

Table 5.1 Participants' demographic characteristics and self-reported questionnaires

Self-reported	Stoop lifting posture (n=10)		Range	Squat lifting posture (n=10)		Range	*p*-Value
	Mean	**±SD**		**Mean**	**± SD**		
Age (years)	28.80	4.54	22-38	27.00	3.40	22-32	0.33
Height (m)	1.74	0.08	1.63-1.86	1.75	0.10	1.58-1.88	0.83
Weight (kg)	70.90	6.85	57-80	71.10	11.08	57-87	0.96
BMI (kg/m^2)	23.44	1.98	20.20-6.26	23.17	2.50	20.42-29.41	0.79
ODI (%)	3.80	10.00	0-12	0.80	1.40	0-4	0.36

Note: SD= standard deviation; BMI= body mass index; ODI= Oswestry Disability Index.

5.3.1 Experimental design and procedure

Participants rated the perceived exertion/pain threshold of their body parts on an 11-point (0 to 10) Borg categorical rating scale (Borg CR 10) where 0 indicates '*no pain*' and 10 indicates '*the worst imaginable pain*' (Borg, 1998), before marking the site of their body pain on a body diagram (Rustoen et al., 2004). Within the industry, three rebar workers often work as a group to repetitively lift four (4 no.) to ten (10 no.) pieces of reinforcing bar (weighing approximately 7.1kg to 17.8kg) from the floor to the target location (e.g. at waist level) (Figure 5.1a-b). Pilot study observational research trials conducted (pre-full laboratory testing) reveal that either a stoop or squat lifting posture is used in repetitive movements with an average of 10 lifting cycles per minute. One-third of the weight of four (4 no.) and ten (10 no.) pieces of rebars were comparable to approximately 5% and 15% of an individual's maximum lifting strength (MLS) as measured using an isometric strength testing device (Chattecx Corporation, USA). Thus, to simulate lifting loads of rebar, participants were instructed to repetitively lift and lower three different weights that corresponded to 5%, 10% and 15% of their MLS. Each participant was instructed to start in either a stoop or a squat position and then visualize the handle (of the isometric strength testing device) as a bundle of rebars and gradually pull the handle upward until the subjective perceived MLS was achieved. This procedure was repeated after a 2-minute break. The highest value generated on the digital force monitor (Piezotronics, New York Inc., USA) during the two trials was assumed to be the participant's MLS.

(a)

(b)

Figure 5.1 Two lifting postures: (a) Stoop posture; and (b) Squat posture. +ve and –ve represent flexion and extension trunk movements in the cartesian plane, respectively.

Participants were then randomly assigned using the Latin Square (an *n* x *n* array) to perform the trial. The lifting sequence of the weights was randomized to counterbalance the accumulative effect of different weights. For safety purposes, instead of lifting a bundle of rebars in a laboratory, the target lifting load was placed in a wooden box (measuring 30 × 30 × 25 cm) with hole handles at either side. Using both hands, participants lifted the box from floor level to a bench at waist level, waited for three (3 no.) seconds (without losing contact with the box) and then lowered the box back to the floor and waited another three (3 no.) seconds before resuming the next cycle. Each participant was instructed to lift each of the three weights repetitively until subjective fatigue was reached (i.e., the participant could not complete a cycle of lifting after strong verbal encouragement). A metronome provided a beat to guide the task (approximately 10 cycles/minute). Prior to data collection, participants were allowed to practice once with each of the target weights using the assigned lifting posture (Straker, 2003). A twenty-minute rest was interspersed between the lifting of different weights.

5.3.1.1 Surface electromyography measurements

Two pairs of wireless bipolar Ag/AgCl surface electrodes (Noraxon TeleMyo sEMG System, Noraxon USA Inc., USA) were attached to the bilateral lumbar erector spinae (LES) at the L3 level (Figure 5.2) (Hermens et al., 1999; Wong et al., 2016). The diameter of the electrode was

15mm and the inter-electrode distance was 20mm. A standardized skin preparation procedure was administered (including skin abrasion with light sandpaper, cleaning with alcohol and shaving of hair if necessary) to ensure the skin impedance was below 10 kΩ (Xie et al., 2015). Raw sEMG signals were sampled at a frequency of 1500Hz with the common mode rejection ratio of 100db and then digitized by a 16-bit analog to digital (A/D) converter.

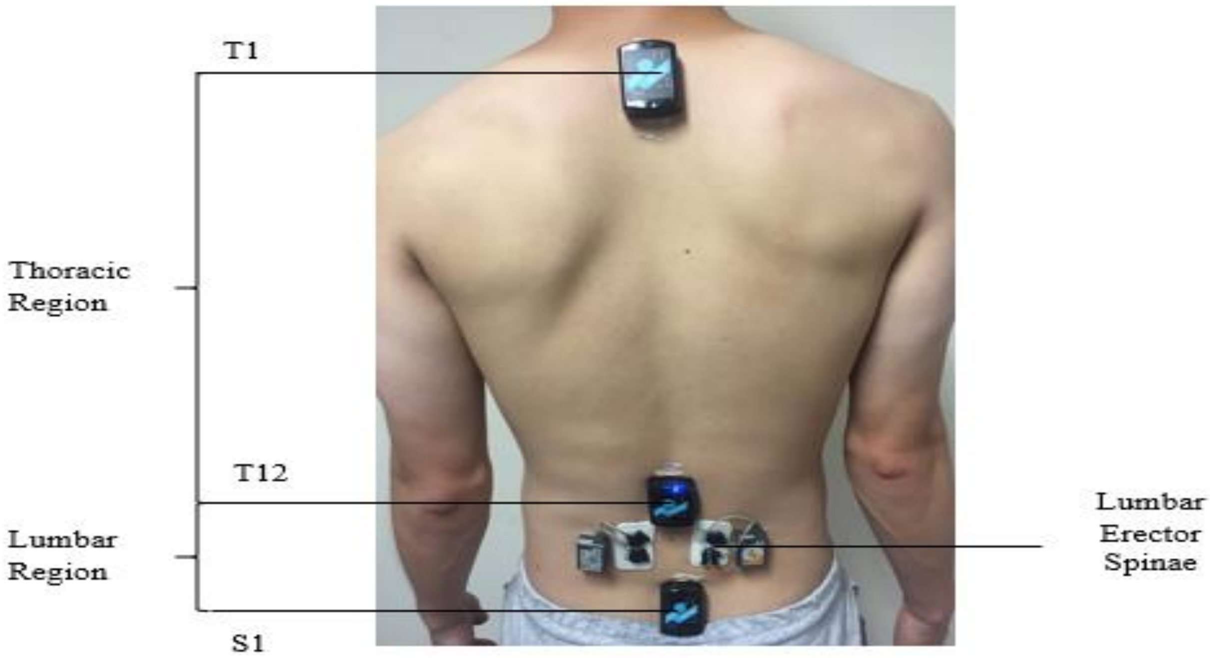


Figure 5.2 Motion sensor and surface EMG electrodes placement

Prior to performing the lifting task, participants were instructed to perform two trials of back extension MVC against manual resistance. The participants maintained the MVC for 5 seconds with a 2-minute rest between trials (Hu et al., 2009; Wong et al., 2016). The maximum root mean square (RMS) of the sEMG signal for each LES muscle was identified using a 1000ms moving window passing through the sEMG signals during the two MVCs. The highest RMS sEMG signal of each LES muscle was chosen for normalization. Raw electrocardiography signals were filtered from sEMG channels using an electrocardiography-reduction algorithm (c.f. Konrad, 2005). The resulting sEMG signals were band-pass filtered between 20 Hz and 500 Hz. A notch filter centered at 50 Hz was used to eliminate power-line interference. The rectified and processed sEMG signals with an averaging constant of 1000ms were used to provide the root mean square (RMS) sEMG signals. The RMS sEMG signals from the left and right of the LES muscle were averaged because the paired *t*-test found no significance between-side difference in sEMG signals during the repetitive lifting tasks ($p > 0.05$). The sampled RMS sEMG data were normalized to the highest RMS sEMG during MVC and expressed as a percentage MVC (%MVC) sEMG.

To quantify back muscle fatigue, two major phenomena were measured. First, the median frequency (MF) of raw sEMG signals for each LES muscle (during each lifting period) was partitioned into twenty epochs (without overlap). The MF of the sEMG power spectrum in each epoch was analyzed by a Fast Fourier Transform technique with a smoothing Hamming window digital filter (Smith, 2003; Kellis and Katis, 2008). The MF of sEMG for each of the 20 epochs was normalized with respect to the initial MF obtained prior to lifting. An observed decrease in normalized MF values between the beginning and end of the lifting task (i.e., a negative slope on the normalized MF plot) represented muscle fatigue. Second, the endurance time (time to fatigue) recorded at the end of each lifting weight task were compared as an additional quantitative measure of back muscle fatigue. Decreases in time to fatigue were taken as an indicator of global back muscle fatigue.

5.3.1.2 Spinal kinematic measurements

Three inertial measurement unit motion sensors (Noraxon MyoMotion system, Noraxon USA Inc., USA) were attached to the spinous processes at the T1, T12 and S1 levels (Figure 5.2) and kinematics data were sampled at 100Hz. Motion sensors estimated the spatial orientation of body segments by integrating the signals of multiple electromechanical sensors (accelerometers, gyroscopes and/or magnetometers using specific sensor fusion algorithms) (Umer et al., 2016). The thoracic and lumbar kinematics were estimated from the relative differences in 3-dimensional movements namely: i) flexion/extension; ii) lateral bending; and iii) axial rotation) between the sensors attached to the T1 and T12 levels and the T12 and S1 levels respectively (Figure 5.2).

5.3.2 Analysis of sEMG and kinematic data during lifting

Signals from sEMG electrodes and motion sensors were synchronized using the Noraxon MR 3.8 software (Noraxon USA Inc., USA). Standard Amplitude Analysis (SAA) normalized the sEMG signals of LES and spinal kinematic signals during the repetitive lifting task.

Specifically, SAA divided the lifting task period into three equal time phases (initial, middle and final) so that temporal changes in kinetics and kinematics during lifting with different weights or postures could be estimated. The mean kinetics and kinematics in the middle lift phase of SAA were used to represent the average spinal biomechanics during lifting, thus allowing comparisons between different lifting weights or postures to be made.

5.3.2.1 Statistical analysis

Demographic characteristics and the self-reported pain/perceived exertion measures (using the Borg scale) between the two lifting posture groups were compared by separate independent *t*-tests. Since the Shapiro-Wilk tests revealed that sEMG and kinematic data were normally distributed, a separated (2×3) mixed-model repeated measures analysis of variance (ANOVA) was used to evaluate the effect of lifting postures (*between-group factor*) and lifting weights (*within-subject factor*) on the corresponding sEMG and spinal kinematics (thoracic or lumbar range of motion). A separated one-way repeated measures ANOVA then evaluated the difference between the normalized MF of sEMG and time to fatigue data whilst post hoc pairwise comparisons were conducted with the Bonferroni adjustment. The Statistical Package for the Social Science version 20.0 (IBM, USA) was used for statistical analysis and significance was $p < 0.05$.

5.4 RESULTS

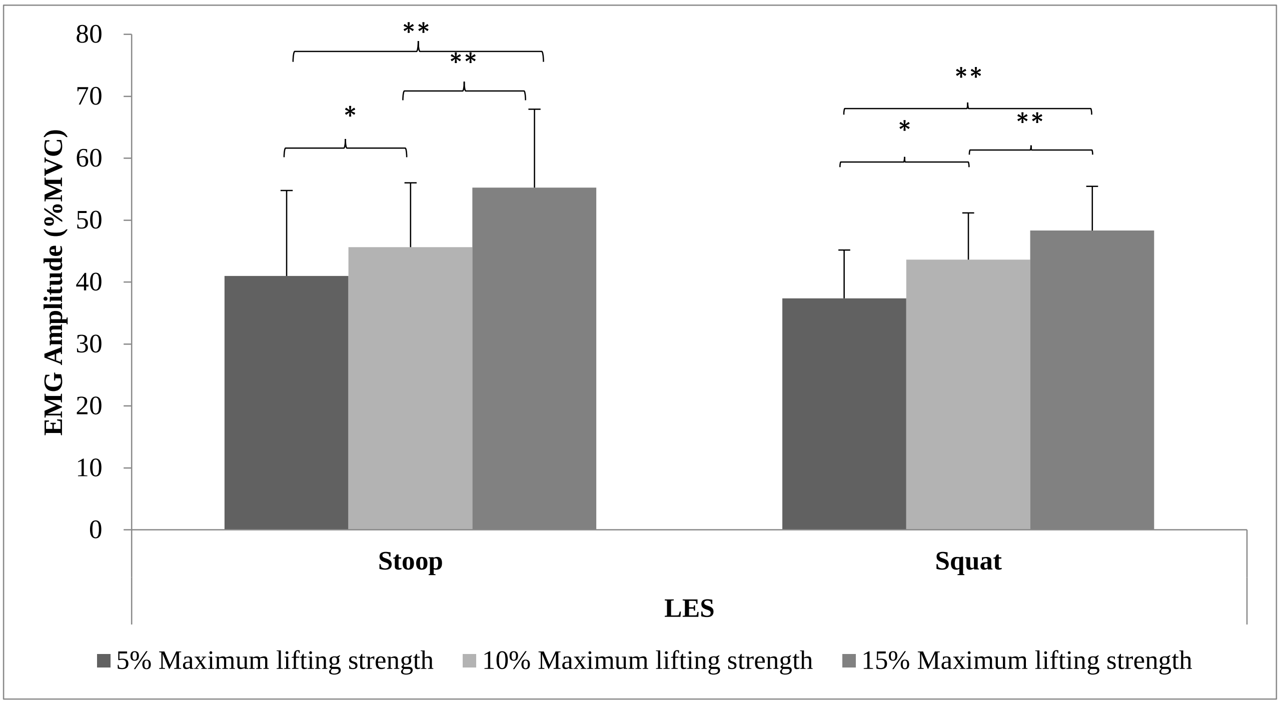
5.4.1 Effect of lifting weights on sEMG activity and trunk kinematics

The middle SAA results illustrate that the sEMG activity of LES muscles significantly increased as the lifting weights of the repetitive task increased (Table 5.2). Post hoc pairwise comparisons revealed that heavier lifting weights led to significantly higher LES activity (Figure 5.3). The lifting weight corresponding to 15% MLS caused the highest LES muscle activity (approximately 55% MVC sEMG), regardless of lifting postures.

Table 5.2 Mean and standard deviation (SD) values for initial, middle, and final phases of standard amplitude analysis of normalized muscle activity at the lumbar erector spinae muscles during repetitive rebar lifting tasks

Muscle	Time phase (SAA)	Lifting posture	5% Maximum lifting strength	10% Maximum lifting strength	15% Maximum lifting strength	Lifting posture *p*-Value	Lifting weight *p*-Value	Lifting posture×lifting weight *p*-Value
LES	Initial	Stoop Squat	39.14 (13.05) 35.00 (7.23)	43.48 (9.80) 37.00 (7.92)	50.07 (15.12) 41.71 (6.73)	0.17	0.00[a]	0.28
	Middle	Stoop Squat	40.97 (13.85) 37.39 (7.77)	45.64 (10.39) 43.61 (7.58)	55.27 (12.63) 48.32 (7.13)	0.34	0.00[a]	0.18
	Final	Stoop Squat	39.31 (12.46) 34.11 (8.05)	40.32 (9.48) 38.62 (8.55)	52.41 (14.28) 43.41(10.12)	0.25	0.00[a]	0.06

Note: SAA= standard amplitude analysis; LES= lumbar erector spinae. [a]Significant difference between the three different weights with $p < 0.05$.



NB: EMG= Electromyography; %MVC= percentage of maximum voluntary contraction. *$p < 0.01$, **$p < 0.001$; the vertical error bar indicates standard deviation.

Figure 5.3 Lumbar erector spinae (LES) muscle activity during stoop or squat lifting with different weights in the middle phase of standard amplitude analysis**.**

Because the independent *t*-tests displayed no significant difference in the negative slope of normalized sEMG MFs (or time to fatigue between the two lifting posture groups), the sEMG MFs and time to fatigue data from both groups were averaged to analyze the effect of different lifting weights on LES muscle fatigue and time to fatigue. Heavier lifting weights led to significant decreases in the normalized sEMG MF of LES muscles ($p < 0.05$) (Figure 5.4). The negative slopes of sEMG MFs of back muscles for 5%, 10%, and 15% of MLS were -0.08, -0.12, and -0.18 respectively ($p < 0.05$). Similarly, the time to fatigue significantly decreased as the lifting weights increased ($p < 0.05$). The average lifting durations for 5%, 10%, and 15% of MLS were 205.6 seconds, 131.6 seconds and 87 seconds respectively (Figure 5.5).

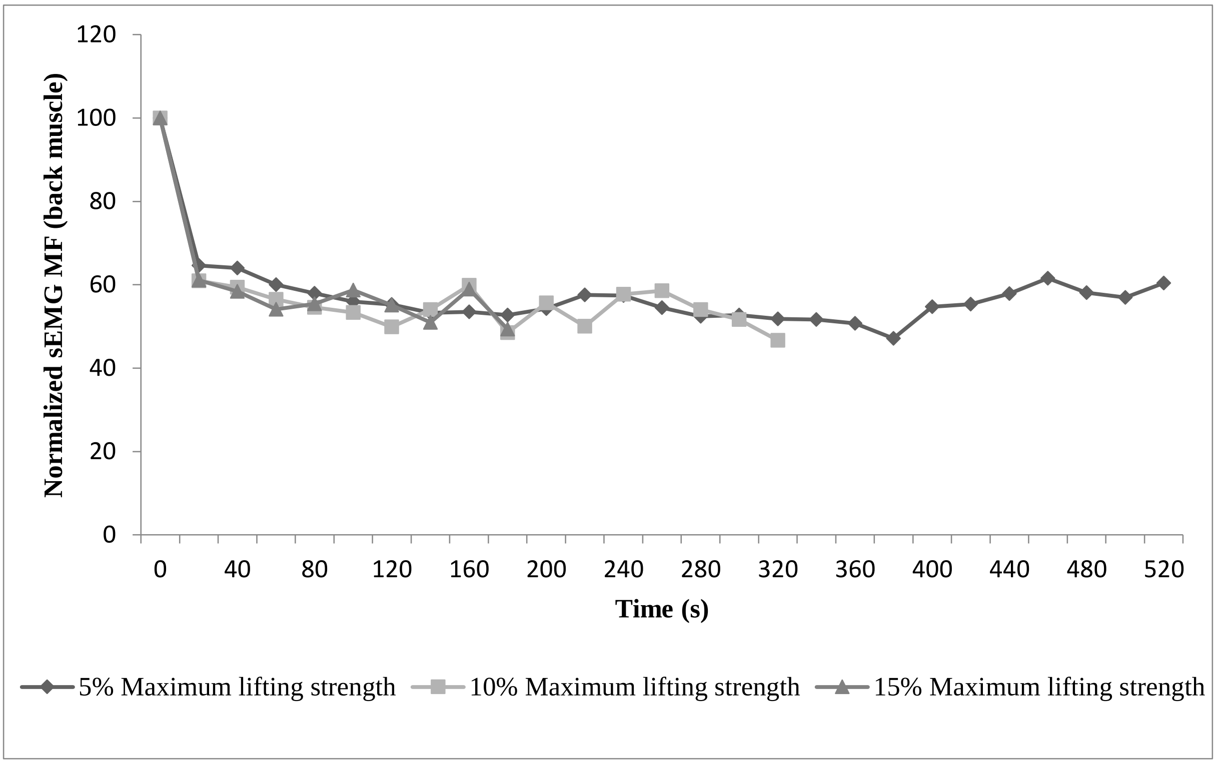


Figure 5.4 Normalized sEMG median frequency (MF) averaged across groups for the three rebar weights across time to fatigue of the back muscles.

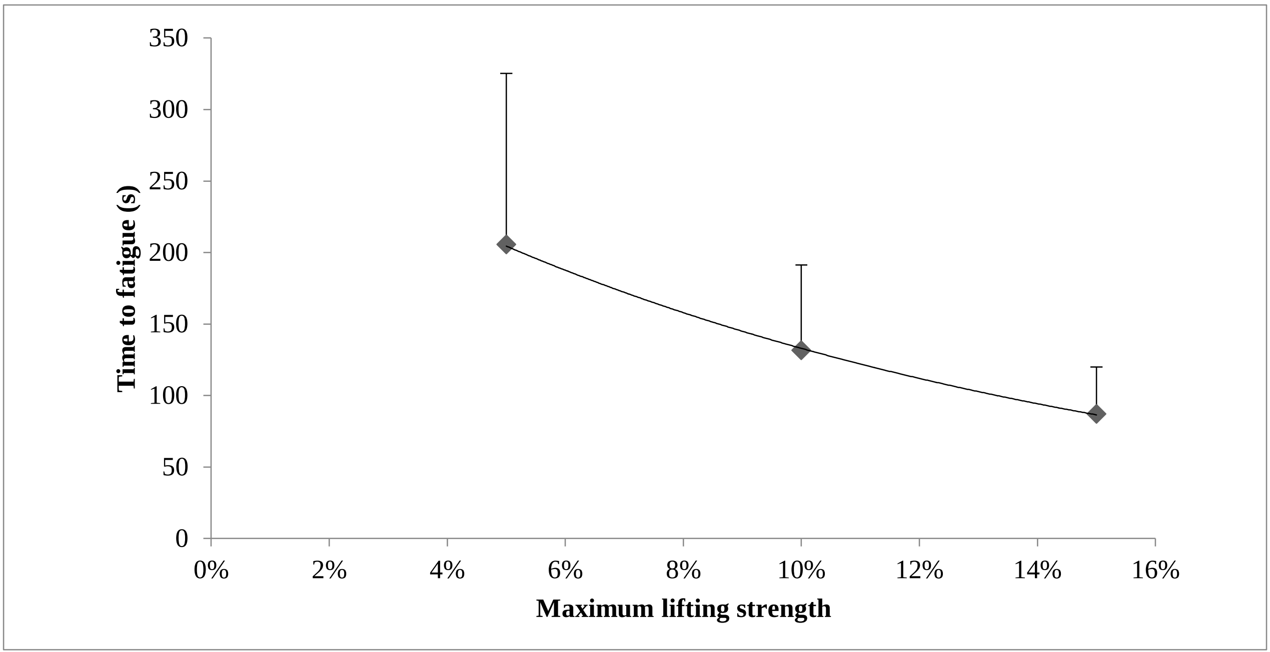


Figure 5.5 The means and standard deviations of time to fatigue and the relationship between different rebar weights and time to fatigue. Vertical error bars indicate standard deviation

Although there was no significant difference in spinal motion angles (lumbar and thoracic regions) during all phases of lifting at the three different lifting weights (Table 5.3), a consistent trend of increases in middle SAA lumbar flexion angles was observed as the lifting weight increased, regardless of the lifting posture (Table 5.3). Heavier lifting weights resulted in significant increases in perceived exertion/pain intensity for both lumbar and quadriceps/calf muscles ($p < 0.05$).

Table 5.3 Mean angle and standard deviation (SD) values of thoracic and lumbar range of motion at the initial, middle and final phases of standard amplitude analysis during repetitive rebar lifting tasks

Spinal region		**Time phase (SAA)**	**Angle (degrees)**						**Group, tasks, and group × task *p*-Value**
			Stoop lifting posture Maximum lifting strength			**Squat lifting posture Maximum lifting strength**			
			5%	**10%**	**15%**	**5%**	**10%**	**15%**	
Lumbar region	Flexion	Initial	29.58 (6.16)	30.23 (7.78)	31.29 (6.03)	21.43 (4.95)	26.10 (6.48)	29.16 (8.18)	N/S
		Middle	33.25 (6.82)	33.48 (8.79)	33.53 (8.50)	29.70 (8.52)	29.90 (8.82)	33.22 (9.17)	N/S
		Final	32.40 (7.36)	32.87 (8.84)	33.66 (8.51)	23.90 (5.58)	28.08 (11.76)	30.88 (8.81)	N/S
Average difference in the lumbar flexion range of motion between the initial and final phase of SAA			2.82 (4.24)	2.64 (3.86)	2.37 (4.45)	2.47 (2.64)	1.98 (8.22)	1.72 (2.45)	N/S
Thoracic region	Flexion	Initial	5.55 (5.33)	4.84 (7.21)	3.72 (7.75)	0.29 (7.22)	1.38 (8.16)	1.81 (7.68)	N/S
		Middle	5.75 (7.96)	4.96 (8.20)	4.84 (8.50)	1.05 (7.55)	2.05 (8.69)	1.63 (8.72)	N/S
		Final	5.38 (8.22)	4.58 (8.12)	4.44 (8.51)	1.67 (7.78)	2.79 (8.55)	1.92 (8.88)	N/S
Average difference in the thoracic range of motion between the initial and final phase of SAA			-0.17 (4.24)	-0.26 (2.70)	0.72 (3.04)	1.37 (2.77)	1.41 (2.42)	0.11 (2.57)	N/S

Note: Positive values represent flexion; Negative range of motion values represent hyperextension; SAA = standard amplitude analysis. N/S= No significant difference in lumbar flexion and thoracic flexion angles regardless of lifting weights or postures.

5.4.2 Effect of lifting postures on sEMG activity and trunk kinematics

There was no significant difference in the middle SAA sEMG activity of LES muscles between the two lifting posture groups (p = 0.34) nor any group and weight interaction effect (p = 0.18). However, the stoop lifting posture displayed a higher absolute LES muscle activity during the middle SAA sEMG activity than squat lifting across all three lifting weights (Figure 5.3).

Similarly, lifting postures had no significant effect on spinal kinematics regardless of the lifting weight, although the stoop lifting posture demonstrated higher absolute lumbar and thoracic flexion angles than those in the squat lifting posture (Table 5.3). Interestingly, there was a decreasing trend in thoracic flexion angles as the lifting weights increased during different phases of stoop lifting. However, no such trend was noted in the thoracic regions during squat lifting (Table 5.3). Participants in the stoop lifting posture group experienced significantly higher discomfort/pain at their lower back, while those in the squat lifting posture group suffered from significantly higher discomfort at quadriceps and calf muscles (Table 5.4).

Table 5.4 Pain intensity experienced during repetitive lifting of three different weights in two lifting postures

Maximum lifting strength	Borg categorical ratio scale of pain (out of 10)			
	Stoop lifting posture		Squat lifting posture	
	Back muscle pain (n=10) Mean±SD	Quadriceps and calf muscles (n=10) Mean±SD	Back muscle pain (n=10) Mean±SD	Quadriceps and calf muscles (n=10) Mean±SD
5%	7.40±0.70*	1.40±0.52#	1.40±0.52*	7.60±0.52#
10%	7.80±0.63*	1.70±0.48#	2.30±0.48*	7.80±0.42#
15%	8.60±0.52*	2.90±0.74#	3.40±0.52*	8.60±0.52#

Note: *Significant difference between different lifting weights and different lifting postures for back muscle pain, $p < 0.05$. #Significant difference between different lifting weights and different lifting postures for quadriceps and calf muscles pain, $p < 0.05$.

5.5 DISCUSSION

The analysis results reveal that an increase in lifting weight significantly increased lumbar muscle activity and decreased fatigue (as measured by sEMG MFs)/ time to fatigue. However, lifting weights had no significant effect on spinal kinematics regardless of lifting posture adopted. Conversely, lifting posture had no statistically significant effect on any of the spinal biomechanical parameters, although stoop lifting posture appeared to elicit higher absolute LES sEMG amplitude and larger absolute thoracic and lumbar flexion angles. Participants in the stoop lifting group experienced significantly higher pain intensity in the lumbar region when compared to those in the squat lifting group.

5.5.1 Effect of lifting weights on spinal biomechanics and pain perception during lifting

Heavier lifting weights significantly increased the activity and pain intensity of back muscles. These findings concur with prior studies that found increased back muscle activity during lifting tasks might increase the risk of LBDs (Lavender et al., 2003). Davis et al. (2010) similarly found an increase in muscle activity (~15% MVC) when masonry workers lifted heavy bags (42.7kg) compared to a half-weight bag (21.4kg). While this aforementioned study (*ibid*) evaluated a 50% reduction in weight, the current study evaluated 10% reduction of rebar weight (from 15 to 5% MLS) with similar increases in muscle activity (14.3% MVC). These findings concur with previous studies (c.f. Potvin et al., 1991; Van Dieen et al., 1994) which estimate peak lumbar loads for stoop lifting to be 5% greater than squat lifting posture.

Yingling and McGill (1999) proffer that the lifting capacity of an individual is related to the respective internal tolerances, such as the physical and physiological capacity of a body to cope with external loading. Lifting heavy weights also increases the amount of back muscle compressive forces acting upon the lumbar spine (Callaghan and McGill, 2001) and challenges an individual's internal tolerance (Granata and Marras, 1999). Although spinal motions appeared to be unaffected by lifting weight, the absolute value of lumbar flexion angles increased as lifting weights increased. These results concurred with findings reported by Dolan and Adams (1998) and Wong and Wong (2008). Dolan and Adams (1998) for example, observed an increase in lumbar flexion angles (from 54.9°±8.7° to 55.7°±8.9°) as the lifting weight of a repetitive lifting task increased. Thus heavier lifting weights appear to increase an individual's ability to maintain a neutral/upright body posture. Since increased trunk flexion heightens mechanical loading on the lumbar region, this partly explains the increased lumbar muscle activity and increased risk of LBDs for heavy manual lifting (Granata and Marras, 1999).

Heavier lifting weights led to faster muscle fatigue as evidenced by a temporal decrease in sEMG MF and time to fatigue as corroborated by previous research (Sparto et al., 1999; Mawston et al., 2007; Granata and Gottipati, 2008). Sparto et al. (1999) found a significant reduction in sEMG MF of the back muscles as the repetitive lifting increased from 35% to 70%

of the average maximal lifting force. Consequently, the findings presented substantiate that repetitive lifting of heavyweights increases the risk of back muscle fatigue and the possible development of LBDs. To minimize risk, therefore, rebar workers should perform alternative tasks with different physical exposures and use frequent breaks to minimize back muscle fatigue (Seo et al., 2016).

5.5.2 Effect of lifting postures on spinal biomechanics and pain perception during lifting

The insignificant effect of lifting postures upon spinal biomechanics observed concurs with prior research (De Looze et al., 1994a). For example, Hagen and Harms-Ringdahl (1994) found no significant difference in lumbar loading between stoop lifting and squat lifting when participants lifted an 8.5kg or 17kg weight. The negative findings reported upon herein might be attributed to other reasons. First, a redundancy in the recruitment of motor units, within and between lumbar muscles (c.f. Hodges and Tucker, 2011), may mean that participants use heterogeneous back muscle recruitment strategies to perform the same task, which might lead to negative results. Second, the experimental protocol adopted resulted in a fast onset of back muscle fatigue and rapid task termination, hence subtle differences in back muscle activity or trunk kinematics between the two lifting postures might have been missed. Future research may use different lifting parameters (e.g. lifting speed) to detect the potential effect of different lifting postures on spinal biomechanics. Third, because participants were tested in repetitive symmetrical lifting tasks, the results might be different had asymmetrical lifting tasks been performed (e.g. combined lifting and twisting).

Although no statistically significant difference in biomechanical parameters was found between the two lifting postures, the stoop lifting posture demonstrated higher absolute LES activity and lumbar flexion angles. These findings concur with previous research that show higher muscle activity and spinal motion for the stoop lifting posture when compared to the squat lifting posture (Straker and Duncan, 2000; Albers and Hudock, 2007). Importantly, increased lumbar flexion during the stoop lifting posture may cause creep and related laxity of spinal ligaments (Solomonow et al., 2003), and impose greater loading to back muscles and ligaments that increase the risk of back injury (Wang et al., 2000). Therefore, the findings presented support a prior recommendation to adopt the squat lifting posture (Garg and Moore, 1992). Akin to previous research (Hagen and Harms-Ringdahl, 1994), stoop lifting elicited significantly higher back discomfort/pain than squat lifting, where the latter may increase the risk of back injury (Straker, 1997).

5.6 IMPLICATIONS

The research findings obtained from trunk kinematics suggest that rebar workers should lift a small number of rebars (i.e., 4 pieces of rebars) to minimize the muscle activity and fatigue of back muscles. Several other factors were identified and further exacerbate the risk posed (i.e., lifting weights, muscle fatigue, awkward posture and repetitive motions) and provide new insights into understanding the assessment/analysis methods during repetitive lifting tasks. Training workers in health and safety issues provide a basis for consistent awareness, identification, analysis, and control of musculoskeletal disorders. Therefore, construction/safety managers on site should consider these identified risk factors and provide suitable training programs for rebar workers and other ‘at risk’ construction trades (e.g. masons and carpenters) (Albers and Estill, 2007). The results obtained from biomechanical and psychological criteria (e.g. muscle activity, trunk kinematics and muscle fatigue) and subjective pain intensities (using Borg’s scale) also suggest that squat postures should be adopted during repetitive rebar lifting tasks. Furthermore, non-stop lifting and lowering of rebar can rapidly cause lumbar muscle fatigue and pain. Consequently, rebar workers are recommended to lift rebar using assistive devices where possible (e.g. exoskeletons or back belts) (Kraus et al., 1996) to mitigate risks posed and to take frequent rest (20mins break) before the onset of subjective fatigue. The recommended lift weight is 7.1 kg (5% MLS) at a rate of 10 cycles/min when working in a confined space with feet stationary.

5.7 CHAPTER SUMMARY

This chapter discussed an identified need to study laboratory-based simulated task conducted to investigate the risk of developing LBDs among rebar workers primarily caused by repetitive rebar lifting. During simulated repetitive rebar lifting tasks, trunk muscle activity and spinal kinematics were recorded using surface electromyography and motion sensors respectively. Test results revealed that lifting different weights causes disproportional loading upon muscles, which shortens the time to reach working endurance and increases the risk of developing LBDs among rebar workers. Future research is required to: broaden the research scope to include other trades; investigate the effects of using assistive lifting devices to reduce manual handling risks posed, and develop automated human-condition based solutions to monitor trunk muscle activity and spinal kinematics.

CHAPTER 6

WEARABLE INSOLE PRESSURE SYSTEM FOR AUTOMATED DETECTION AND CLASSIFICATION OF AWKWARD WORKING POSTURES IN CONSTRUCTION WORKERS[5]

6.1 INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) are the leading cause of nonfatal occupational injuries in the construction industry (Eaves et al., 2016). According to the Bureau of Labor Statistics (BLS) in the United States, WMSDs accounted for 32% of all injuries that resulted in work absenteeism in all industries (BLS, 2015). In the United Kingdom, approximately 9.5 million of work days were lost due to WMSDs—on the average of 17 days were lost in each WMSD case, which represented 40% of all days lost in the construction industry (Health and Safety Executive, 2015). Additionally, WMSDs can cause substantial chronic conditions, permanent disabilities, and direct and indirect costs in construction (Inyang et al., 2012; Bhattacharya, 2014). Symptoms of WMSDs are numerous ranging low back pain, neck/shoulder pain, tendonitis, carpal tunnel syndrome, etc. (Umer et al., 2017a). Given the above, there is a crucial need to introduce effective and practical solutions for identifying potential risk factors which may lead to WMSDs among construction workers.

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Construction workers are frequently exposed to numerous biomechanical (physical) risk factors that may lead to WMSDs (Wang et al., 2015a). Examples of these risk factors include awkward working postures, force exertions, repetitive motions, extreme temperature, and high vibration (Wang et al., 2015a; Umer et al., 2016; Umer et al., 2017b). Among the numerous biomechanical risk factors, awkward working postures are widely known to be the main cause of WMSDs (McGaha et al., 2014; Grzywiński et al., 2016). Awkward working postures or non-neutral static trunk postures such as overhead working, squatting, stooping, semi-squatting, and one-legged kneeling, are frequently observed in workers' manual handling activities (Umer et al., 2016; Antwi-Afari et al., 2017a, b; Chen et al., 2017; Antwi-Afari et al., 2018a). Amongst various construction trades, masonry and concrete workers are at a higher risk of developing WMSDs, with more than 110 cases per 10,000 full-time workers (The Center for Construction Research and Training (CPWR), 2013). Moreover, while carpet and tile installers spend more than 80% of their working time in kneeling, crouching or stooping, bricklayers spend 93% of their time bending and twisting the body (CPWR, 2013). Furthermore, roofers spend more than 75% of their working time in stooping, crouching, kneeling, and crawling postures (CPWR, 2013; BLS, 2015). Overall, awkward working postures overload the workers' musculoskeletal system and increase their vulnerability to developing WMSDs, especially lower back disorders (Inyang et al., 2012).

Since a construction worker's performance is associated with the amount of manual lifting loads, type of working postures, duration of each posture and the recovery time between postures (Antwi-Afari et al., 2018a), safety managers should minimize workers' awkward working postures through training, intervention, and site layout redesign (Chen et al., 2017). However, the current ergonomic risk assessment methods of WMSDs (e.g., self-reports, observational methods) are either intrusive or rely on subjective differences in individuals' intuition, experiences, and knowledge for identifying risk factors for WMSDs (Balogh et al., 2004; David, 2005). As a result, it has been difficult to improve ergonomic risk assessments and to develop effective preventive strategies for reducing WMSDs among construction workers.

Therefore, this research proposes a novel and non-invasive method to automatically and continuously detect and classify awkward working postures based on the foot plantar pressure distribution data captured by a wearable insole pressure system. It was hypothesized that each awkward working posture creates unique patterns of foot plantar pressure distribution data, which enabled the detection and classification of different awkward working postures. A simulated laboratory experiment was conducted to examine different awkward working postures using four types of supervised machine learning classifiers (i.e., artificial neural network (ANN), decision tree (DT), *K*-nearest neighbor (KNN), and support vector machine

(SVM)). Combined features (e.g., time-domain, frequency-domain, spatial-temporal features) were extracted from raw foot plantar pressure distribution data and used as input variables for all classifiers. These findings could help develop an automated wearable insole system that uses foot plantar distribution data as an informative source to minimize the exposure of workers to awkward working postures, which may lead to WMSDs.

6.2 RESEARCH BACKGROUND

6.2.1 Ergonomic risk assessment methods to identify potential risk factors for WMSDs in construction

In the extant literature, ergonomic risk assessment methods of WMSDs in construction are categorized into four thematic groupings, namely: (1) self-reported methods; (2) observational-based methods; (3) vision-based methods; and (4) direct measurements methods.

In the self-reported methods, both physical and psychosocial factors are collected through interviews and questionnaires such as Nordic Musculoskeletal Questionnaire (Kuorinka et al., 1987), and Borg Scale (Borg, 1998). These approaches have the advantages of low initial cost, ease of use and applicable to a wide range of workplace situations (David, 2005). However, it has been revealed that workers' self-reports on exposure level are often imprecise, unreliable, and biased (Balogh et al., 2004).

Observational-based methods (e.g., *Assessment of Repetitive Task (ART)* (Health and Safety Executive, 1999); *Manual Handling Assessment (MAC)* (The Health and Safety Executive, 2002); *Ovako Working Analysis System (OWAS)* (Kivi and Mattila, 1991); *Posture, Activity, Tools, and Handling (PATH)* (Buchholz et al., 1996); *Rapid Upper Limb Assessment (RULA)* (McAtamney and Corlett, 1993; McGorry and Lin, 2007); *Rapid Entire Body Assessment (REBA)* (Hignett and McAtameny, 2000)) have been traditionally used to assess risk factors of WMSDs. These methods rely on direct observation and rating onsite or video recording and rating offsite (Valero et al., 2016). Despite being inexpensive and practical for a wide range of work situations, these methods are time-consuming, disruptive in nature, and are subjected to intra- and inter-observer variability (David, 2005).

Vision-based methods have been used to identify risk factors for WMSDs on construction sites (Ray and Teizer, 2012; Seo et al., 2014; Yan et al., 2017). For instance, marker-based optical motion tracking systems have been widely used due to their precision (Hwang et al., 2009). Similarly, markerless optical motion tracking systems have been investigated using video cameras or depth cameras due to their non-invasiveness (Ray and Teizer, 2012). While these methods have been proven to be useful in studying awkward working postures and in classifying different movements (Valero et al., 2017), they are limited by the fact that a direct line of sight is required to register the movements (Han and Lee, 2013).

Direct measurement methods such as inertial measurement units (IMUs) and surface electromyography (sEMG) sensors have been used to assess WMSDs risk factors. In simulated laboratory settings, Antwi-Afari et al. (2018a) and Umer et al. (2017b) correlated the self-reported discomfort with spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers using sEMG and IMUs. However, these methods are usually used for monitoring construction workers' body movements of a few muscles, such that, they are difficult to acquire the ground reaction force data of the whole body (Chen et al., 2017). In addition, these methods require sensors to be attached to the workers' skin (Umer et al., 2016; Antwi-Afari et al., 2017b; Antwi-Afari et al., 2018a), which make them feel uncomfortable and inconvenient while performing a given task (Chen et al., 2017). While direct measurement methods might help identify risk factors for developing WMSDs, scant research has been conducted to detect and classify awkward working postures by collecting foot plantar pressure distribution data captured by a wearable insole pressure system.

6.2.2 Automated wearable sensing systems for WMSDs' risk prevention—using foot plantar pressure distribution measured by a wearable insole pressure system

Generally, wearable sensing systems for WMSDs' risk prevention present great potential for precise and unobtrusive risk assessment of construction tasks. The most commonly used wearable sensing systems are wearable IMU-based systems. Several researchers have successfully employed wearable IMU-based systems for WMSDs' risk prevention. Schall et al.

(2015) used wearable IMU-based systems to measure thoracolumbar trunk motion and evaluated the potential risk of WMSDs (e.g., low back pain) when workers performed manual material-handling activities. Valero et al. (2016) characterized unsafe WMSDs postures of construction workers based on the motion data from wearable IMU-based systems integrated into a body area network. Chen et al. (2017) used a wearable IMU-based system to recognize awkward postures from sequencing actions for ergonomic interventions in construction. Although wearable IMU-based systems have satisfactory accuracy and repeatability (Yan et al., 2017), these methods have several disadvantages. First, wearable IMU-based systems can only monitor body motions based on velocity, acceleration, orientation, and gravitational forces output data. Second, these output data are mostly collected using multiple wearable IMU-based systems from a few muscles at different body parts. Third, they use indirect forms of attachments such as straps, belts, wristbands, or other accessories to prevent detachment of sensors from the body when performing a given task. Since the location of wearable sensing systems has a direct impact on the measurement of a targeted output (McAdams et al., 2010), wearable IMU-based systems may lead to workers' discomforts and inconveniences, which may interfere with construction activity and reduce productivity (Guo et al., 2017).

Given the limitations above of wearable IMU-based systems, it is essential to develop a new non-invasive system to continuously monitor and detect awkward working postures. Of various wearable sensing technologies, a wearable insole pressure system may be a feasible method. Previous studies have used wearable insole pressure systems to: (1) assess fall risks and evaluate balance and gait stability in elderly (Best and Begg, 2006; Mickle et al., 2011); (2) analyze athletes' body segmental movement in various sports events in order to improve coaching exercises (Salpavaara et al., 2009); and (3) monitor stroke patients healing progress in rehabilitation (Edgar et al., 2010). Compared to wearable IMU-based systems, a wearable insole pressure system can measure ground reaction force data when workers use their feet as the main support of the whole body. Most importantly, it can be easily inserted or detached from workers' safety boots, and can also be wirelessly connected to computers, smartphones, smart watches, or other wearable devices. By using a wearable insole pressure system, multiple footsteps of construction workers can be continuously monitored, and repeatable foot plantar pressure distribution data can be achieved. Furthermore, the outcomes of using foot pressure sensitive features extracted from plantar pressure distribution data could be used to: (1) design workers' footwear; and (2) generate biofeedback to assist workers who are at higher risk of developing WMSDs. In addition, a wearable insole pressure system not only minimizes restrain in body movement and but also discomfort. Ultimately, it is a non-invasive method to allow for real-time fall monitoring and WMSDs' risk prevention among construction workers on sites.

6.3 RESEARCH OBJECTIVE AND CONTRIBUTIONS

The objective of this study was to propose a novel and efficient method to automatically and continuously detect and classify awkward working postures based on foot plantar pressure distribution data measured by a wearable insole pressure system. The main contributions of this research were to: (1) propose a wearable insole pressure system for detecting, classifying and continuous monitoring of awkward working postures based on foot plantar pressure distribution data; and (2) automatically evaluate awkward working postures to identify potential risk factors for WMSDs in construction. Specifically, our novel approach examined combined features (e.g., time-domain, frequency-domain, spatial-temporal features) of foot plantar pressure distribution patterns for WMSDs' risk prevention. Overall, the findings would help develop a continuous safety monitoring system to assist researchers and safety managers to understand the causal relationship between awkward working postures and WMSDs among construction workers.

6.4 RESEARCH METHODS

Participants were mainly novice volunteers. Foot plantar pressure distribution data was collected using a wearable insole pressure system. Collected raw foot plantar pressure distribution data was segmented into smaller window size containing a certain number of data points. Next, several features were calculated within each window. Each segment was then labeled based on the corresponding types of awkward working postures performed at the time identified by the timestamp of the collected data. In order to train a predictive model, four supervised machine learning classifiers were used to detect and classify awkward working postures performed in the simulated laboratory experiments. Figure 6.1 depicts the experimental flowchart for recruiting participants to detect and classify awkward working postures. All data processing (including the statistical computation of features, training, testing, and validation of the classifiers) were performed using Toolbox in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA).

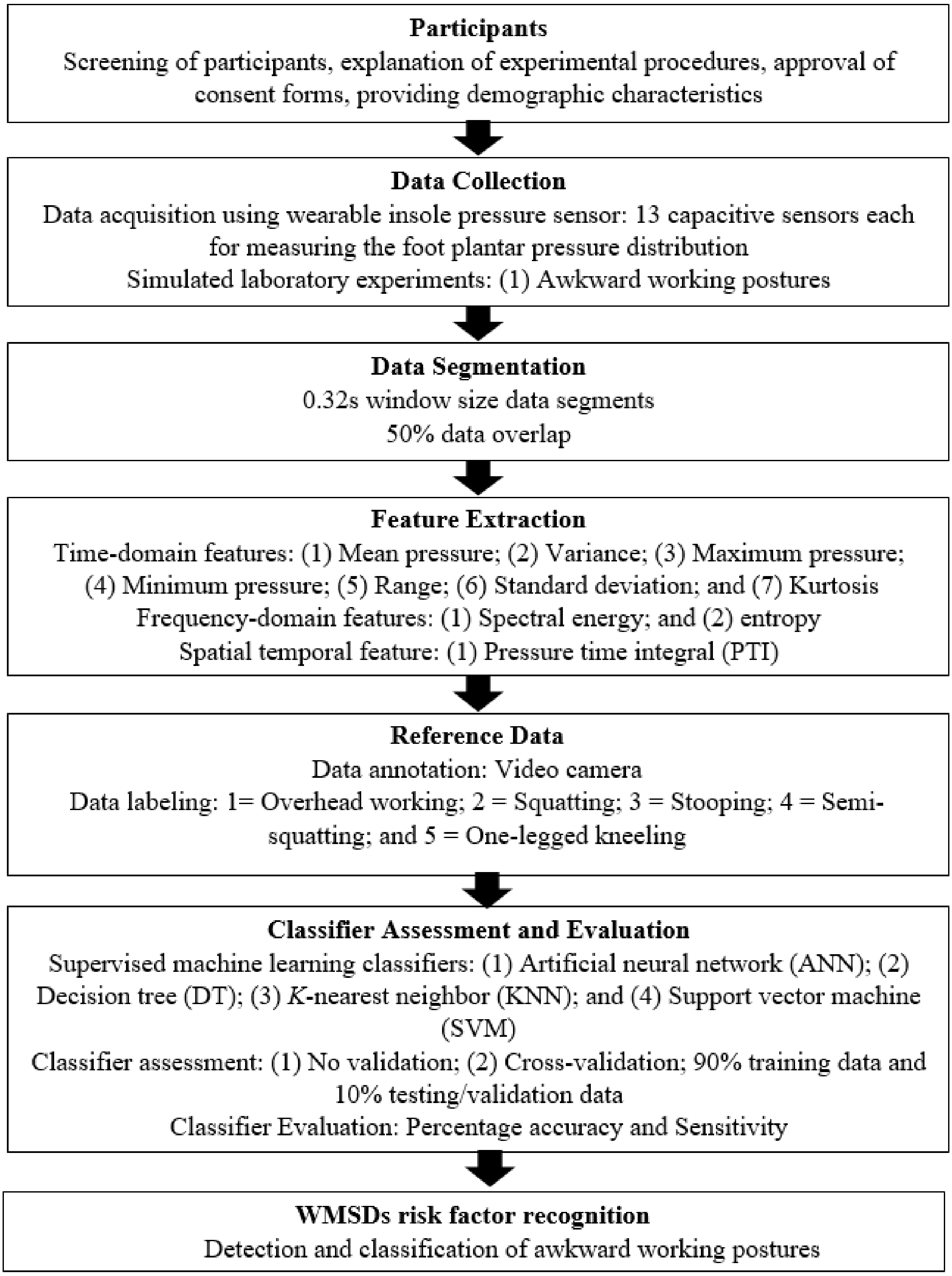

Figure 6.1 Experimental flowchart for detection and classification of awkward working postures using a wearable insole pressure system

6.4.1 Participants

Ten asymptomatic male participants were recruited from the student population of the Hong Kong Polytechnic University to participate in the current experiment. All participants had no history of mechanical pain/injury of upper extremities, back, or lower extremities. The experimental procedures were explained to each participant. Participants provided their demographic characteristics (Table 6.1) and informed consent in accordance with the procedure approved by the Human Subject Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20170605001).

Table 6.1 Participants' demographic characteristics

Demographic characteristics	Mean	Standard deviation	Minimum	Maximum
Age (years)	27.00	3.40	22	32
Height (m)	1.75	0.10	1.58	1.88
Weight (kg)	71.10	11.08	57	87

6.4.2 Data collection

6.4.2.1 Data acquisition using a wearable insole pressure system

The current study proposed an OpenGo system (Moticon GmbH, Munich, Germany), which is a wearable insole pressure system for measuring foot plantar pressure distribution data. The overview of the OpenGo system is depicted in Figure 6.2. It consists of two sensor insoles (containing 13 capacitive sensors each, Figure 6.2) that measure the foot plantar pressure distribution. Each insole sensor electronically incorporates 3-dimensional micro electro mechanical systems (MEMS) accelerometer (Bosh Sensortech BMA 150), which is located at the center (Figure 6.2). Each insole sensor also incorporates a processing unit, a rechargeable battery, an internal memory storage (16 MB flash memory each) and a wireless module that is used for data transmission and for controlling the insole sensor. The OpenGo insole sensors were calibrated by the manufacturer using homogeneously distributed loads, covering specified loads ranging from 0 to 40 N/cm^2. Manufacturer's guidelines indicate that no further calibration is needed within the specified lifetime of 100-km range; hence, no update calibration was performed in the current study.

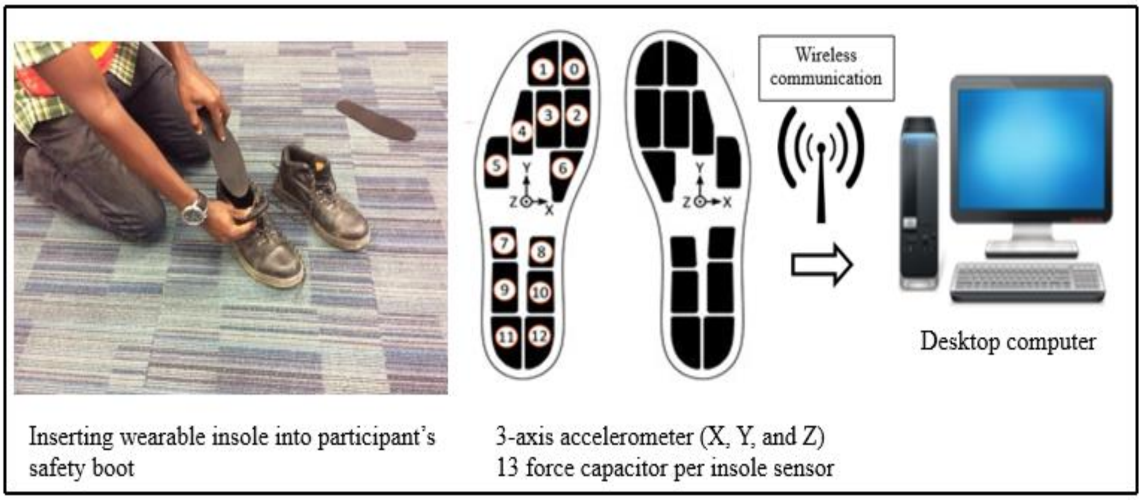

Figure 6.2 Overview of the wearable insole pressure system

6.4.2.2 Experimental design and procedure

The current study adopted a randomized crossover study design in a single visit. Simulated laboratory experiments (Figure 6.3) were conducted to collect foot plantar pressure distribution data. In order to identify potential risk factors for developing WMSDs in the construction industry, different types of awkward working postures were designed and conducted. Awkward working postures were defined as static postures that deviated significantly from the neutral position and might cause WMSDs after sustained for a long time (Karwowski, 2001). Participants performed five different types of awkward working postures: overhead working, squatting, stooping, semi-squatting, and one-legged kneeling. The overhead working posture required the participant to stand upright to work with the hands touching a bar above the head (Figure 6.3a). Squatting required the participant to maintain full squat (Figure 6.3b). Stooping involved full trunk flexion with bilateral knee extension in standing (Figure 6.3c). Semi-squatting involved bilateral knee bending (Figure 6.3d). One-legged kneeling involved bending of either knee to work in a kneeling position (Figure 6.3e). These awkward working postures exceeded the internationally recommended trunk inclination for the angles of various body parts for static working postures as defined by the International Organization for Standardization (ISO 11226:2000) (ISO, 2006).

The simulated tasks were performed in a random sequence based on the random number generated by a random number generator. Participants were allowed to practice twice with each awkward working posture prior to the actual data collection. After the familiarization, the participants performed different types of awkward working postures. Each participant performed ten trials of each static awkward working posture for 30 seconds. In order to prevent fatigue, the participants were given a 10-minute break between two successive trials.

(a) (b) (c) (d) (e)

Figure 6.3 Laboratory experimental setup of awkward working postures: (a) Overhead working; (b) Squatting; (c) Stooping; (d) Semi-squatting; and (e) One-legged kneeling

6.4.3 Data segmentation

A sliding window technique, which divided raw foot plantar pressure distribution data into smaller time segments, was adopted during data segmentation (Preece et al., 2009). This technique does not require pre-processing of the plantar pressure signals and is suitable for real-time applications (Preece et al., 2009). The sampling frequency was set at a rate of 50 Hz (i.e., 50 data samples were obtained) and then digitized by a 16-bit analog to digital (A/D) converter. The collected data was transferred to the based computer using a wireless universal serial bus (USB) stick. This sampling frequency has been used in previous research to detect and classify of slip, trip, and loss of balance events (Antwi-Afari et al., 2018c). A single experimental trial of a given awkward working posture (e.g., overhead working) lasted for approximately 30 seconds, which corresponds to 1500 (= 50×30) data samples. Overall, a total of 750,000 (= 1500 ×10 participants ×10 trials × 5 postures) data samples were analyzed. A window size data segment of 0.32s was used. This window size data segment was chosen for two specific reasons. First, the conversion of the time-domain to frequency-domain using fast Fourier transforms (FFT) in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA) requires the window size to be a power of 2 (Akhavian and Behzadan, 2016). Second, our recent studies found that a window size of 0.32s was considered to be optimum (Antwi-Afari et al., 2018b), and within the most precise window sizes (0.25s to 0.5s) in activity recognition studies (Banos et al., 2014). As such, the window size of 0.32s corresponds to 16 (2^4) data samples. A 50% overlap of the adjacent windows was considered in this research (Ravi et al., 2005). Previous research in this area has indicated that data segmentation by overlapping adjacent windows reduces the error caused by transition state noise (Su et al., 2014).

6.4.4 Feature extraction

In order to provide input variables for the classifiers, feature extraction must be performed (Ravi et al., 2005). Figure 6.4 (a) to (e) illustrates the representative left and right foot plantar pressure distribution maps of various awkward working postures. As shown in Figure 6.4 (a) to (e), each awkward working posture has a unique plantar pressure map. Compared with "overhead working" posture (Figure 6.4a), the "squatting" (Figure 6.4b) and "semi-squatting" postures (Figure 6.4d) demonstrated greater pressure magnitudes on the forefoot. The foot plantar pressure distribution between the left and right foot looked similar in "overhead working" (Figure 6.4a) and "stooping" postures (Figure 6.4c) but looked very different from "one-legged kneeling" posture (Figure 6.4e). Different color patterns of each foot in the figure indicate the magnitude of different pressure associated with each awkward working posture. As such, the distinct plantar pressure patterns indicate the possibility of detecting and classifying awkward working postures among construction workers. Specifically, these findings support the use of wearable insole pressure sensors for automated detection and classification of awkward working postures, which may be used as a novel ergonomic risk assessment tool for preventing WMSDs in construction workers.

Several time-domain and frequency-domain features that have been commonly used in human activity recognition and fall risk detection studies were selected for this study (Lim et al., 2016; Antwi-Afari et al., 2018c). In particular, seven time-domain features such as mean pressure, variance, maximum pressure, minimum pressure, range, standard deviation, and kurtosis were used (Lim et al., 2016; Antwi-Afari et al., 2018b). Besides, the plantar pressure distribution data in time-domain was converted to frequency-domain by using the fast Fourier transform (FFT) function (Bao and Intille, 2004; Akhavian and Behzadan, 2016). Spectral energy and entropy were the two frequency-domain features extracted (Bao and Intille, 2004). While spectral energy describes the distribution of the signal's energy by the frequency; the spectral entropy measures the irregularity of the signal by calculating the normalized information entropy of the discrete FFT component magnitudes (Bao and Intille, 2004). Additionally, the current study used a feature extraction method, namely pressure time integral (PTI) (Eq. 1), based on the spatial-temporal plantar pressure intensity (Antwi-Afari et al., 2018c). PTI describes the cumulative effect of pressure over time, and thus provides a value for the total load exposure of a particular foot area (Sausen et al., 1999). Since the cumulative exposure could help in identifying different types of awkward working postures, this feature may be sensitive to recognize risk factors for WMSDs. Eq. 1 represents the spatial-temporal feature based on the PTI.

$$PTI_{(i)} = \sum_{t=0}^{N} P_i(t) \times t \qquad (1)$$

Where N = number of data samples, i = index of sample data (i.e., 0 to 25 sensor streams), P = pressure values, t = time within each sliding window.

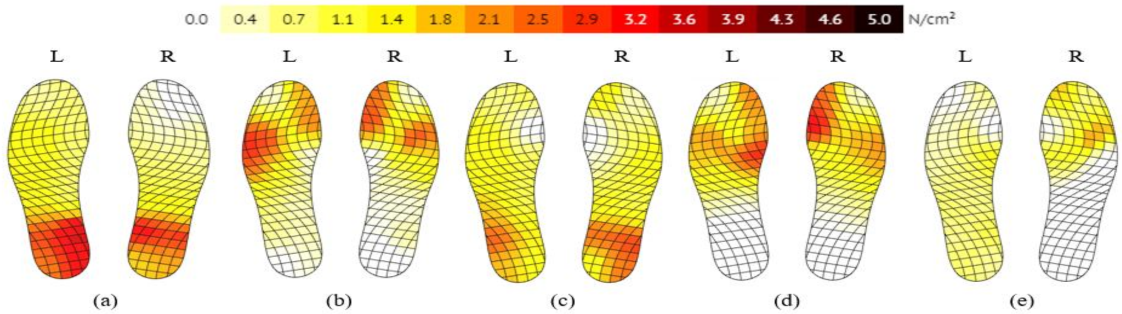

Figure 6.4 Foot plantar pressure distribution of different types of awkward postures: (a) Overhead working; (b) Squatting; (c) Stooping; (d) Semi-squatting; and (e) One-legged kneeling. L and R are left and right foot, respectively

6.4.5 Reference data

Initially, raw foot plantar pressure distribution data were stored in the flash memory of the sensor insoles. After data collection, the collected data were wirelessly downloaded onto a desktop computer for data processing. Time-stamped foot plantar pressure distribution data were logged into a comma-separated values (CSV) spreadsheets. The entire experiment was videotaped for data annotation. As such, the time-stamped foot plantar pressure distribution data were synchronized with the timer of the video camera for data annotation process. This procedure provided the ground truth to evaluate the performance of the supervised machine learning classifiers that were developed for detecting and classifying awkward working postures. Finally, the corresponding awkward working postures' class labels (output variables) were assigned to the extracted features (input variables).

6.4.6 Classifier assessment and evaluation

6.4.6.1 Classifier assessment: supervised machine learning classifiers

Following class labeling of extracted features, the corresponding data were used as input variables to train a supervised machine learning classifier. Researchers have used different types of supervised machine learning classifier for activity recognition and fall risk detection in previous studies (Ravi et al., 2005; Reddy et al., 2010; Lim et al., 2016; Antwi-Afari et al., 2018c). As such, four types of supervised machine learning classifiers: ANN, DT, KNN, and SVM were selected in this study.

6.4.6.1.1 Artificial neural network (ANN)

An ANN can be likened to a flexible mathematical function configured to represent complex relationships between its inputs and outputs variables (Preece et al., 2009). Generally, the structure of the ANN consists of an input layer, an output layer, and a hidden layer. As such, ANN is initially presented with a set of training data, and some form of the optimization process is employed to enable known outputs to be predicted for a given set of inputs (Preece et al., 2009). To train an ANN, the activation function, error function, learning algorithm, and the learning rate must be selected. A symmetrical sigmoid function was used for the activation function. Mean squared error was used for error evaluation during training. A scaled conjugate gradient backpropagation training algorithm was used, with a learning rate of 0.7 (Fulk et al., 2012). Once trained, the ANN was then used to obtain the outputs for any set of inputs (Preece et al., 2009). The advantages of the ANN-based classifier are their high tolerance for noisy data, and the ability to classify samples on which have not been trained (Lai et al., 2011).

6.4.6.1.2 Decision tree (DT)

It is one of the oldest and simplest classifiers used in supervised machine learning that shows the relationship between different decisions (Bishop, 2006). This classifier works by examining the discriminatory ability of the extracted features, one at a time, to create a set of rules which ultimately leads to a complete classification system (Preece et al., 2009). In this study, the classification and regression tree (CART) decision tree method were used (Akhavian and Behzadan, 2016).

6.4.6.1.3 K-nearest neighbor (KNN)

The KNN classifier is simple, straightforward, and flexible to implement (Wang et al., 2017). To classify a new observation, the KNN algorithm uses the principle of similarity function (i.e., distance) between the training set and new observation (Attal et al., 2015). The new observation is assigned to the respective class through a majority vote of its *K*-nearest neighbors (Attal et al., 2015). The distance of the neighbors of observation is calculated using a distance measurement such as Euclidean distance (Akhavian and Behzadan, 2016). A new example is assigned to a class that is commonest amongst its *K*-nearest examples by considering the Euclidean distance that is used as the metric in this research (Akhavian and Behzadan, 2016).

6.4.6.1.4 Support vector machine (SVM)

Compared to DT and KNN, SVM is considered to be an intuitive, and more powerful classifier, which has successful applications in practice (Akhavian and Behzadan, 2016). The SVM classifier not only minimizes an empirical risk (as a cost function) but also maximizes the margin between the hyperplane and the data (Attal et al., 2015). Generally, SVMs are linear classifiers in their standard formulation. However, non-linear classification can be achieved by extending SVM by using kernels methods (Scholkopf and Smola, 2001). The key idea of kernels methods is to project the data from the original data space to a high dimensional space called feature space by using a given non-linear kernel function (Attal et al., 2015). The kernel function used for non-linear classification in this research is the Gaussian radial basis function (RBF) which has been successfully applied in existing studies (Chen et al., 2008; Akhavian and Behzadan, 2016).

6.4.6.2 Classifier evaluation and performance

In this study, the performance of the classifiers was assessed in two ways. First, the training accuracy of each classifier was calculated without validation. This means that all the data collected were used for both training and testing, which provided an overall insight into the performance of a host of detection and classification of different types of awkward working postures based on foot plantar pressure distribution data. Second, a more robust approach in assessing the classifiers was adopted. In particular, *p*-fold stratified cross-validation was used, and the results of the *p* replications of the training and testing were averaged out to report the overall accuracy. In 10-fold cross-validation, we randomly split the dataset into $p = 10$ mutually exclusive partitions of equal size and employed 10-fold cross-validation. As a result, we use 9 (*p-1*) partitions for training and reserve the remaining partition for testing (validation). When this was repeated for each partition, training and validation partitions crossed over in 10 successive rounds, and each record in the dataset got a chance of validation (Ö zdemir and Barshan, 2014).

The performance indicators used to evaluate the classifiers were the accuracy and sensitivity (Attal et al., 2015). While the accuracy was measured as the ratio of the sum of true positive and true negative over the total instances, the sensitivity was measured as the ratio of true positive instances over the entire set of the positive instance. In order to visualize the performance of the classifier of different types of awkward working postures, the result of the best classifier was presented in a confusion matrix (see Figure 6.5).

6.5 RESULTS AND DISCUSSION

This is the first study to use foot plantar pressure distribution data measured by a wearable insole pressure system to detect and classify awkward working postures, which may lead to WMSDs among construction workers. The raw plantar pressure data collected from all participants were combined to detect and classify different types of awkward working postures.

The performance and evaluation of the classifiers were assessed using either training (i.e., no validation) or 10-fold cross-validation technique. This evaluation allows for further investigation of whether appending new data collected in future instances to existing data would result in acceptable detection and classification of awkward working postures for the prevention of WMSDs.

Table 6.2 shows the results of training and 10-fold cross-validation classification accuracy of all combined foot plantar pressure distribution data, which were collected during awkward working postures. According to Table 6.2, over 99% training accuracy was achieved for classifying awkward working postures based on the SVM classifier. However, except for the SVM classifier (i.e., best classifier), all other classifiers such as ANN, DT, and KNN resulted in less than 99% training accuracy. These results substantiate the hypothesis that each awkward working posture creates a unique pattern of foot plantar pressure distribution data captured by a wearable insole pressure system. However, training accuracy may not be the best measure to assess the feasibility of using foot plantar pressure distribution data for detecting and classifying awkward working postures. Nevertheless, the stratified 10-fold cross-validation results confirmed that awkward working postures could be detected and classified with over 97% accuracy using any of the four classifiers. Overall, it was found that the SVM classifier provided the best accuracy (i.e., 99.70%) followed by the KNN (98.60%), DT (98.10%), and

ANN (97.60) (Table 6.2). The high level of accuracy achieved by the SVM classifier substantiates the hypothesis that each awkward working posture creates unique patterns of foot plantar pressure distribution data. As such, the findings of this study indicate that the SVM classifier could be reliably used to detect and classify the exposure of workers to awkward working postures, which is one of the main causes of WMSDs among construction workers. Our experimental study was conducted to collect foot plantar pressure distribution data of different types of static awkward working postures among construction workers. This may explain why the SVM classifier performed well when compared with other classifiers. Notably, the SVM classifier can efficiently classify different types of events by using kernels to implicitly map inputs into high-dimensional feature spaces (Scholkopf and Smola, 2001). Given that SVM can be easily extended to multiclass classification through optimization, it is highly suitable for detecting and classifying awkward working postures that may increase the risk of developing WMSDs.

A thorough investigation of the classification results in each awkward working posture can help understand the accuracy in classifying each awkward working posture. In order to achieve this, the confusion matrix of stratified 10-fold cross-validation from the best classifier (i.e., SVM) is presented in Figure 6.5. As presented in Figure 6.5, the rows show the percentage of true (i.e., actual) instances, and the columns reveal the percentage of predicted instances of awkward working postures. For example, while 99.42% of the actual instances was positively classified as squatting postures, 0.57% and 0.01% were predicted as overhead working and stooping postures, respectively (Figure 6.5). Figure 6.5 reveals that the SVM classifier demonstrates more than 99% accuracy in classifying all awkward working postures. This supports that each awkward working posture creates unique foot plantar pressure patterns, which are significantly deviated from the foot pressure pattern during the neutral/upright standing position. As indicated in Figure 6.5, the overhead working posture was the most accurately classified posture. In contrast, the two most confused awkward working postures were stooping and overhead working postures as indicated by 0.88% accuracy (Figure 6.5). This might be attributed to the fact that the stooping and overhead working postures showed similar foot plantar pressure distributions due to bilateral knee extension in both awkward postures, which might have led to more misclassified instances. In other words, these two awkward working postures have similar static lower limb positions, and thus foot plantar pressure distribution data, making them difficult to be distinguished.

Table 6.2 Classifier performance accuracy (%) of awkward working postures

	ANN	**DT**	**KNN**	**SVM**
Training	98.20	98.40	98.70	99.90
10-fold cross-validation	97.60	98.10	98.60	99.70

True class \ Predicted class	Overhead working	Squatting	Stooping	Semi-squatting	One-legged kneeling
Overhead working	100.00%	0.00%	0.00%	0.00%	0.00%
Squatting	0.57%	99.42%	0.01%	0.00%	0.00%
Stooping	0.88%	0.00%	99.08	0.04%	0.00%
Semi-squatting	0.64%	0.00%	0.02%	99.34%	0.00%
One-legged kneeling	0.36%	0.00%	0.00%	0.00%	99.64%

Figure 6.5 Confusion matrix of 10-fold cross validation for awkward working postures of SVM classifier

6.6 IMPLICATIONS AND POTENTIAL APPLICATIONS

The current study provides research and practical implications for both researchers and practitioners in the construction industry. First, the findings of this research are sought to contribute to the Prevention through Design (PtD) initiatives taken by the National Institute for Occupational Safety and Health (NIOSH). One of the goals of PtD initiatives is to identify and minimize the exposure of ergonomic risk factors such as awkward working postures to an acceptable level at the source and as early as possible in a project life cycle (NIOSH, 2014a). Unlike traditional ergonomic risk assessment methods such as self-reported, observational-based, and vision-based methods that are either unreliable or costly, the proposed approach can allow researchers and safety managers to continuously and objectively evaluate awkward working postures that may lead to WMSDs among construction workers. Second, the proposed approach could enable safety managers to use a wearable insole pressure system as a personal protective equipment to automatically identify and evaluate awkward working postures in construction workers. In particular, this wearable insole pressure system can be inserted into workers' safety boot to generate biofeedback to alert workers whenever they remain in awkward working postures for a prolonged period. These objective data can also help safety managers to adopt different strategies (e.g., work schedule modification) to mitigate the risks of WMSDs. Third, it is noteworthy that although the present results primarily focused on static awkward working postures, the proposed approach can be slightly modified to take other types of risk factors such as gender, age, vibrations, and temperature into account in ergonomic risk assessments. For example, plantar pressure distribution data, which is stored in the flash memory of the wearable insole pressure system, can allow enable safety managers and/or researchers to analyze the effect of workers' ages and vibrations on plantar pressure patterns for effective ergonomic training. Moreover, the collected plantar pressure distribution data can be developed as a real-time proactive fall risk monitoring and warning tool to detect fall portents and other potentially dangerous motions in construction workers (e.g., loss of balance, gait abnormalities, unsteady footsteps). Collectively, the proposed wearable insole pressure system for WMSDs' risks prevention amongst construction workers has practical values and economic benefits due to its ubiquity, small size, low procurement and maintenance cost, and ease of use. Thus, there is a great potential for the implementation of such a wearable insole pressure system for personalized safety and health monitoring, detection of environmental (unsafe) conditions, and providing warning signals to alert workers when they are exposed to danger zones on construction sites.

6.7 CHAPTER SUMMARY

This chapter discussed a novel approach and efficient method to automatically detect and classify construction workers' awkward working postures based on foot plantar pressure distribution measured by wearable insole pressure system. Ten asymptomatic participants conducted simulated laboratory experiments that examined different types of awkward working postures (i.e., working overhead, squatting, stooping, semi-squatting, and one-legged kneeling). The findings substantiated the feasibility of using a wearable insole pressure system to identify risk factors for developing WMSDs and could help safety managers eliminate workers' exposure to awkward working postures on construction sites.

CHAPTER 7

EFFECTS OF DIFFERENT WEIGHTS AND LIFTING POSTURES ON BALANCE CONTROL FOLLOWING REPETITIVE LIFTING TASKS IN CONSTRUCTION WORKERS[6]

7.1 INTRODUCTION

Fall injuries are a leading cause of fatal injuries and the second most common cause of non-fatal injuries in the construction industry (Center to Protect Workers' Right, 2007). According to the United States Bureau of Labor Statistics (BLS), fall injuries in the construction industry accounted for 32% of all work-related deaths (BLS, 2006a) and 34% of non-fatal injuries (BLS, 2006b). Fall-related injuries are also prevalent amongst the general public, especially among the elderly (Zigel et al., 2009; Jiang et al., 2011). Slips, trips and loss of balance are common contributing factors to fall injuries on a level surface (Hsiao and Simeonov, 2001; Lipscomb et al., 2006). While slips and trips can be mitigated by ergonomic design of the working environment, balance control is inherently far more complex and relies upon the coordination of multiple sensory systems (visual, vestibular, and proprioception/somatosensory), the motor system and central nervous system (Punakallio, 2005; Horak, 2006). Impaired balance control (i.e., increased postural sway) has been linked to an increased risk of falls (Prieto et al., 1996;

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[6] Presented in a published paper: **Antwi-Afari, M. F**., Li, H., Edwards, D. J., Pärn, E. A., Seo, J., & Wong, A. Y. L. (2017a). Effects of different weight and lifting postures on postural control during repetitive lifting tasks. *International Journal of Building Pathology and Adaptation*, *35*(3), 247-263. DOI: https://doi.org/10.1108/IJBPA-05-2017-0025.

Corbeil et al., 2003; Paillard, 2012). Therefore, any potential interventions to minimize workplace falls and concomitant injuries sustained must ensure that balance control is not impaired by personal, environmental and task-related risk factors (Hsiao and Simeonov, 2001).

Amongst the many task related hazards confronting construction workers, repetitive lifting tasks present a prominent and significant risk (Marras et al., 1995; Sparto et al., 1997a; Latza et al., 2002). Repetitive lifting tasks involving different weights and/or awkward lifting postures (e.g., stoop or squat) are common for tradesmen handling masonry, concrete reinforcement, scaffolding and paving (Goldsheyder et al., 2002; Hess et al., 2003; Albers and Estill, 2007). For example, rebar workers repetitively lift different weights of rebars (ranging from 7 to 17kg) during their typical working day. In turn, different weights have differential effects upon spinal biomechanics (e.g., causing muscle fatigue) and heavyweights can affect workers' balance control (Hagen and Harms-Ringdahl, 1994; Straker and Duncan, 2000). The stoop lifting posture induces greater back extensor muscle activity, and stronger perceived back muscle fatigue than squat lifting (Hagen and Harms-Ringdahl, 1994). However, postural perturbations during repetitive lifting (using either posture) overload the musculoskeletal tissue and impair balance control thus elevating the risk of loss of balance, fall incidents and consequential injuries (Chow et al., 2005). This is because postural perturbations during repetitive lifting tasks shift the body's center of mass to move beyond the base of support to create an excessive center of pressure (CoP) displacement (Kincl et al., 2002; Chow et al., 2005).

Muscle fatigue is also attributed to impaired balance control and elevated risk of fall injuries (Yaggie and McGregor, 2002; Corbeil et al., 2003). Research into muscle fatigue is well documented and has thus far included assessing: a muscle's peripheral characteristics such as reductions in maximal voluntary contraction and/or relaxation (Davidson et al., 2009; Paillard et al., 2010b); a muscle's output using characteristics of its surface electromyogram (sEMG) (Caron, 2004; Paillard et al., 2007); aspects relating to dehydration and different postural stances (Lion et al., 2010; Bisson et al., 2010a); and its effect upon the sensory systems (Hiemstra et al., 2001; Forestier et al., 2002). Muscle fatigue's impact upon the sensory system could be explained by the accumulation of metabolites leading to: altered muscle spindle function (Hiemstra et al., 2001); altered central processing of proprioception via group III and IV afferents (Forestier et al., 2002); and effects on the efferent sensory pathways (Taylor et al., 2000). However, research illustrates that the mechanisms involved in muscle fatigue are dependent upon the fatigue methods conducted to fatigue the muscles (task dependency) (Enoka and Duchateau, 2008).

Consequently, the mechanisms involved in muscle fatigue induced by performing repetitive lifting tasks under conditions of postural perturbation are essential to any meaningful analysis conducted. Additionally, construction workers (e.g., masons, rebar workers) perform manual repetitive lifting tasks in which they are exposed to different weights and lifting postures for extended periods of time (Jaffar et al., 2011). Although previous studies have investigated the influence of repetitive lifting tasks on spinal movement or paraspinal muscle response, the direct effects of different weights and lifting postures following repetitive lifting task on balance control remained unexplored. Against this contextual setting, this study seeks to evaluate the effects of different weights and lifting postures on balance control following simulated repetitive lifting tasks. With regards to the stated aim, the objectives of the present study were: i) to compare the effects of stoop and squat lifting postures on balance control during quiet standing balance tests, and ii) to assess the effects of the magnitude of weights on balance control following fatiguing repetitive lifting tasks (i.e., by comparing standing balance tests performed on a stable and an unstable supporting surfaces. Two hypothesis are proposed, namely: i) that a stoop lifting posture would induce a significantly greater adverse effect upon an individuals' balance control than a squat lifting posture following a fatiguing repetitive lifting task; and ii) that heavy lifting weight would jeopardize the balance control on both stable and unstable surfaces (although the adverse effect would be greater on an unstable surface).

7.2 RESEARCH METHODS

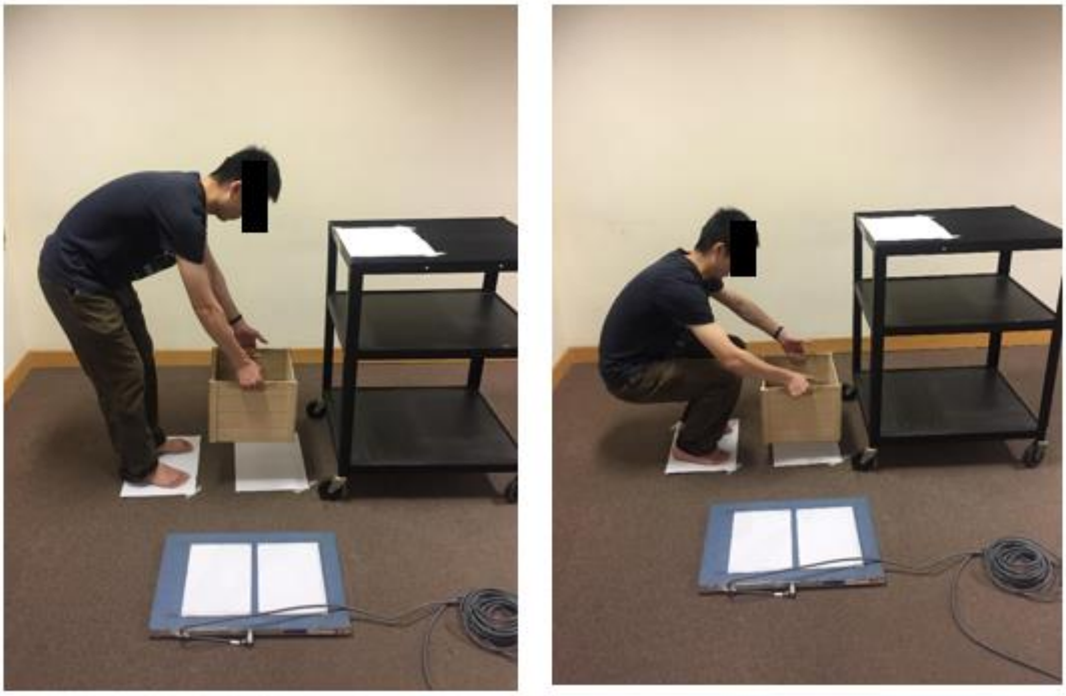
An experimental laboratory controlled test procedure was adopted for this research. Twenty healthy participants (all males) were recruited from the student population of the Hong Kong Polytechnic University to participate in this study. The participants mean age was 27.9 ± 4.0 years, weight was 71.0 ± 8.97 kg, and height was 1.74 ± 0.09 m. There was no significant difference in age, height, and weight of participants in both groups. Test entry criteria for participants were: i) no history of upper limb, back or lower limb pain/injury; and ii) no history of neurological and/or vestibular disorders or other conditions that might affect balance control. Participants provided their informed consent as approved by the Human Subject Ethics Subcommittee of The Hong Kong Polytechnic University (reference number: HSEARS20160719002). Upon consent being given, participants provided their demographic data and were randomized into either a stoop lifting or a squat lifting group (10 participants each). Each participant's maximum lifting strength (MLS) in a stoop or squat lifting posture was then assessed by a back-leg lift dynamometer (Chattecx Corporation, USA). Each group of participants was assigned an allotted lifting posture (i.e., stoop or squat lifting) and requested to gradually pull up the handle of the dynamometer until they reached their perceived MLS. Each participant performed the test twice with a two-min break in between; the highest value of the two trials recorded on the dynamometer represented the participant's MLS (Piezotronics, New York Inc., USA). As a result, the participants' mean MLS for stoop and squat lifting postures was 95.4 ± 17.4 kg and 110.7 ± 13.86 kg, respectively.

The participant then underwent standing balance tests (pre- and post-fatiguing repetitive lifting tasks) that involved three conditions: i) eyes opened on a force plate (EOS); ii) eyes closed on a force plate (ECS); and iii) eyes closed on a foam placed on a force plate (ECF) (where the foam simulated an unstable surface) (refer to Figure 7.1). The three standing balance tests were chosen to reflect the variety of visual and support surface conditions encountered by construction workers during their course of workplace activities (Wade and Davis, 2008). Balance tests sought to evaluate shifts in the body's center of pressure (CoP) under these conditions and required participants to stand upright in a relaxed position with their arms by their sides for 15 seconds (c.f. Doyle et al., 2005). Their feet had to remain in the same position marked on a piece of transparent sheet that covered the force plate (except ECF condition). The participant was instructed to look ahead during the EOS test, while vision was occluded by a non-transparent goggle (ANSI Z 136, USA) during ECS and ECF tests. To minimize external sound stimuli, participants wore hearing protection during all tests conducted (CE EN 352, Australian standard). The force plate was positioned next to the lifting task experimental set up to minimize the time interval between the fatiguing lifting tasks and the CoP measurements. Previous studies have demonstrated that CoP displacements from a force plate provide objective, accurate and reliable balance control measurements (Prieto et al., 1996; Lafond et al., 2004).

The CoP displacement test data was collected using a portable 8 channel multiplexing and amplitude modulation circuit force plate (KISTLER Instrumente. AG, Winterthur, Switzerland). The CoP data were sampled at 50Hz and low passed filtered with a second-order Butterworth filter (10Hz). MATLAB 7.9 software (Matlab, The MathWorks Inc., MA, USA) was used to analyze the CoP movements. The displacements of CoP were quantified from: the total sway area, the root mean square (RMS) of the anterior/posterior (A/P) and medial/lateral (M/L) displacements and mean velocity (MV) sway in the A/P and M/L displacement. These CoP parameters have been used in previous studies to evaluate the balance control of an individual; where large displacement of CoP values indicates poor balance control that may increase the risk of falls (Prieto et al., 1996; Bisson et al., 2010a).

Figure 7.1 A foam (39 cm × 39 cm × 10 cm thickness) on a force plate

In order to eliminate any possible biases and differences between and within the two lifting posture groups, each participant was randomly assigned to either a stoop or squat lifting postures, and then performed three separate sets of fatiguing repetitive lifting tasks at 5%, 10% and 15% of MLS. As such, the mean weights of the stoop lifting postures for 5% MLS, 10% MLS, and 15% MLS were 4.77 ± 0.87 kg, 9.54 ± 1.74 kg, and 14.31 ± 2.61 kg, respectively. Similarly, the mean weights of the squat lifting postures for 5% MLS, 10% MLS, and 15% MLS were 5.54 ± 0.69 kg, 11.07 ± 1.39 kg, and 16.61 ± 2.08 kg, respectively. These three percentages of MLS were chosen because previous pilot study research observed that rebar workers on construction sites usually lifted reinforcement bars within these boundaries. Specifically, the repetitive experimental task (using either stoop or squat lifting posture) involved each participant standing upon a demarcated area, with explicit instructions not to move their feet, and lifting a wooden box (of dimensions 30 x 30 x 25 cm) that contained the target weight (refer to Figure 7.2). Each participant had to lift the box from the floor to the waist level using the assigned lifting posture until subjective fatigue was reached despite strong verbal encouragement (that is, a point in time at which the participant could not continue lifting further). Immediately after each lifting task, the standing balance tests were repeated. To standardize the lifting cycle, a metronome was used to guide the lifting at a rate of 10 cycles per minute. Participants received a 20-minute rest between each lifting task to prevent muscle fatigue.



(a) (b)

Figure 7.2 Two lifting postures: (a) Stoop posture; and (b) Squat posture

7.2.1 Statistical analysis

Independent *t*-tests were conducted to compare between-group differences (stoop vs. squat) and each balance test for all CoP parameters. Once results of the Shapiro-Wilks test confirmed data normality ($p > 0.05$), a separate three-way (3×3×2) repeated measures analyses of variance (ANOVA) for weights (5% MLS vs. 10%MLS vs. 15% MLS), balance tests (EOS vs. ECS vs. ECF) and fatigue (pre- vs. post-fatigue) were conducted for each CoP parameter. Given statistically significant F ratios (refer to Table 7.1), post-hoc pairwise comparisons were conducted with Bonferroni adjustment. Partial eta squared (η_p^2) values were reported to estimate the effect sizes. Statistical Package for the Social Science (SPSS) version 20.0 (IBM, USA) was used for the statistical analysis and statistical significance was set at $p < 0.05$.

7.3 RESULTS

Figure 7.3a-e summarizes the arithmetic mean and standard deviation (SD) for RMS of CoP A/P displacement, RMS of CoP M/L displacement, MV of CoP A/P displacement, MV of CoP M/L displacement and total sway area for each balance test condition immediately after the stoop and squat lifting tasks. All CoP parameters revealed no significant difference between lifting postures in the three balance test conditions ($p > 0.05$) although the absolute value of all CoP parameters following the repetitive squat lifting task was larger than those following a stoop lifting posture under all balance test conditions (refer to Figure 7.3a-e).

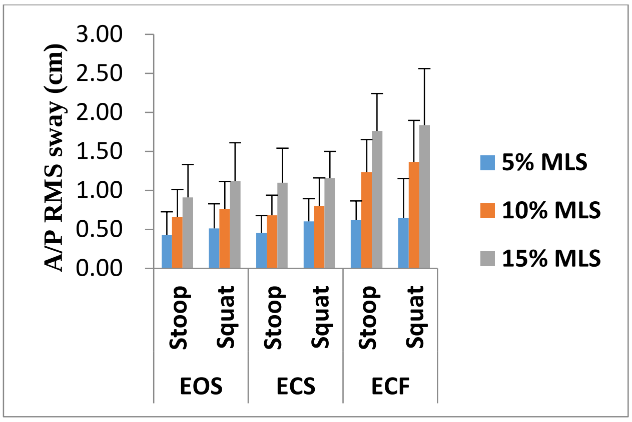


Figure 7.3(a) RMS of anterior/posterior displacement of CoP

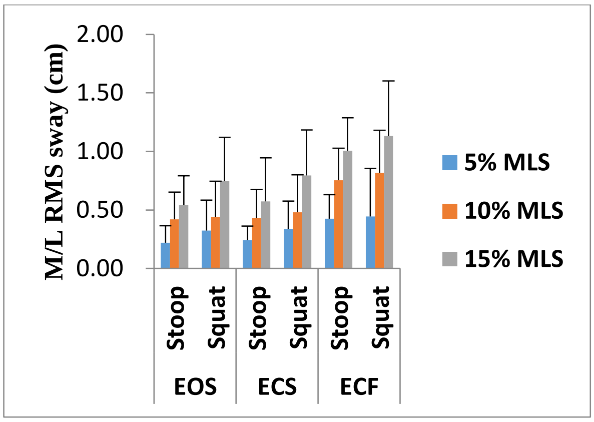


Figure 7.3(b) RMS of medial/lateral displacement of CoP

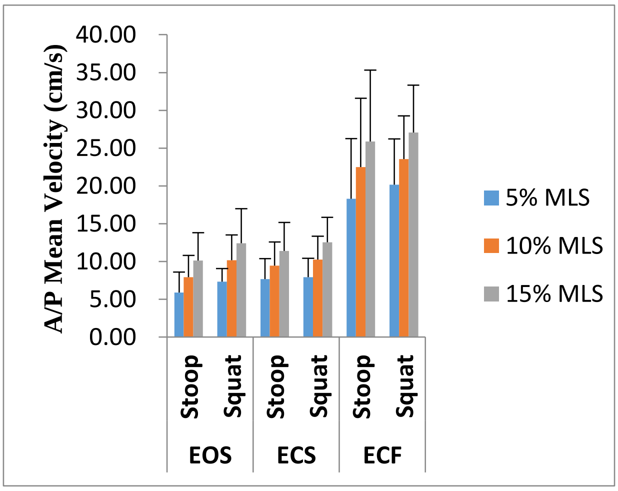


Figure 7.3(c) MV of anterior/posterior displacement of CoP

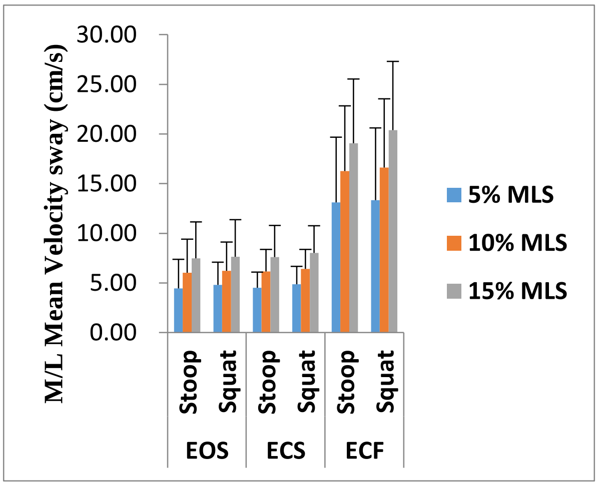


Figure 7.3(d) MV of medial/lateral displacement of CoP

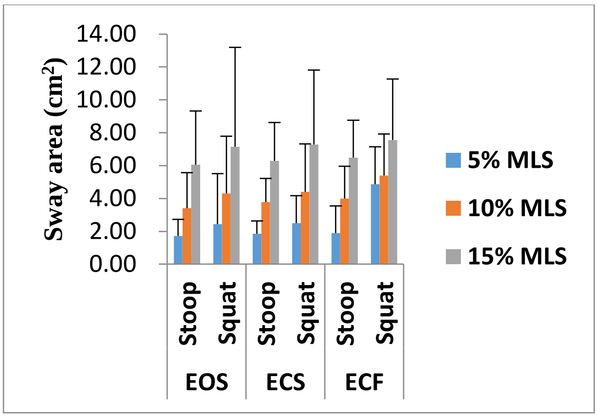


Figure 7.3(e) Total sway area

Figure 7.3a-e The different center of pressure (CoP) parameters during balance test following fatiguing repetitive lifting tasks with different weights and lifting postures.

7.3.1 Balance stability parameters comparison of different weights, balance tests, and fatigue

The ANOVA results for CoP parameters are presented in Table 7.1. Since the main effect of the lifting posture groups (stoop vs. squat) and all relevant interactions were not significant ($p > 0.05$) (see Figure 7.3a-e), the following results only described the effects of different weights, balance test conditions and fatigue on CoP parameters based on pooled data from the two lifting postures.

Table 7.1 Analysis of variance results for center of pressure (CoP) parameters: *F* ratios and *P*-values

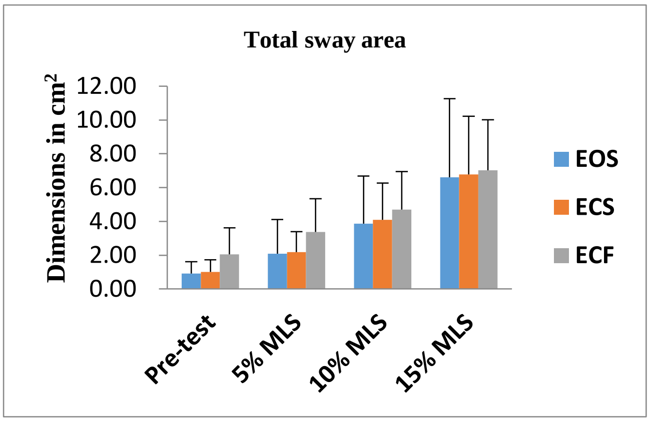
Effects	**Sway area**	**A/P RMS**	**M/L RMS**	**A/P MV**	**M/L MV**
	***F* ratio**	***F* ratio**	***F* ratio**	***F* ratio**	***F* ratio**
Main effect					
Weight	127.27*	137.40*	92.21*	105.69*	149.58*
Fatigue	112.98*	346.17*	114.85*	174.41*	179.91*
Postural task	2.17	7.56*	6.07*	61.11*	51.37*
Interaction					
Weight × balance test	0.66	10.81*	3.09*	6.22*	12.15*
Fatigue × balance test	0.17	16.49*	11.16*	15.39*	31.76*
Weight × fatigue	127.27*	137.40*	92.21*	105.69*	149.58*
Weight × balance test × fatigue	0.66	10.81*	3.09*	6.22*	12.15*

Note: A/P RMS = Root mean square of anterior/posterior CoP displacement; M/L RMS = Root mean square of medial/lateral CoP displacement; A/P MV = Mean velocity of CoP in anterior/posterior directions; M/L MV = Mean velocity of CoP in medial/lateral directions. *Indicates statistically significant effects with $p < 0.05$.

7.3.1.1 Total sway area

Three-way repeated measures ANOVA revealed no significant interaction between weight by balance test by fatigue for total sway area ($F = 0.66$, $p = 0.53$, $\eta_p^2 = 0.03$) (refer to Table 7.1). The total sway area demonstrated a significant interaction between weight and fatigue ($F = 127.27$, $p = 0.00$, $\eta_p^2 = 0.87$) but all other two-way interaction effects were not significant. Significant main effects for weight ($F = 127.27$, $p = 0.00$, $\eta_p^2 = 0.87$) and fatigue ($F = 112.98$, p

= 0.00, η_p^2 = 0.86) were found. The effect of weight significantly increased the total sway area immediately after lifting tasks. The total sway areas after lifting 5%, 10%, and 15% of MLS were 92.16%, 218.17%, and 412.97% larger than the respective pre-fatigue conditions (Figure 7.4).



NB: No significant difference was found in all conditions.

Figure 7.4 Total sway area (Mean and Standard Deviation) of the different postural tasks before (baseline) and after fatiguing repetitive lifting task.

7.3.1.2 Root mean square (RMS) of CoP displacement

At baseline, balance test conditions revealed no significant difference of RMS of CoP A/P or M/L displacement across all balance test conditions (EOS, ECS and ECF). However, significant two-way and three-way interactions (i.e., weight and fatigue, and balance test condition) were observed on RMS of CoP A/P and M/L displacement (refer to Table 7.1 and Figure 7.5a-b).

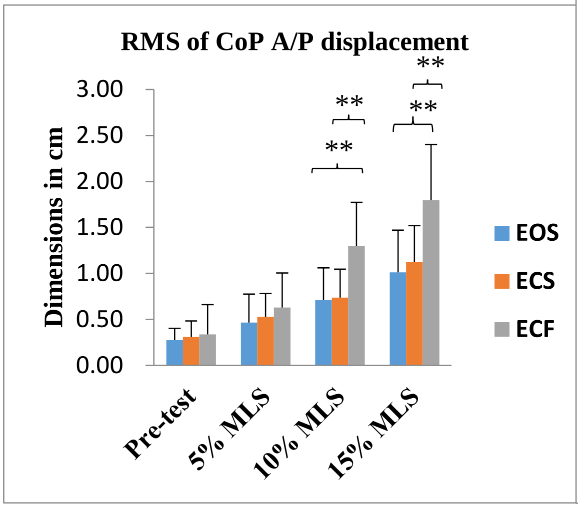


Figure 7.5a - RMS of anterior/posterior (A/P) CoP displacement

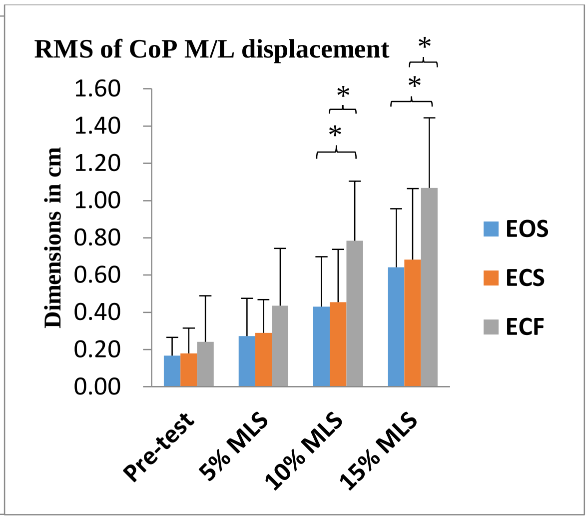


Figure 7.5b - RMS of medial/lateral (M/L) CoP displacement

NB: **p* significant at <0.05, ***p* significant at <0.01.

Repetitive lifting at 5% MLS had no significant effect on RMS of CoP A/P displacement across all balance test conditions (p > 0.05). However, repetitive lifting at 10% MLS or 15% MLS significantly increased RMS of CoP A/P displacement as compared to the baseline. Interestingly, the effect of weight induced significantly larger RMS of CoP A/P displacement in the ECF condition when compared to the EOS and ECS conditions. Similarly, repetitive lifting at 15% MLS caused significantly larger RMS of CoP A/P displacement under ECF condition than EOS and ECS conditions (refer to Figure 7.5a). For 15% MLS lifting, ECF caused an increase in RMS of CoP A/P displacement by 70.37% and 55.96% when compared to EOS and ECS, respectively. When compared to the baseline, repetitive lifting at 5% MLS, 10% MLS and 15% MLS increased RMS of CoP A/P displacement by 75.97%, 197.73%, and 325.65%, respectively. Taken together, 3-way interaction revealed that repetitive lifting at 10%

and 15% MLS caused significantly greater RMS of CoP A/P displacement under ECF condition (at 10%MLS: 82.70% and 76.02%) and (at 15%MLS: 77.74% and 59.88%) as compared to EOS and EOS respectively (Figure 7.5a).

Similarly, significant 3-way interaction revealed that repetitive lifting at 10% MLS and 15% MLS significantly increased RMS of CoP M/L displacement at ECF condition (10% MLS: 82.09% and 72.09%; 15% MLS: 66.25% and 56.52%) compared to EOS and ECS conditions, respectively ($p < 0.05$; Figure 7.5b), while there was no significant difference of 5% MLS lifting weight on RMS of CoP M/L displacement across all balance test conditions. Moreover, the main effect results revealed that RMS of CoP M/L displacement under ECF condition was 70.09% and 60.08% greater than ECS and EOS after fatiguing repetitive lifting ($p < 0.05$) (Figure 7.5b). Furthermore, lifting weight (at 5% MLS, 10%, MLS, and 15% MLS) significant increased RMS of CoP M/L displacement by 69.39%, 183.16% and 307.14% after fatiguing.

7.3.1.3 Mean velocity (MV)

The MV of CoP A/P and M/L displacement analyses revealed significant main effects of weight, balance and fatigue, and significant two-way and three-way interactions (refer to Table 7.1, Figure 7.6a-b). Repetitive lifting at 5% MLS, 10% MLS, and 15% MLS increased MV of CoP A/P displacement under the ECF condition by 207.79% and 153.74%; 180.86% and

144.91%; and 163.26% and 135.23% when compared to EOS and ECS conditions respectively (refer to Figure 7.6a). In addition, increased lifting weight significantly increased MV of CoP A/P displacement in all EOS and ECS pairwise comparisons ($p < 0.05$). Fatigue significantly increased MV of CoP A/P displacement in all balance tests ($p < 0.05$). Repetitive lifting at 5% MLS, 10% MLS and 15% MLS increased MV of CoP A/P displacement by 27.66%, 59.04%, and 88.53% respectively. The 3-way interaction test revealed that heavier fatiguing repetitive lifting task had significantly greater effect on MV of CoP A/P displacement under ECF condition when compared to EOS or ECS conditions ($p < 0.05$). Specifically, repetitive lifting at different weights (at 5% MLS: 190.98% and 146.56%; at 10% MLS: 154.40% and 133.87%; at 15% MLS: 134.73% and 121.31%) had differential increases in MV of CoP A/P displacement under the ECF condition when compared to EOS or ECS conditions.

Similarly, greater MV of CoP M/L displacements (at 5% MLS: 252.62% and 229.88%; at 10% MLS: 228.13% and 207.74%; at 15% MLS: 214.02% and 194.66%) at the ECF condition were noted as compared to both the EOS and ECS conditions (Figure 7.6b). However, no significant difference of MV of CoP M/L displacement was observed for all EOS and ECS pairwise comparisons ($p > 0.05$). Fatigue significantly increased MV of CoP M/L displacement in all balance test conditions ($p < 0.05$). Moreover, lifting at 5%, 10%, and 15% MLS significantly increased MV of CoP M/L displacement by 27.74%, 63.76% and 99.06%, respectively. The 3-

way interaction revealed that although post-fatigue MV of CoP M/L displacement under the ECF condition was consistently higher than either the EOS or ECS conditions, heavier repetitive lifting weights (5% MLS: 186.87% and 182.10%; at 10% MLS: 168.45% and 161.63%; at 15% MLS: 160.82% and 152.57%) caused differential increases in MV of CoP M/L displacement under ECF condition when compared to the EOS and ECS conditions.

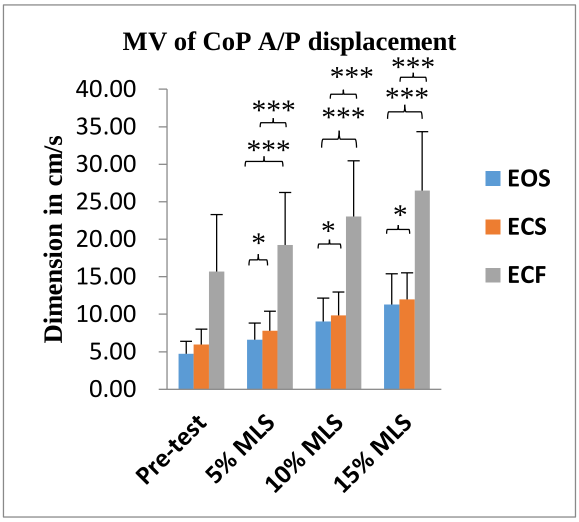


Figure 7.6a - MV of anterior/posterior (A/P) CoP displacement

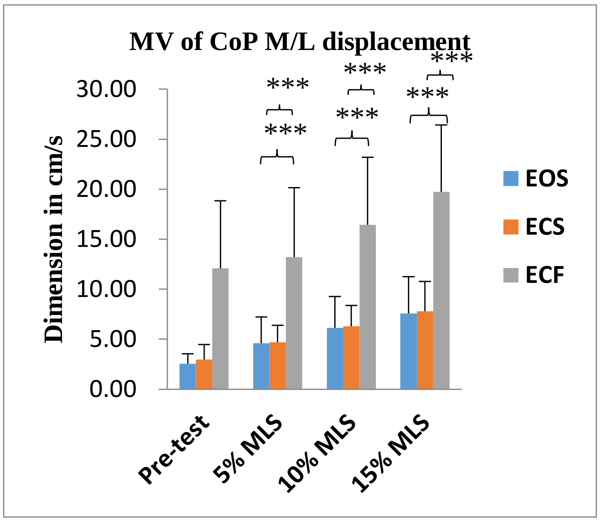


Figure 7.6b - MV of medial/lateral (M/L) CoP displacement

NB: *p significant at <0.05, ***p significant at <0.001.

7.4 DISCUSSION

Analysis results revealed no significant difference between lifting postures after the fatiguing lifting task across all balance test conditions. This finding indicates that fatiguing repetitive stoop and squat lifting postures induce a similar balance control deficit. Consequently, this finding refutes our first hypothesis that the stoop lifting posture would induce greater variations in balance control than squat lifting postures following fatiguing repetitive tasks. In addition, while increased repetitive lifting weight significantly produced a larger increase in CoP parameters (both RMS and MV of CoP A/P and M/L displacement analyses), under ECF condition (when compared to either EOS or ECS condition), increased lifting weight caused no significant difference in CoP parameters (total sway area, RMS of CoP A/P and M/L displacement and MV of CoP M/L displacement) between EOS and ECS conditions. These findings confirm our second hypothesis that the fatiguing repetitive lifting tasks cause poorer balance control on an unstable surface when compared to the stable surface (Yaggie and McGregor, 2002; Corbeil et al., 2003).

7.4.1 Comparison of repetitive lifting postures: stoop and squat

Test results demonstrate that fatiguing repetitive stoop and squat lifting postures induced similar impairments in balance control, which is contrary to findings reported upon in previous studies (c.f. Sparto et al., 1997a; Commissaris and Toussaint, 1997; Chow et al., 2005). Chow et al. (*ibid*) reported a significant difference in CoP parameters during a test that involved lifting four different weights (20, 40, 60, 80N) at a rate of five lifting cycles per minute using two different lifting postures (symmetric stoop and squat lifting) after a sudden release of weight. Although the lifting postures were similar to the present study, the discrepancy in results may be attributed to differences in lifting weights, lifting speed, and the absence of a sudden release of weight. Sparto et al. (1997a) found a significant effect of lifting postures upon balance control by instructing their participants to lift at their maximal lifting rate until they: i) cannot continue; and ii) attained an aerobic limit (heart rate of 180 beats/minute). Several methodological differences exist in the literature regarding the contradictory effects of lifting postures on balance control as compared to previous studies. First, the current study performed the stoop or squat lifting posture from ground floor to the waist level of each participant, which was contrary to Commissaries and Toussaint (1997) study, where participants underwent the same lifting postures at acromion height. Second, there was no vertical distance between the load and the ground in the present study, however, these authors standardized the lowest position at 14% of the participant's body height. Consequently, these results cannot be directly compared to the present study due to differences between research protocols adopted. However, our experimental protocol reflects the vertical height of static repetitive lifting posture since we conducted a pilot site observational study of construction workers (e.g., rebar workers) lifting postures in Hong Kong.

7.4.2 Effects of different weights, balance tests, and fatigue on balance control

Research results presented indicated that increased weight significantly increased postural sway (i.e., poorer balance control) following a fatiguing repetitive lifting task. This suggests that repetitive lifting with relatively heavy weights may indirectly increase the risk of fall injuries (Corbeil et al., 2003; Paillard, 2012). Findings presented concur with previous research that evaluated the impact of adding weights until fatigue and its impact upon balance control (Ledin and Odkvist, 1993; Punakallio et al., 2003; Lee et al., 2008). Punakallio et al. (2003) reported a significant increase in CoP parameters in the A/P and M/L directions after wearing firefighting clothing weighing 25.9 kg for 40 seconds in an upright standing position. Similarly, Ledin and Odkvist (1993) found that putting weight (totaling 20% of body mass) on the chest and back of participants' impaired their ability to remain in equilibrium during 45 seconds. Unfortunately, these studies did not compare the effects of different weights on CoP parameters; whereas the present study reveals increases in CoP parameters as lifting weight is increased from 5% to 15% of the participant's MLS. Overall, the findings of the current study can be used to improve the balance control with subsequent fall injuries of construction workers involved in repetitive lifting tasks of weight in range between 5 to 17 kg.

The current study revealed that lifting weights have a differential effect upon balance controls. Repetitive lifting had a similar effect on balance control in A/P and M/L direction on a stable support surface regardless of the presence/absence of vision. In the current study, the visual system is thought not to be a contributing factor in impairing balance control for two reasons: firstly, during the eyes open standing balance test (i.e., EOS), the participants focused on a standard white sheet at a uniformed distance, and secondly the participants' eyes were closed during the eyes closed standing balance test condition (i.e., ECS). Previous studies have suggested that visual target placed at informed distance can impair balance control (Vuillerme et al., 2001; Vuillerme et al., 2006). Vuillerme et al. (2001) showed that a visual target placed at 1 m could attenuate the effect of fatigue on balance control during quiet standing balance task. Conversely, the impact of lifting weight on balance control was more profound on an unstable supporting surface with vision occlusion (i.e., ECF) than the other two standing balance conditions. Since an individual relies more on proprioceptive inputs from lower limb and trunk to maintain balance on an unstable surface during vision occlusion (Derave et al., 2002; Maurer et al., 2006; Horak and Macpherson 1996; Bhattacharya et al., 2003), the presence of fatigue may affect an individual's ability to provide correct proprioceptive signals to the brain for balance control (Simeonov et al., 2003). Therefore, repetitive lifting of heavyweights may heighten the risk of fall injuries (Corbeil et al., 2003; Paillard, 2012). Hence, the lifting weight should be reduced for repetitive lifting tasks in order to minimize the risk of falls among workers working on an unstable supporting surface. Since reducing the lifting weight may sometimes be practically infeasible, construction workers should adopt proper ergonomic interventions (e.g. exoskeletons, back belts and lifting equipment) to enhance the mechanical advantages of workers during lifting tasks (Kraus et al., 1996).

The effect of muscle fatigue upon balance control was consistent with several previous studies using different fatigue protocols (c.f. Vuillerme et al., 2001; Yaggie and McGregor, 2002;

Corbeil et al., 2003). These findings support the notion that repetitive lifting induces muscle fatigue, which may cause proprioceptive deficiency and suboptimal efferent muscle responses that compromise balance control (Hiemstra et al., 2001; Forestier et al., 2002). Although the evidence of muscle fatigue in the current experimental protocol was subjective, our previous studies measured muscle fatigue by using normalized median frequency (MF) and root mean square (RMS) of normalized sEMG amplitude based on similar protocols (Antwi-Afari et al., 2018a). Although these objective assessment of muscle fatigue are outside the scope of the current study, the results shown decreased MF values and increased muscle activity at the lumber erector spinae and quadriceps muscles, which also concur with previous studies during repetitive lifting tasks (Sparto et al., 1999; Davis et al., 2010). The interaction effects of weight and fatigue after repetitive lifting task were significant for all CoP parameters. This finding indicates impaired balance control with increased weight after fatigue is in line with previous studies (c.f. Punakallio et al., 2003; Schiffman et al., 2006; Lee et al., 2008). The current study assessed balance control by using CoP parameters measured from a force plate. With regards to the directional-specific effects of muscle fatigue, the research findings indicated that balance control in the A/P and M/L directions showed a similar increase in perceived lower back and calf/quadriceps muscles fatigue following stoop and squat lifting postures, respectively. These results are in accordance with findings of Gribble and Hertel (2004a) and Soleimanifar et al. (2012) which observed that balance control in sagittal and frontal planes was impaired after the fatigue of either hip, knee or ankle muscles. Overall, these findings suggest that the effects of fatigue on balance control are specific to the fatigue location and measures of balance control used.

7.5 CHAPTER SUMMARY

This chapter evaluated the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks. Twenty healthy male participants underwent balance control assessments before and immediately after a fatiguing repetitive lifting task using three different weights in a stoop (10 participants) or a squat (10 participants) lifting posture. Balance control assessments required participants to stand still on a force plate with or without a foam (which simulated an unstable surface) while center of pressure (CoP) displacement parameters on the force plate was measured. Findings suggest that repetitive lifting of heavier weights would significantly jeopardize individuals' balance control on unstable supporting surfaces, which may heighten the risk of falls. This research offers an entirely new and novel approach to measuring the impact that different lifting weights and postures may have upon worker stability and consequential fall incidents that may arise.

CHAPTER 8

AUTOMATED DETECTION AND CLASSIFICATION OF CONSTRUCTION WORKERS' LOSS OF BALANCE EVENTS USING WEARABLE INSOLE PRESSURE SENSORS[7]

8.1 INTRODUCTION

Falls are the primary cause of construction workers' injuries (Hu et al., 2011). In Hong Kong, statistics show that workers' injuries associated with falls accounted for almost half of construction injuries (Chan et al., 2008), and about HK$ 40 million of total compensation in 2008 (Li and Poon, 2009). Especially, falls on the same level are one of the most significant causes of construction workers' injuries in Hong Kong, accounting for about 20% of construction accidents (Development Bureau HKSAR, 2017). Compared with falls from height, the severity of injuries from falls on the same level is relatively low (generally leading to non-fatal injuries), but they are the most frequent types of injuries in construction, accounting for 40% of non-fatal fall injuries (CPWR, 2013; BLS, 2016). Given that these fall injuries can cause a delay in the construction schedule, decrease productivity, and increase economic burden (Earnest and Branche, 2016), the prevention of falls on the same level is an important priority in the construction industry (Lehtola et al., 2008).

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Previous studies have shown that falls on the same level occur when workers suddenly lose their balance because of loss of balance events such as slips, trips, unexpected step-downs and twisted ankles (Bentley and Haslam, 2001; Kincl et al., 2002; Lipscomb et al., 2006). Numerous intrinsic and extrinsic risk factors can lead to loss of balance events on construction sites (Gauchard et al., 2001). While some intrinsic risk factors are non-modifiable (e.g., cerebellar problems) and modifiable (e.g., physical fitness, agility, fatigue, and attention etc.) (Gauchard et al., 2001), most of the extrinsic risk factors for falls on the same level on construction sites are related to unsafe environmental surface conditions such as uneven work surfaces, the presence of an obstacle or contaminant, and slippery surfaces (Gauchard et al., 2001; Hsiao and Simeonov, 2001). For safety officers and managers at construction sites, identifying and detecting loss of balance events associated with unsafe environmental surface conditions are crucial to prevent same-level fall accidents. However, previous studies usually relied on experts' judgments and retrospective data (e.g., accident reports) for injury analysis and identifying loss of balance events associated with fall risk factors (Huang and Hinze, 2003; Chi et al., 2005). Despite the value these prior studies, their approaches not only might involve a subjective bias or missing data (Hallowell and Gambatese, 2009), but also might unable to prevent continuous monitoring of fall risk factors due retrospective nature of these studies (Lipscomb et al., 2006).

To address these issues, we propose real-time detection and classification of loss of balance events by using wearable pressure insole sensors that measure foot plantar pressure distributions. Each loss of balance event (e.g., slips, trips, unexpected step-downs and twisted ankles) is associated with specific unsafe environmental surface conditions (e.g., slippery floors, uneven surfaces or obstacles on the path etc.), creating unique foot plantar pressure distribution patterns measured by using wearable insole pressure sensors. Supervised machine learning algorithms were developed to classify types of loss of balance events by using spatial and temporal features that reflect the unique plantar pressure data patterns. Detecting workers' loss of balance events provide useful information for (1) diagnosing potential causes (i.e., types of unsafe environmental surface conditions) of falls on the same level and (2) implementing appropriate interventions for construction workers who are more vulnerable to a loss of balance under given conditions. To test the detection performance, we conducted laboratory experiments to collect foot plantar pressure distribution data from simulated loss of balance events, and applied developed supervised machine learning algorithms. Based on the testing results, the feasibility of the proposed approach and its potential application areas were discussed.

8.2 RESEARCH BACKGROUND

8.2.1 Fall risk factors and preventive measures of falls on the same level

Understanding the underlying mechanisms of fall risk factors that may lead to falls on the same level is essential to identify and detect loss of balance events, and this could eventually help safety managers to implement effective preventive measures (Chang et al., 2016). Figure 8.1 presents the role of intrinsic and extrinsic risk factors that may lead to falls on the same level. As shown in Figure 8.1, intrinsic risk factors are related to either an individual's perceptual ability to identify any existing unsafe conditions or motor control ability to recover from imbalance. Besides, extrinsic risk factors are associated with occupational environments and work organization (Gauchard et al., 2001). Amongst the extrinsic risk factors (see Figure 8.1) that may lead to falls on the same level, unsafe environmental surface conditions such as the presence of obstacles, uneven work surfaces, and slippery surfaces have been reported to be the most prevalent risk factors (Manning et al., 1988; Bentley, 1998). By analyzing more than 20,000 recorded falls in the United Kingdom, Manning (1988) found that there are four major types of loss of balance events that could lead to falls on the same level: 1) slips; 2) trips; 3) unexpected step-downs; and 4) twisted ankles. These four events account for more than 90% of unsafe environmental surface conditions that resulted in falls on the same level (Manning, 1988). They are directly associated with specific unsafe environmental surface conditions (i.e., extrinsic risk factors), such as a slippery surface (a slip), an obstacle on a walkway (a trip when striking it and a twisted ankle when stepping on it) and an uneven surface (unexpected step-down) (Lehtola et al., 1990). As a result, identifying loss of balance events associated with specific unsafe environmental surface conditions are of importance to safety managers to propose appropriate interventions to prevent falls on the same level injuries.

Kaskutas et al. (2013) reported that the two most effective preventive measures used to minimize the risk of falls on the same level are: (1) safety training programs (Im et al., 2009; Sacks et al., 2013), and (2) behavior-based management techniques such as goal-setting, motivational technique etc. (Duff et al., 1994; Lingard and Rowlinson, 1997). However, current methods such as observations, surveys and retrospective reports that are used to assess the aforementioned preventive measures may encounter some inherent challenges on construction sites for identifying loss of balance events (Hallowell and Gambatese, 2009). These challenges include but not limited to the: (1) dynamic and continuous changing of construction working environment; (2) differences in individuals' intuition, background, experiences and knowledge in reviewing these methods; (3) increase in resources and supply components at various stages of construction; and (4) inability of safety managers to assess the severity and frequency of occurrences of multiple risk factors in real time (Yang et al., 2017; Umer et al., 2018). Taken together, there is a crucial need to introduce an efficient approach and a novel method for automated detection and classification of loss of balance events associated with specific unsafe environmental conditions that could help address such limitations and enhance the implementation of effective fall preventive measures.

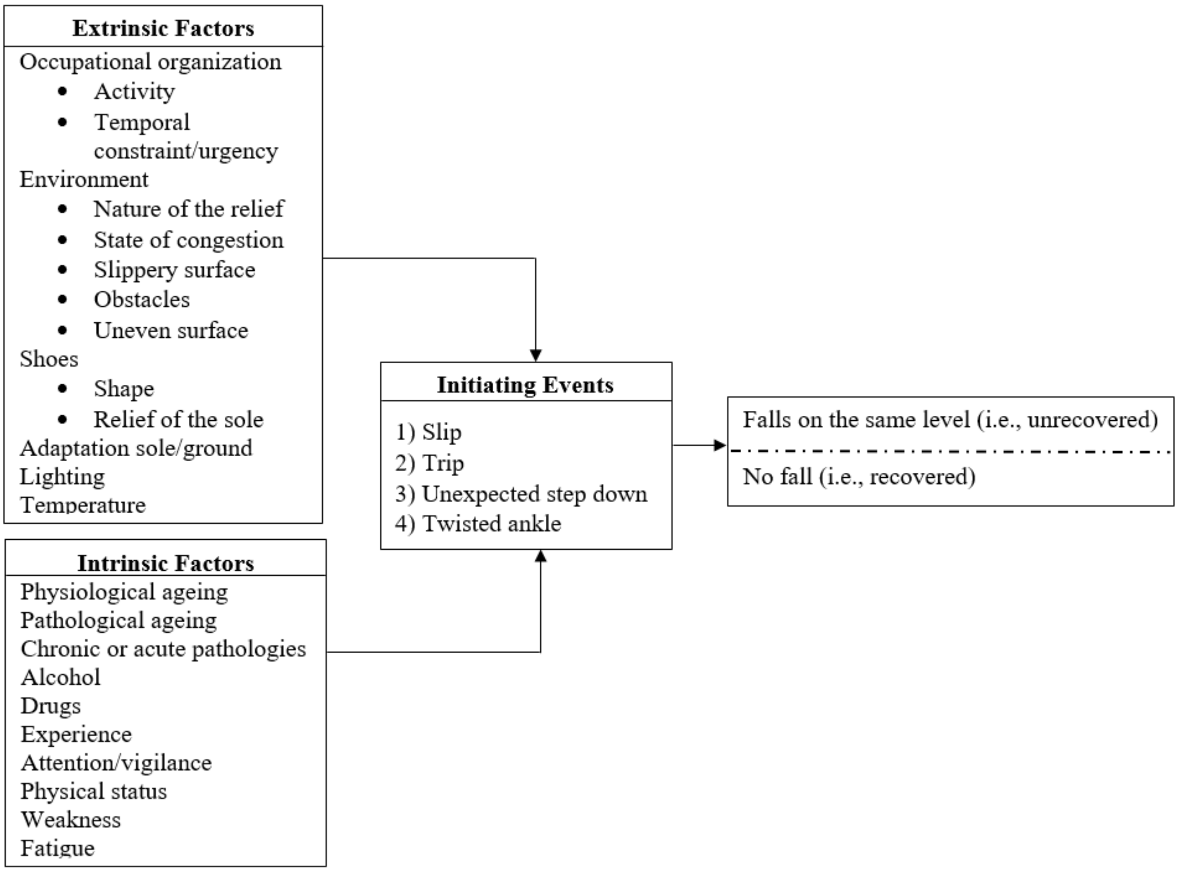


Figure 8.1 Mechanisms of falls on the same level (Adopted from Gauchard et al., 2001)

8.2.2 Wearable sensor-based approaches for fall risk detection and classification

Identifying potential fall risk factors at sites is challenging, especially in construction where work environments and workforce are continuously changing. Generally, fall risk detection relies on subjective and qualitative measures such as questionnaires or surveys on injured people (Howcroft et al., 2013). For a more detailed investigation, quantitative measures such as motion sensors, force plates or electromyography sensors are required (Antwi-Afari et al., 2017a, b; Antwi-Afari et al., 2018a). However, even though these measures provide useful information on fall risks, they are reactive and time-consuming, such that they may not be suitable for construction where working environments are continuously changing.

For a continuous and objective fall risk monitoring, body-worn accelerometers have gained attention in rehabilitation and clinical research areas (Mathie et al., 2004; Culhane et al., 2005; Giansanti, 2006; Preece et al., 2009; Howcroft et al., 2013). Accelerometers attached to the body continuously measure body movements that can be used to detect any disturbance of body balance (Howcroft et al., 2013). In construction, the use of accelerometers for detecting near-miss falls has been successfully validated through laboratory tests (Lai et al., 2011; Jebelli et al., 2016; Yang et al., 2016). These studies developed fall risk assessment models to classify fallers and non-fallers, or assessment scores to predict the likelihood of future falls based on variables (e.g., position, angle, angular velocity, linear acceleration, gait speed etc.) from acceleration signals. However, despite the advantages of being light-weight, low-cost and easy to collect real-time data, acceleration-based approaches are limited to binary classification of fall risks (e.g., no-risk or fall-risk).

Even though foot plantar pressure measurement devices such as wearable insole pressure sensors have not been applied in construction, they have been widely used in diverse areas such as rehabilitation, sport science, daily activity monitoring and gait analysis (Salpavaara et al., 2009; Edgar et al., 2010; Brassard et al., 2012; Gagnon et al., 2013; Ayena et al., 2016). Wearable insole pressure sensors measure the force acting on each sensor during foot contact (Orlin and McPoil, 2000). Generally, multiple sensors are located at different areas of shoe insoles, providing pressure distribution data. As the pressure distribution pattern is an indicator of gait instability or body balance, these sensors can be used for detecting gait abnormality associated with falls (Tao et al., 2012). Spatial and temporal pressure distributions could vary depending on types of loss of balance events, and thus these data have great potential for classifying different types of fall-initiating events (e.g., slips, trips, unexpected step-downs, and twisted ankles) that cannot be distinguishable by using accelerometers.

8.3 METHODS

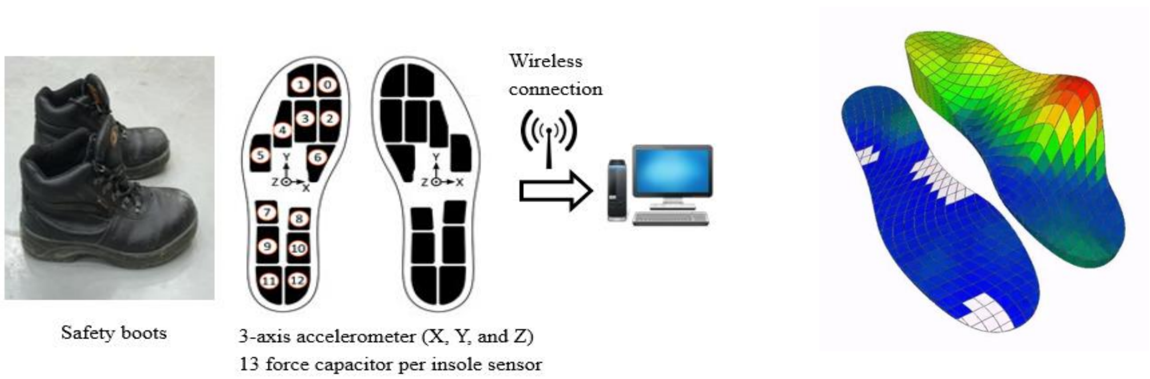
8.3.1 Participants

A convenience sample (n = 10) of healthy male volunteers ranging in age between 20 and 35 years (mean 26 ± 3.2 years), weight between 60 and 80 kg (mean 70 ± 10.5 kg), and height between 1.4 and 1.8 m (mean 1.6 ± 0.1 m) were recruited from the student population of the Hong Kong Polytechnic University. Exclusion criteria were: 1) a history of injuries on upper extremities, a low back, and lower extremities; and 2) a history of neurological disabilities or other conditions that could affect body balance functionality. All participants provided their informed consent forms in accordance with the procedure approved by the Human Subject

Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20170605001).

8.3.2 Experimental apparatus

Foot plantar pressure distribution data for each loss of balance event was collected at laboratory settings by using Moticon SCIENCE (Moticon GmbH, Munich, Germany, http://www.moticon.de), a wearable insole pressure sensor system. Figure 8.2 shows an overview of Moticon SCIENCE. It provides a novelty in conducting research based on foot plantar pressure distributions in both laboratory and field conditions. It consists of two sensor insoles (containing 13 capacitive sensors each) that measure the foot plantar pressure distribution (Figure 8.2a). Figure 8.2b depicts an example of foot plantar pressure distribution patterns. Each insole sensor incorporates a wireless module for data transmission and sensor configuration control.



(a) Sensor configuration (b) Example of pressure data

Figure 8.2 An overview of Moticon SCIENCE

8.3.3 Experimental design and procedure

The current study adopted a randomized crossover study design in a single testing session. In particular, four different types of loss of balance events (i.e., slip, trip, unexpected step-down, and twisted ankle) were conducted in a laboratory setting to collect foot plantar pressure distribution data (Figure 8.3). Before data collection, the experimental procedure was explained to the participants. Afterward, they provided their demographic data and informed consent. To simulate loss of balance events similar to real conditions, all participants were asked to wear safety boots and a hard hat during the testing sessions. Also, a safety harness and a 30-cm thick layer of high-density gymnasium mattress were provided to prevent any possible injuries (Figure 8.3b). Before the testing sessions, they observed representative videos of real-life loss of balance events and were instructed to perform in a similar fashion. For more realistic simulations, specific unsafe environmental surface conditions such as a low-density polyethylene (#1. slips), concrete bricks on the path (#2. trips and #4. twisted ankles) and a platform with 20 cm height (#3. unexpected step-downs) were used in the present study (Figure 8.3a).

During the testing session, the participant was instructed to walk at a comfortable pace and along a particular path even though there might be an unsafe environmental surface condition. In the slip event, the participant walked over a low-density polyethene which caused a rapidly translating between the foot and the floor surface. In the trip event, the participant's foot naturally hit a concrete brick. In the unexpected step-down event, the participant suddenly lost their balance upon landing on a surface lower than expected. In the twisted ankle event, the participant naturally stepped on an unstable concrete brick. In all events, the participant did not have prior knowledge of the unsafe environmental surface conditions and was instructed to look straight ahead during data collection. The sequence of the experimental trials was randomized. To measure the replicability of foot plantar pressure distribution data, each participant conducted ten repeated trials of each loss of balance event. Each trial was estimated for a duration of 6 s (4 s for normal gait plus 2 s for each loss of balance event). To reduce fatigue, the participants were allowed for 3 minutes rest between two successive trials.

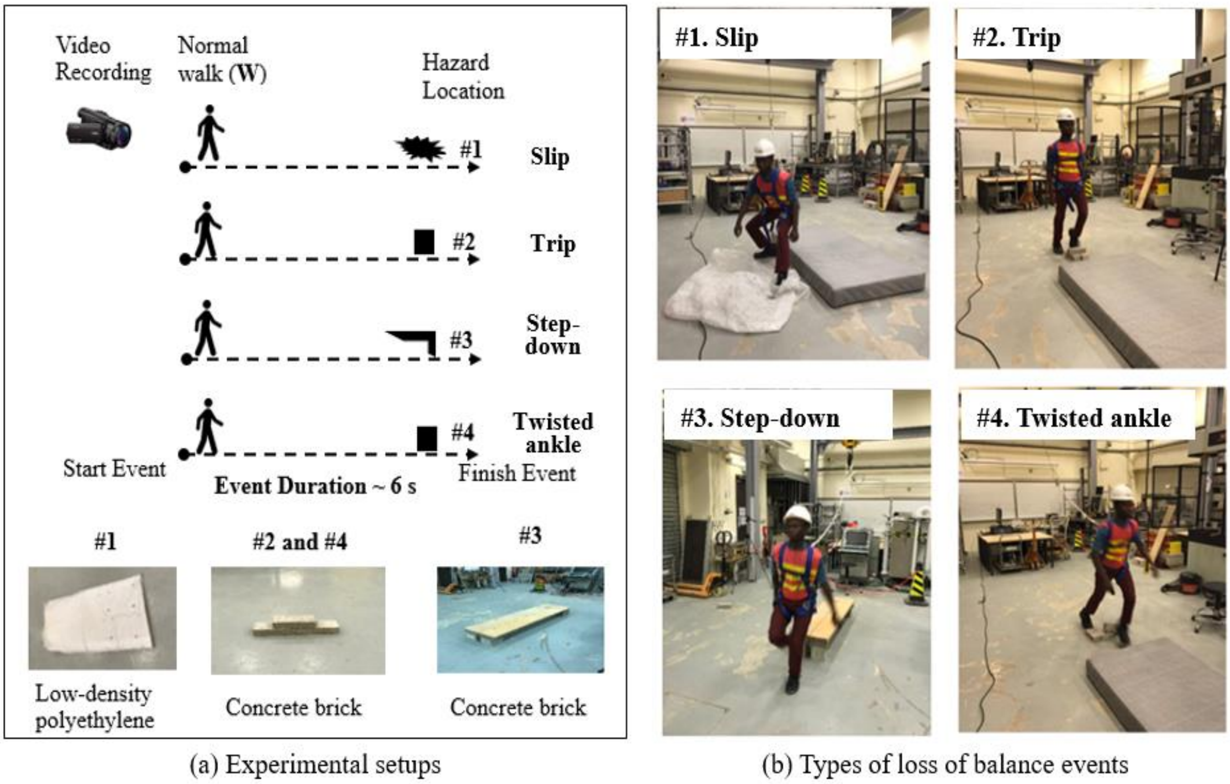


Figure 8.3 Experimental overview and data collection

8.3.4 Data processing and analysis

During data collection, each event was filmed using a video camera, and foot plantar pressure distribution data was synchronized. Based on the recorded video data and the walking steps (i.e., normal gait) of each event, time-series pressure data were labeled by types of events as the ground truth. The insole sensors collected foot plantar pressure distribution data at a rate of 50 Hz by a 16-bit analog to digital (A/D) converter and transferred the data via a wireless connection, or a universal serial bus (USB) stick to the base computer. The sampling frequency was shown to be sufficient in previous experiments to measure foot plantar pressure distribution data (Jeong et al., 2017).

Figure 8.4 shows examples of labeled pressure data from the sensors (i.e., pressure-time curves). The numbers of sensors indicate the positions on insoles as shown in Figure 8.2a. For example, Sensor 1, 7, 8 and 12 represent different regions of interest such as toes, a mid-left foot, a mid-right foot and a heel foot, respectively. These data qualitatively support the hypothesis that each loss of balance event creates unique pressure patterns from insole sensors, and thus by analyzing the patterns, each event can be classified. Depending on types of loss of balance events, unique patterns on pressure-time curves are observed at each region, allowing us to understand mechanisms of these events. For example, during walking (graphs denoted as ‘A’), cyclic alternating patterns on pressure-time curves are observed (Figure 8.4). However, when loss of balance events (denoted as ‘B’, ‘C’, ‘D’ and ‘E’) occur, unique abnormal curve patterns are shown according to types of events. Generally, during a typical slip event, the foot slides forward against the floor, and thus a relatively long pattern of pressure data is found at the middle of the foot (e.g., Sensor 7 and 8). During a trip, the left foot hits an object (i.e., concrete brick), creating a very short peak pressure on Sensor 1, and shortly after this, higher peak pressure values on the right foot are observed as the subject tries to be recovered from a trip by supporting the body on the other foot. Unexpected step-down creates sudden body mass transfer, resulting in higher peak pressures on the foot contacting the ground. Twisted ankles could occur when a worker steps on a small or an unstable object. After landing, the pressure moves to the left to right as an ankle is rotated. As shown in Figure 8.4, foot plantar pressure data implicitly reflect one's representative bodily reactions during the contact of the lower extremities with the ground. As a result, wearable insole pressure sensors can provide richer information than accelerometers to classify each loss of balance event.

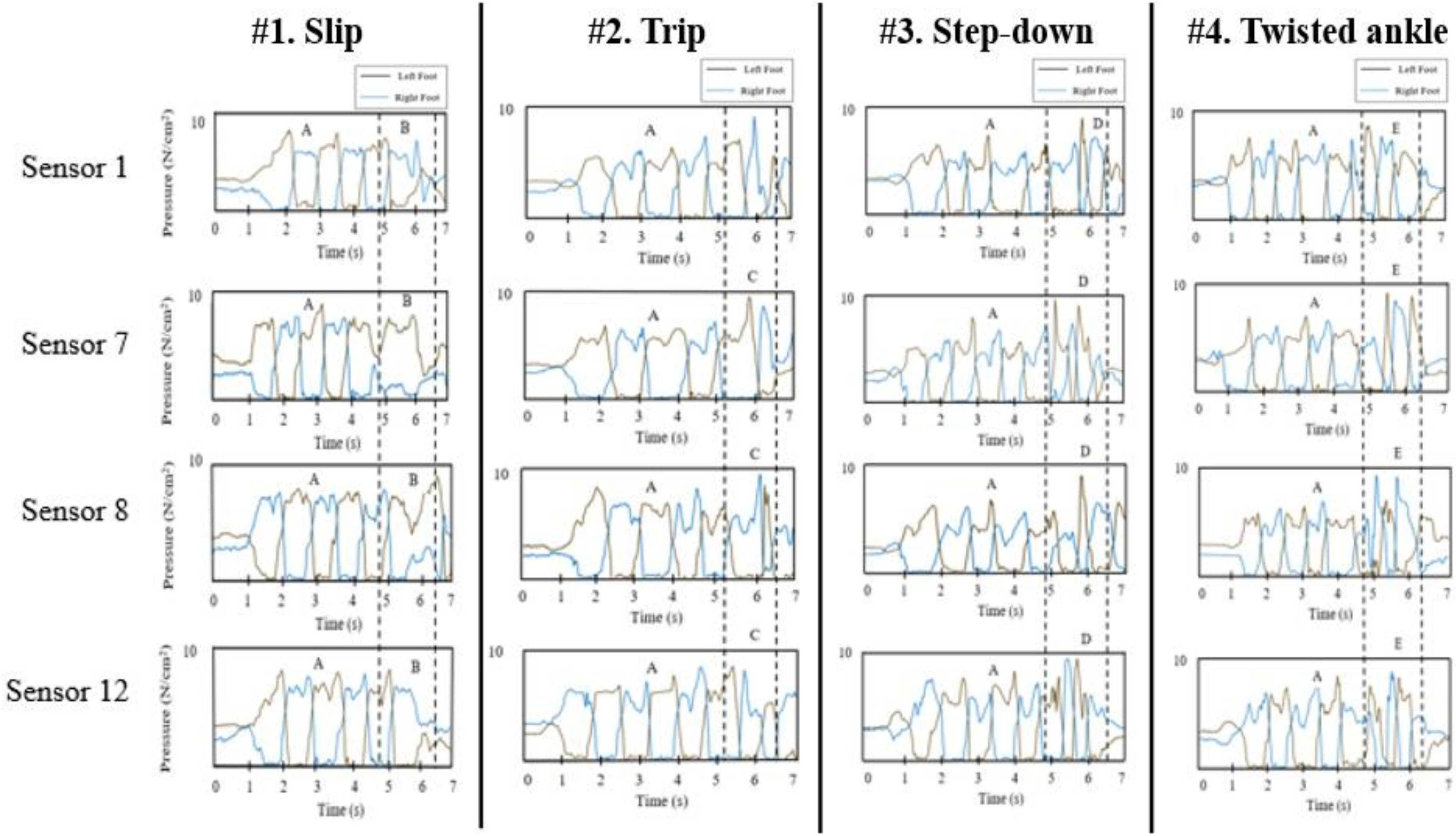


Figure 8.4 Examples of labeled foot plantar pressure distribution data

Note: Dotted lines indicate regions of detecting loss of balance events in each pressure sensor. A = Normal walk; B = Slip; C = Trip; D = Unexpected step-down; E = Twisted ankle

8.3.5 Developing supervised machine learning algorithms

Given unique foot plantar pressure patterns based on features that reflect both spatial (according to locations of pressure sensors in the wearable insoles) and temporal (dynamic loading patterns over time) changes of pressure data, classifying different types of loss of balance events from time-series foot plantar pressure data are sequential supervised machine learning problems. Even though sequential supervised machine learning algorithms have been widely applied in many fields, achieving adequate performance (i.e., accuracy) with computational efficiency is still an important research issue (Dietterich, 2002). Generally, procedures for developing sequential supervised machine learning consist of 1) data segmentation, 2) feature extraction, 3) classifier learning, and 4) classifier model assessment and performance evaluation (Wei and Keogh, 2006). The goal of these steps is to determine an optimal combination of methods for data segmentation, feature extraction, and classifier learning.

8.3.5.1 Data segmentation

Data segmentation is a data preprocessing strategy to convert sequential supervised learning problems into traditional supervised learning problems (Wei and Keogh, 2006). A sliding window technique is one of the widely used methods for time-series data segmentation (Dietterich, 2002). Specifically, for an observed time-series data $\mathbf{x_i}=(x_{i,1}, x_{i,2}, \ldots, x_{i,l})$, this method divides x_i into smaller time segments $<x_{i,t-d}, x_{i,t-d+1}, \ldots, x_{i,t}, \ldots, x_{i,t+d-1}, x_{i,t+d}>$ in a window of a fixed size w as the window slides through x (let $d=(w-1)/2$) (Wei and Keogh, 2006). Then, the classification can be performed for segmented data from each window independently through traditional supervise learning. Selecting an appropriate window size has a great impact on classification performance, especially in activity recognition problems (Banos et al., 2014). As shown in Figure 8.4, foot plantar pressure distribution data have unique patterns according to types of loss of balance events. Therefore, the window size should be large enough to include these patterns, and at the same time, should be smaller not to include noisy signals.

Previous research efforts on activity recognition have tested different window sizes, ranging from 0.1s to over 10s in steps of 0.25s, 0.5s or 1s, and it has been concluded that short window sizes (e.g., less than 3s) lead to better classification performance (Banos et al., 2014). Also, the window sizes can be affected by types of features used in the algorithms. For example, one of the features widely used for sequential supervised learning is frequency-domain features using the fast Fourier transform (FFT) function, which will be described below. One of the limitations of using the FFT function is that the number of sample data points in the segment must be a power of two (Akhavian and Behzadan, 2016). Considering the finding by Banos et al. (2014) and the use of the frequency-domain features, we selected four different window sizes of 0.32s, 0.64s, 1.28s and 2.56s that corresponds to 16 (2^4), 32 (2^5), 64 (2^6) and 128 (2^7) data samples, respectively. In this study, a 50% overlap of the adjacent windows was used (Ravi et al., 2005). Su et al. (2014) reported that data segmentation by overlapping adjacent windows reduces the error caused by transition state noise.

8.3.5.2 Feature extraction

Because of the high dimensionality of foot plantar pressure distribution data (26 data points from both feet per instance), it is important to extract relevant information subsets (i.e., features) from raw signals for better performance. As shown in Figure 8.4, the pattern of foot plantar pressure data from each sensor differently changes over time depending on types of loss of balance events. The temporal changes and fluctuations can be reflected by time- and frequency-domain features. For time-domain features, we used seven time domain features (i.e., mean pressure, variance, maximum pressure, minimum pressure, range, standard deviation, and kurtosis) that have been commonly used for activity recognition and classification (Akhavian and Behzadan, 2016; Lim et al., 2016; Antwi-Afari et al., 2018b, c). Also, to extract frequency-domain features, the raw data in time domain will be converted into frequency domain by using the FFT function, and then spectral energy and entropy were computed to be used as two frequency domain features (Bao and Intille, 2004).

In addition to time and frequency domain features, we applied a new feature extraction method based on pressure time integral (PTI). PTI is a variable that describes the cumulative foot loading over time, providing useful information on chronic foot problems (Bus and Waaijman, 2013). In Figure 8.4, each stride during the normal walks shows similar areas under the lines. However, during each loss of balance event, the cumulative foot loading that can be characterized by the area under the lines looks different because of the combined effect of body weight, movement of body mass and external forces acting of feet (e.g., hit by objects). As a result, the PTI can serve as a feature that reflects temporal changes of patterns over time, giving a distinguishable power for classifying different loss of balance events. The PTI was calculated using the following equation:

$$PTI_{(i)} = \sum_{t=1}^{N} P_i(t) \times \Delta t \qquad (1)$$

Where N is the total number of data samples in a window, i is an index of sensors (i.e., 1 to 26 sensor streams), P_i is a pressure value at time t, and $\Delta\mathrm{t}$ is the duration of that data sample.

8.3.5.3 Classifier learning

To classify different types of loss of balance events, supervised machine learning classifiers were used to learn unique signal patterns from foot plantar pressure data based on extracted features. Howcroft et al. (2013) investigated the best classification methods used in the studies for acceleration-based fall risk detection and found that neural networks, naïve Bayesian classifier, Mahalanobis cluster analysis and a decision tree have performed better than other classifiers. However, as the classifier performance could vary depending on types of data, window sizes and types of features, it is necessary to test diverse classifiers that fit best for detecting loss of balance events from foot plantar pressure data. In this research, classifiers to be tested include but not limited to 1) Artificial Neural Network (ANN), 2) Decision Tree (DT), 3) Random Forest (RF), 4) *K*-Nearest Neighbor (KNN), and 5) Support Vector Machine (SVM). Notably, a majority of studies have demonstrated that there is no single best classifier (Murthy, 1998; Liang et al., 2015). As such, a comparison of the different types of individual supervised machine learning classifiers may still be necessary to select the best model parameters that should be used in training a particular dataset. In this research, we selected the best model parameter from each type of individualized supervised machine learning classifier by training our experimental foot plantar pressure distribution data using Toolbox in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA). The following section describes the best-selected model parameters used in each supervised machine learning classifier.

8.3.5.3.1 Artificial neural network (ANN)

An ANN is a robust method that can use training samples to learn dependencies in a dataset and then apply the trained model to recognize previously unseen dataset (Haykin, 2009). In this research, a multilayer feed-forward neural network or multilayer perceptron (MLP) was used (Haykin, 2009). The input layer consists of the different combinations of extracted features at a particular window size. By default, the number of hidden layers was set at 10. The number of output layer was equal to the five simulated events (i.e., four loss of balance events plus normal gait). In order to prevent over-fitting of the dataset, a regularization parameter was used to decrease the magnitude of the trained model to recognize unseen dataset (Haykin, 2009). In this research, a scaled conjugate gradient backpropagation neural network was used for training the dataset. Also, a mean squared error was used for error evaluation during training

(Fulk et al., 2012). In order to minimize the cost function during the training process, the Levenberg-Marquardt algorithm with a sigmoid transfer function was used in this study (Pradhan et al., 2015).

8.3.5.3.2 Decision tree (DT)

DT is one of the most powerful classifiers for human activity classification and recognition (Bishop, 2006). This classifier works by examining the discriminatory ability of the extracted features one at a time to create a set of rules that ultimately leads to a complete classification system (Preece et al., 2009). This research used the decision tree method of the classification and regression tree (CART) (Akhavian and Behzadan, 2016). CART tree classifies patterns based upon sequence of questions in which the next question asked depends on the answer to the current question. Notably, CART was the best-selected model parameter because it is useful for analyzing nonparametric data that does not require any notion of metric (Duda et al., 2001). In this research, the best optimization criterion (i.e., Gini diversity index) was used (Akhavian and Behzadan, 2016). A node is considered as pure if it has a Gini index of zero. To prevent over-fitting of training dataset, the process of splitting leaf nodes is repeated continuously until a minimum number of observation of a class was reached.

8.3.5.3.3 Random forest (RF)

The RF classifier is an ensemble learning technique for classification that consists of a combination of decision-trees (Breiman, 1984). The classification performance of each decision tree in a RF classifier is built by using a bootstrap aggregating (i.e., bagging) method and a random feature selection (Attal et al., 2015). This approach helps in reducing the model variance and minimizing the over-fitting of training dataset (Breiman, 1984). Since each node in a RF classifier is split into a limited number of randomly predicted variable, it is considered to be more powerful classifier when compared to other classifiers such as SVM and ANN

(Wang et al., 2017). There are only two model parameters that need to set when training a dataset with a RF classifier (Lehmann et al., 2007). These are (1) mTry, which represents the number of input variables in the random subset at each node; and (2) nTree, which represents the number of trees to grow for each forest. By default values, mTry and nTree were set at 6 and 500 respectively. However, it is well-established that the classification outcome is not highly sensitive to the choice of these parameters (Liaw and Wiener, 2002).

8.3.5.3.4 K-nearest neighbor (KNN)

The KNN classifier is a simple and straightforward classifier but requires no training time (Wang et al., 2017). Training dataset is identified by an unknown window of class labels which are spread over the feature space (Akhavian and Behzadan, 2016). A new dataset is assigned to a class label based on the single closest neighbor or *K*-nearest examples (i.e., *K*-neighbor of 1) considering the Euclidean distance (Akhavian and Behzadan, 2016). Based on a heuristic method to achieve the best classification, this metric was selected in this research (Pradhan et al., 2015).

8.3.5.3.5 Support vector machine (SVM)

The SVM constitutes a popular classifier which is based on finding optimal separating decision hyperplanes between classes with the maximum margin between patterns of each class (Preece et al., 2009). It can benefit from a maximum margin hyperplane in a transformed feature space using a kernel function to map the dataset into an inner product space in order to create a non-linear structure (Pradhan et al., 2015). For non-linear classification in this research, the Gaussian radial basis function (RBF) was used as the kernel function (Akhavian and Behzadan, 2016). In order to enable a multi-class pattern recognition problem (i.e., identifying and detecting different types of loss of balance events) to be solved in a single optimization, this research used a multi-class one-against-one approach to train the SVM (Debnath et al., 2004).

8.3.5.4 Classifier model assessment and performance evaluation

The final step is to determine the model parameters (e.g., window sizes, types of features and classifiers) to achieve the best performance for classifying the different types of loss of balance events. The performance of the classifiers was evaluated by a 10-fold cross-validation, which is a model validation technique to assess the accuracy and validity of statistical models. In the 10-folds cross-validation, the dataset is randomly split into 10 approximately equal size exclusive subsets. Then, each part is reserved as test datasets, and the remaining parts are performed as training datasets with a particular classifier (Özdemir and Barshan, 2014). According to Refaeilzadeh et al. (2009), 10-fold cross validation is reliable to estimate the performance of classifiers because it makes predictions with 90% of dataset, which can be generalizable to the full dataset.

8.4 RESULTS

We tested the proposed algorithms by using the data collected through laboratory experiments described above. The primary purpose of the test was to determine the best combination of window sizes, types of features and classifiers through cross-validation. Additionally, we also tested classification accuracy by varying the window positions to explore where the most distinguishing plantar pressure patterns exist during conducting each loss-of-balance event.

8.4.1 Best combination of window sizes, groups of features and classifiers

The proposed algorithms have three key parameters that would determine the classification performance: 1) window sizes; 2) types of features; and 3) types of classifiers. For window sizes, we selected four different window sizes of 0.32s, 0.64s, 1.28s, and 2.56s, considering both the optimal range of window sizes and the number of data samples required for extracting frequency-domain features. The proposed algorithms use three groups of features: 1) seven time-domain features; 2) two frequency-domain features; and 3) PTIs. Generally, supervised machine learning-based classification algorithms include feature selection that aims to identify optimal subsets of features not only for better classification accuracy but also for data understanding (Guyon and Elisseeff, 2003). This paper applied the wrapper approach suggested by Kohavi and John (1997) that assesses the subsets of features in terms of the prediction performance. Instead of an exhaustive search for all possible subsets, we tested subsets of combinations of three feature groups (e.g., time-domain, frequency-domain and PTI features) to understand the role of each feature group. As a result, seven subsets of three feature groups such as 1) time-domain features only (TF), 2) frequency-domain features only (FF), 3) PTI only (PTI), 4) time- and frequency-domain features (TF + FF), 5) time-domain and PTI features (TF + PTI), 6) frequency-domain and PTI features (FF + PTI), and 7) all three feature groups (TF + FF + PTI) were tested. For classifiers, we chose 1) ANN, 2) DT, 3) RF, 4) KNN, and 5) SVM.

Table 8.1 shows overall classification accuracies (i.e., the proportion of correct classifications in percentage) by cross-validation for five events (i.e., normal walking and four loss of balance events) based on combinations of different window sizes, feature group subsets, and classifiers. The testing results indicate that the classification performance could vary depending on the combination of algorithm parameters, emphasizing the need for finding the optimal parameters. The overall classification accuracies ranged from 20.3% to 97.1%, and each classifier shows the best performance on different combinations of feature groups and window sizes. For example, the best classification accuracy of each classifier was 74.7% (TF + FF and 0.32s) in ANN, 82.7% (TF + PTI, 2.56s) in DT, 97.1% (TF + FF + PTI, 0.32s) in RF, 95.2% (PTI only, 0.32s) in KNN, and 95.0% (FF + PTI, 2.56s) in SVM, respectively (Table 8.1). Among the five classifiers, the best performance was achieved by the RF classifier when using all feature groups with the smallest window size (0.32s) (Table 8.1). One of the interesting results was that the RF classifier is less sensitive to the selection of features and window sizes, showing over 90% overall accuracies regardless of types of features and window sizes. Regarding the effect of window sizes, contrasting results were observed according to types of classifiers. Specifically, the longer window sizes led to better performance in ANN, DT, and SVM while RF and KNN showed the best performance when using the smallest window size. In addition, using all feature groups would not always result in better performance. Except for the RF classifier, the best performance was observed when using only subsets of feature groups in the other four classifiers.

Table 8.1 Overall classification accuracies (%)

	ANN*				DT*				RF*				KNN*				SVM*			
	0.32s	**0.64s**	**1.28s**	**2.56s**	**0.32s**	**0.64s**	**1.28s**	**2.56s**	**0.32s**	**0.64s**	**1.28s**	**2.56s**	**0.32s**	**0.64s**	**1.28s**	**2.56s**	**0.32s**	**0.64s**	**1.28s**	**2.56s**
TF only**	30.6	25.4	20.4	56.5	67.4	61.7	58.7	82.2	96.0	95.1	94.9	94.9	87.8	86.8	85.9	92.1	56.8	85.6	84.1	93.3
FF only**	53.2	47.9	47.0	66.5	67.9	59.3	56.5	79.9	94.6	93.8	93.4	93.0	92.0	91.6	90.8	92.4	89.1	87.2	83.9	91.9
PTI only**	48.2	43.7	27.4	24.3	66.8	63.8	58.0	74.1	96.3	94.5	93.3	93.5	**95.2**	92.9	92.8	94.0	87.9	85.3	85.0	89.0
TF + FF	**74.7**	25.6	20.3	49.6	78.1	68.0	67.8	81.7	95.6	95.0	94.3	95.2	93.7	93.4	93.0	93.5	92.1	91.1	90.6	94.0
FF + PTI	58.4	30.7	28.2	53.9	69.5	62.3	85.3	80.5	96.8	95.4	95.0	94.4	93.9	93.2	92.2	94.3	90.9	89.8	87.7	**95.0**
TF + PTI	50.7	46.6	41.0	61.4	69.0	65.4	61.4	**82.7**	96.3	96.2	95.4	95.0	90.4	89.8	88.6	93.8	89.6	88.6	87.1	92.8
TF + FF + PTI	51.5	41.5	61.4	72.0	70.5	64.8	59.9	81.8	**97.1**	96.2	95.5	95.5	94.8	94.4	94.3	94.5	93.9	93.6	93.3	94.7

Note: * ANN: Artificial Neural Network, DT: Decision Tree, RF: Random Forest, KNN: k-Nearest Neighbor, SVM: Support Vector Machine

** TF: Time-domain features, FF: Frequency-domain features, PTI: Pressure Time Integral feature

True class	Normal walk	Slip	Trip	Unexpected step down	Twisted ankle
Normal walk	99.2%	0.1%	0.2%	0.1%	0.4%
Slip	0.1%	97.7%	0.2%	1.4%	0.6%
Trip	0.5%	0.2%	96.9%	1.5%	0.9%
Unexpected step down	2.4%	0.3%	0.5%	95.6%	1.2%
Twisted ankle	1.1%	0.8%	2.3%	0.9%	94.9%

Predicted class

Figure 8.5 Confusion matrix when using RF with all feature groups at a window size of 0.32s

Figure 8.5 shows how each loss of balance event was detected using RF classifier (best classifier) with all feature groups at 0.32s window size data segment. As presented in Figure 8.5, the rows show the percentage of true (i.e., actual) instances, and the columns reveal the percentage of predicted instances of loss of balance events. For example, whilst 97.7% of the actual instances was positively detected and classified as slip event, 0.1%, 0.2%, 1.4%, and 0.6% were predicted as normal walk, trip, unexpected step-down, and twisted ankle events, respectively (Figure 8.5). Based on the confusion matrix, each event had more than 94.0% in correct detection of the instances (i.e., sensitivity) using all feature groups (Figure 8.5). Figure 8.5 also reveals that whilst normal walk was the most accurately classified and detected event (99.2%), the most confused events were the unexpected step-down and normal walk events (i.e., 2.40%). This might be attributed that unexpected step-down and normal walk events had similar foot plantar pressure patterns and magnitudes during the initial stride, which might have led to more misclassified and undetected instances.

8.4.2 Classification accuracy according to window position

Unlike walking that involves cyclic or repeated movements, loss of balance events such as slips, trips, unexpected step-downs and twisted ankles are one-off events, showing non-cyclic patterns of foot plantar pressure data (Figure 8.4). Also, initial foot plantar pressure patterns could be similar for each loss of balance events, but corresponding foot plantar pressure patterns could vary depending on one's strategies to recover body balance. To understand where distinguishing foot plantar pressure patterns exist during loss of balance events, plantar pressure data during each event was divided into the first, second and third window from the start of the event without overlap, and the overall accuracy was tested by learning a classifier using data from each window, respectively. For this test, the algorithm parameters (RF, all feature groups, and 0.32s window) that resulted in the best performance were used in this study.

Figure 8.6 shows the overall accuracies according to the position of the windows. The first, second and third windows contain foot plantar pressure data from the start of each event to 0.32s, from 0.32s to 0.64s, and from 0.64s to 0.96s, respectively. The RF classifier learned the data from each window only. The result showed that foot plantar pressure data from the first window has better distinguishing power, indicating foot plantar pressure data at the beginning of each event contain more unique and consistent plantar patterns to classifier loss of balance events.

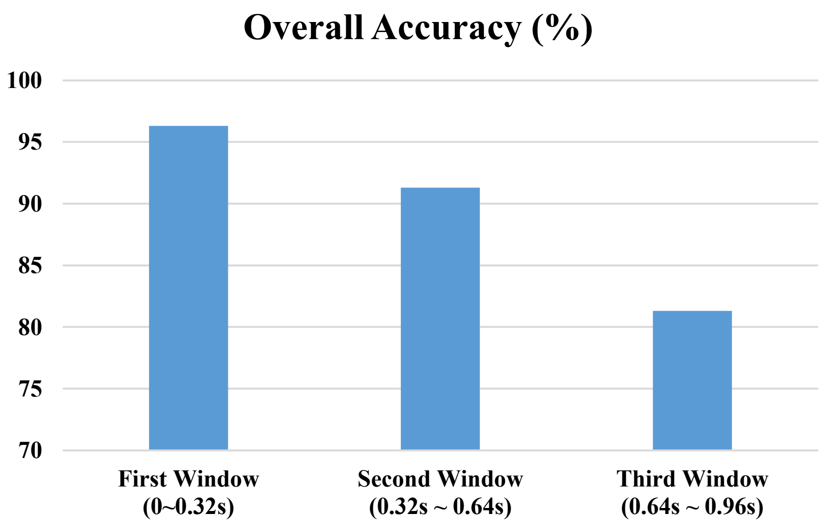


Figure 8.6 Classification accuracies depending on window positions

8.5 DISCUSSION

This study examines foot plantar pressure distribution data for automated detection and classification of loss of balance events which are preceded by falls on the same level using wearable insole pressure sensors. An experimental study was conducted to design supervised machine learning algorithms to classify loss of balance events by analyzing foot plantar pressure data. From the comparative evaluation based on cross-validation, it was found that the RF classifier achieved the best performance for detecting and classifying loss of balance events with an accuracy of 97.1%, and the sensitivity of more than 94% for each event using all feature groups and a window size of 0.32s. Additionally, we performed hold-out validation by randomly splitting the data into two parts (70% for training, 30% for testing). The result also showed 95.9% overall accuracy when using the same algorithm parameters, supporting the robustness of the proposed approach for independent test datasets. This result implies that foot plantar pressure distribution data obtained from wearable insole pressure sensors can effectively detect and classify loss of balance events, which may help to understand the causes of falls on the same level.

Despite the promising performance, the effects of different algorithm parameters such as types of classifiers, features, and window sizes are still not clear due to contrasting results according to different combinations of algorithm parameters. Determining best combination of classifiers, window sizes and features is a difficult task for many reasons such as the differences in experimental protocol, the objectives behind real-time falls on the same level applications, the types of wearable sensors used and their attachment to the human body, the performance evaluation and validation, and the nature of the fall activities conducted. Generally, the decision would be made based on classification performances (Foerster et al., 1999; Foerster and Fahrenberg, 2000; Altun et al., 2010). For the problem that need real-time analysis, the need for data pre-processing and computational time are also important factors to be considered.

The best accuracy achieved from the RF classifier confirmed the hypothesis that each loss of balance event creates unique patterns of foot plantar pressure distributions, even though other classifiers such as KNN and SVM showed comparable performance with slightly less accuracies. Recently, the RF classifier has been widely used in acceleration-based action recognition problems, showing better performance than other classifiers. Compared with other classifiers, several advantages of the RF classifiers have been revealed: 1) the RF can reduce computational time because it needs very little pre-processing of the data; 2) feature selection procedures are not necessary as the algorithm itself evaluates features on its own; and 3) it can minimize over-fitting issues (Pavey et al., 2017). In our results, the RF achieve the best performance when using all feature groups as it internally optimizes features used for training. Generally, the best classifier could vary depending on the selection of features. However, using the RF classifier can eliminate complicating feature selection problems, providing a comparative advantage over other classifiers.

The current study has established that the length of window size data segment and the type of features extracted from foot plantar pressure distribution while performing loss of balance events can influence the classifier performance. As a result, the window size is an important parameter to be considered in fall risk detection and classification studies. The window size of 0.32s can be generally considered as an optimum data segment for signals produced by wearable insole pressure sensor while loss of balance events are performed. In particular, the first window from the start of each event tends to contain distinguishable plantar pressure patterns for loss of balance event classification. With regards to extracted features, it was concluded that using all feature groups do not necessarily lead to better performance for all classifiers except the RF classifier. For instance, higher accuracies were achieved by the ANN, DT, and SVM classifiers during combining TF+FF, TF+PTI, and FF+PTI, respectively. For classifiers (e.g., RF, KNN, SVM) of which best performance is higher than 90%, PTI features have an important role as adding PTI as features increased the classification accuracy. It should be emphasized that PTI describes the cumulative effect of pressure over time in the certain area of the foot, and thus provides a value for the total load exposure of a foot sole area during one step (Sauseng et al., 1999). This indicates that PTI is of added value to understanding temporal changes of foot plantar pressure distributions while performing loss of balance events.

Despite the promising result of the proposed approach, there are several potential issues when applying it in practice, which includes 1) data collection issues and 2) need for location data. First, identifying and removing unsafe environmental surface conditions (e.g., slippery floors) in a timely manner is essential to minimize the risk of falls on the same level. Toward this goal, continuous data transfer and real-time analysis are required. Most wearable sensors including pressure insole sensors use a direct wireless network or a smartphone for data transfer. However, internet disconnection may occur in using wearable sensors and leads to failed data transfer in real time (de Arriba-Pérez et al., 2016). To minimize such risk, the reliability of wearable sensors data transfer should be tested, especially at construction sites where a signal blockage may commonly exist. Besides, the process of collecting foot plantar pressure distribution data measured by wearable insole pressure sensors during normal gait may be affected by the differences in individual risk factors (e.g., age, work experience, gender). To minimize such issues, repetitions of specific risk factor should be conducted to test data variability. Second, even though the proposed system can detect instances of loss of balance events, the location information where the event occurs is also required to be reported so that necessary interventions can be implemented. As such, additional location tracking systems should be used to proactively minimize the fall risks at construction sites.

8.6 CHAPTER SUMMARY

This chapter discussed and developed a method to detect and classify loss of balance events that could lead to falls on the same level by using foot plantar pressure distributions data captured from wearable insole pressure sensors. Ten healthy volunteers participated in experimental trials, simulating four major loss of balance events (e.g., slip, trip, step-down, and twisted ankle) to collect foot plantar pressure distributions data. Machine learning algorithms were used to learn the unique pressure data patterns, and then to automatically detect loss of balance events. The proposed approach can serve as an automated fall risk assessment tool that allows practitioners to take proactive actions to eliminate the fundamental causes of falls on the same level.

CHAPTER 9

CONCLUSIONS AND RECOMMENDATIONS

9.1 INTRODUCTION

This chapter presents a summary of the research findings and highlights the limitations of this study. It also provides suggestions for future research directions.

9.2 SUMMARY OF RESEARCH FINDINGS

The present study aims to evaluate biomechanical risk factors for WMSDs and fall injuries among construction workers. The specific research objectives are as follows: to summarize MSS prevalence in different construction trades, gender and age groups, which may help develop specific ergonomic interventions; to examine the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving OHS through the analysis of articles published between 1996 and 2017 (years inclusive); to evaluate the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment; to examine the self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers; to propose a novel approach and efficient method to automatically detect and classify awkward working postures based on foot plantar pressure distribution data measured by wearable insole pressure system; to evaluate the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks; and to develop a novel method to detect and classify loss of balance events that could lead to falls on the same level by using foot plantar pressure distributions data captured from wearable insole pressure sensors.

9.2.1 Objective 1: To summarize MSS prevalence in different construction trades, gender and age groups, which may help develop specific ergonomic interventions

This is the first systematic review to summarize the prevalence of various MSS in the construction industry. Lumbar, knee, shoulder and wrist MSS are consistently found to be the most prevalent among construction workers. Existing evidence suggests that female construction workers may be more vulnerable to work-related MSS although the relation between age and MSS prevalence among construction workers remains unclear. Collectively, further prevalence and mechanistic studies are warranted to identify the prevalence and underlying causes of different work-related MSS in various construction trades so that effective prevention and treatment strategies for these MSS can be developed/implemented.

9.2.2 Objective 2: To examine the current trends, different types and research topics related to the applications of sensing and warning-based technology for improving OHS through the analysis of articles published between 1996 and 2017 (years inclusive)

The current review has summarized the trends in the applications of sensing and warning-based technology for OHS in the construction industry from 1996 to 2017 (years inclusive). A three-step approach was used to identify relevant articles for data analysis and discussion. Our findings indicated an increasing annual publication trend on sensing and warning-based technology for the construction industry in recent years. While most of the included articles (34.5%) were published in *Automation in Construction*, other journals have started to publish papers relevant to this topic. Of 10 different types of major sensing and warning-based technologies, direct measurement sensors were most commonly used for the investigation of OHS in the construction industry. Other commonly investigated technologies include remote-sensing techniques and RTLS based on RFID technologies. These sensing and warning-based technology applications can closely complement each other to improve OHS, particularly with sensing networks of on-site safety management. This review also identifies six key research topics in the applications of sensing and warning-based technology for OHS in the construction industry: construction site safety management and monitoring; safety risk identification and assessment; intrusion warnings and proximity detection; physiological status monitoring; activity recognition and classification accuracy; and structural health monitoring. Finally, four major research gaps and future directions were identified and discussed including: (1) application of sensing and warning-based technologies in the total life cycle of a construction project; (2) hardware and software design of sensing and warning-based technologies; (3) application of sensing and warning-based technologies from research to practice; and (4) integration of sensing and warning-based technologies and other advanced information technologies. Future researchers and practitioners can conduct more relevant studies and propose pragmatic interventions based on the identified research gaps, to improve the performance and applicability of sensing and warning-based technology for OHS in the construction industry.

9.2.3 Objective 3: To evaluate the effects of lifting weights and postures on spinal biomechanics (i.e., muscle activity and muscle fatigue) during a simulated repetitive lifting task undertaken within a strictly controlled laboratory experimental environment

The results of the analysis revealed that increased lifting weights significantly increased sEMG activity and muscle fatigue of the BB, BR, LES and MG muscles, except the RF muscles. Moreover, muscle activity and muscle fatigue of LES muscle were higher than all other muscles during repetitive lifting tasks. Furthermore, the results found a significant difference in sEMG activity of the lower limb muscles (RF and MG) between lifting postures. These findings indicate that workers frequently involved in risk factors such as lifting weights, lifting durations and lifting postures during repetitive lifting tasks may increase their risk of developing WMSDs. The identified risk factors can contribute to understanding of WMSDs risk assessment methods to enhance worker health and productivity.

9.2.4 Objective 4: To examine the self-reported discomfort and spinal biomechanics (muscle activity and spinal kinematics) experienced by rebar workers

This is the first study to examine the effect of different lifting weights and lifting postures on the spinal biomechanics of individuals during simulated repetitive rebar lifting tasks. The results reveal that heavier lifting weights significantly: i) increase sEMG activity of lumbar muscles and low back pain intensity; and ii) decrease sEMG MFs of lumbar muscles and time to fatigue regardless of lifting postures. The increase in sEMG activity of lumbar muscles and low back pain intensity indicate that heavier lifting weights increase the amount of back muscle compressive forces acting upon the lumbar spine which can increase the risk of LBDs. The current study also estimates the normative time to fatigue for asymptomatic individuals during repetitive lifting of weights similar to the actual rebar work. These preliminary normative data may help develop practical guidelines for repetitive rebar lifting. In addition, rebar workers should consider the normative time to fatigue associated with lifting weights when designing guidelines for lifting activities, especially for repetitive rebar lifting tasks. Although the stoop and squat lifting postures appeared to elicit similar effects on spinal biomechanics of our participants, stoop lifting significantly increased low back pain compared to squat lifting. This observation substantiates the adoption of squat lifting for minimizing LBDs for workers during repetitive rebar lifting.

9.2.5 Objective 5: To propose a novel approach and efficient method to automatically detect and classify construction workers' awkward working postures based on foot plantar pressure distribution measured by wearable insole pressure system

This study evaluated the use of foot plantar pressure distribution data captured by a wearable insole pressure system to automatically detect and classify awkward working postures, which may be associated with WMSDs among construction workers. Five different awkward working postures (i.e., overhead working, squatting, stooping, semi-squatting, and one-legged kneeling) were performed in a simulated laboratory experiment to examine the feasibility of using the proposed approach. The classification performances of four types of supervised machine learning classifiers (i.e., ANN, DT, KNN, and SVM) were compared in order to select the best classifier using a 0.32s window size. Cross-validation results showed that the SVM classifier obtained the best results with 99.70% accuracy, and sensitivity of correctly classifying each awkward working posture was above 99.00%. This study highlights the feasibility and potential applications of such a wearable insole pressure system for the ergonomic risk assessment of posture-related WMSDs in construction. Moreover, our non-invasive method has the potential to allow safety managers to continuously monitor and minimize workers' exposure to awkward working postures on construction sites. Collectively, the current findings lay the foundation for developing an automated wearable insole pressure system to assist researchers and construction managers to use foot plantar pressure distribution data to prevent WMSDs among construction workers.

9.2.6 Objective 6: To evaluate the effects of different weights and lifting postures on balance control using simulated repetitive lifting tasks

This is the first study to evaluate the effects of different lifting weights and lifting postures on balance control following simulated fatiguing repetitive lifting tasks. The results revealed that: i) increased weight regardless of lifting postures significantly increased CoP parameters; ii) stoop and squat lifting postures performed until subjective fatigue induce a similar increase in CoP parameters; and iii) fatigue adversely effected the participant's balance control on an unstable surface than on a stable surface. These results suggest that fatiguing repetitive lifting tasks may alter the proprioception of the lower limb/back that leads to increased postural sway and suboptimal balance control on an unstable supporting surface. Consequently, fatigued-related loss of balance control may limit the safety range of movement of the body's center of gravity, and thus increase the risk of fall injuries. The findings of the present study have research and practical implications. First, the magnitude of weight during repetitive lifting task can significantly impair balance control and as such reduce the risk of loss of balance events with subsequent fall injuries. Second, surface support conditions are dependent on balance control; as such unstable supporting surfaces can significantly reduce the effort for balance control and therefore could be useful in preventing fall injuries among construction workers. To reduce the possibility of losing balance, unstable supporting structures (e.g., scaffold, ramp) used as working surfaces should be minimized when performing static repetitive lifting tasks. Third, the findings demonstrate the potential of the suggested objective balance stability parameters in measuring static repetitive lifting task associated with fall risk resulted from extrinsic (e.g., weights of lift) and intrinsic (e.g., fatigue) factors. Construction workers can benefit from receiving adequate training in recognizing the role of lifting weights and fatigue during static repetitive lifting tasks, which would result in enhanced balance control through redesign of work and improved workers' behavior. Overall, these findings provide preliminary and invaluable information to researchers and practitioners seeking to develop practical interventions to reduce the risk of falls in construction workers (e.g., masons, rebar workers) involved in repetitive lifting tasks. Future studies should investigate the optimal working and rest durations among workers involving in repetitive lifting works in order to reduce the risk of fatigue-related balance deficit.

9.2.7 Objective 7: To develop a method to detect and classify loss of balance events based on foot plantar pressure distributions data captured using wearable insole pressure sensors.

This paper proposed a novel methodology for automated detection and classification of different types of loss of balance events that may lead to falls on the same level. Toward this goal, wearable insole pressure sensors were employed to collect participant's foot plantar pressure distribution data. Based on our experimental trials, the RF classifier obtained the best results with the accuracy of 97.1% and the sensitivity of each loss of balance event above 94.0% using the window size of 0.32s. The findings of this study suggest that foot plantar pressure distribution data measured by using wearable insole pressure sensors contain valuable information for identifying loss of balance events associated with specific unsafe environmental surface conditions. Overall, the proposed approach and novel method may help safety officers and construction managers to proactively conduct automated fall risk monitoring so as to implement effective fall preventive measures to minimize the risk of falls on the same level on construction sites.

9.3 SIGNIFICANCE AND CONTRIBUTIONS

The overall significance and contributions of this research study are:

1. It contributes to an identified need to study laboratory-based simulated tasks conducted to investigate the risk of developing LBDs among rebar workers primarily caused by repetitive rebar lifting.

2. This study substantiated the feasibility of using a wearable insole pressure system to identify risk factors for developing WMSDs and could help safety managers eliminate workers' exposure to awkward working postures on construction sites.

3. It provides preliminary and invaluable information to researchers and practitioners seeking to develop practical interventions to reduce the risk of developing WMSDs among construction workers (e.g., masons, rebar workers), particularly involved in repetitive lifting tasks.

4. Collectively, the proposed approach can serve as an automated risk assessment tool that allows practitioners to take proactive actions to eliminate the fundamental causes of WMSDs and non-fatal falls injuries among construction workers.

9.4 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Like other reviews, our study has several limitations. First, given the heterogeneous populations, case definitions, work-tasks and study designs of the included studies, our estimated 1-year prevalence should be interpreted with caution. Specifically, the current meta-analysis defined pain cases as having at least one episode of pain/MSS in the last year. The use of such a lenient case definition for meta-analysis without considering other factors (e.g., pain intensity, frequency, duration, work-related disability, or work absence) might have limited the generalizability of the meta-analysis results (Bedouch et al., 2012). Previous epidemiological research has shown that using different case definitions (e.g. based on pain intensity or frequency) to evaluate the MSS prevalence of a given population would lead to different conclusions (Beaton et al., 2000; Village, 2000; Hegmann et al., 2014). Although using a more specific case definition (Table 2.1) in the current meta-analysis could have improved the generalizability and homogeneity of findings specific to the case definition, such approach would have also excluded many primary studies from the meta-analysis. To improve future meta-analyses, future epidemiological studies should use standardized case definitions to evaluate the prevalence of MSS in the construction industry. Second, since many included studies adopted self-reported prevalence without validated medical examinations, their reported prevalence might have been underestimated/overestimated. Third, 29 out of the 35 included studies did not report non-respondents' characteristics, which might represent a group with distinct MSS prevalence. Fourth, since included studies used inconsistent study protocols and period prevalence, future studies should adopt standardized measurement tools and study protocols to enable between-study comparisons.

Like other reviews, the current review has some limitations. Firstly, although a comprehensive search strategy was used in the current review, some relevant studies may have been missed. As such, future review studies should consider adding conference proceedings and special issues to broaden the scope of the study. Secondly, while there are other advanced information technologies and digital design for OHS in the construction industry, the present review only focused on articles related to sensing and warning-based technologies for improving OHS published from 1996 to 2017 (years inclusive). Future reviews may consider more recent articles on sensing and warning-based technology for improving OHS and digital designs in order to provide an updated overview in the construction industry.

Although the conclusions support the effectiveness of implementing potential interventions to reduce WMDS risks, some limitations persist, and hence future research is required in five key areas. First, a larger sample of participants is needed to generate a more robust evaluation and comparison between the different lifting postures and how these impact upon spinal biomechanics and the risk of developing WMSDs. Second, experienced construction workers who have accrued considerable experience of repetitive lifting should be evaluated in any future study conducted (vis-à-vis the novice participants used in this study). Third, a construction site should be used in future experiments as opposed to the strictly controlled laboratory experimental environment adopted – such work would seek to excoriate any differences between a real and simulated lifting task. Fourth, future biomechanical studies are required to investigate the effects of external risk factors such as temperature and humidity during repetitive lifting tasks performed by construction workers on a construction site. Fifth, the current study was limited to only repetitive lifting tasks in construction workers, and therefore the study results may not be generalized to other construction activities (e.g., sawing, hauling)—future research should consider different types of construction workers' activities. Such work will invariably improve the accuracy of any future guidance developed.

Although the current research study provides valuable spinal biomechanical information regarding various lifting weights and postures on a relatively small sample of novice male individuals, the findings might not be generalized to experienced rebar workers or other construction trades due to potential differences in terms of the physical and physiological capacity of their bodies, internal tolerance etc. However, the same research protocol can be adapted to investigate the impacts of lifting weights and postures on spinal biomechanics among older rebar workers. The findings not only can improve our understanding of aging in modifying the relation between lifting posture and spinal biomechanics but also can help develop age-specific preventive strategies in future. Furthermore, because the current study was conducted in a laboratory controlled setting, the impact of the external environment (e.g. high temperature) on the lifting capacity of rebar workers remains unknown. Future research is therefore needed to: i) investigate the impact of various lifting weights and postures on the spinal biomechanics so as to develop appropriate lifting guidelines for workers with different working experiences; ii) determine actual lifting capacity/endurance of rebar workers working on site (vis-à-vis laboratory controlled conditions); and iii) adjust the confounding effects of psychosocial factors, gender, and age group in order to quantify the relationship between different lifting parameters (e.g. lifting speed/duration, lifting weights, height, and lifting postures) and LBDs in rebar workers. Future studies should investigate the cost-effectiveness of using various potential ergonomic interventions and assistive devices in enhancing the productivity of rebar workers and reducing their risk of developing LBDs.

Although our findings have shown the potential for detecting and classifying awkward working postures, which may be associated with WMSDs among construction workers, some limitations should be addressed in future studies. First, our experiments were designed and conducted to only include simulated awkward working postures in a homogenous sample.

Other risk factors should be examined in the future. For example, future works should identify the effects of individual factors (e.g., work experience, age, gender) in modifying the classification of awkward working postures. It is also unknown whether other biomechanical exposures such as repetitive motions, high force exertions, and vibration will affect foot plantar pressure distribution data captured by a wearable insole pressure system. Moreover, future research is warranted to integrate other sensors (e.g., vibrations, temperature) to the wearable insole pressure system to monitor a wider range of biomechanical risk factors. Notably, comprehensive evaluation and identification of various biomechanical exposures and individual risk factors can help safety managers to implement practical interventions to minimize workers' exposure to multiple risk factors on construction sites. Second, since our experiments only collected foot plantar pressure distribution data in static awkward working postures, future research should evaluate the performance of the proposed approach based on different types of sequential motions to analyze dynamic postures (e.g., pushing, lifting, pulling) during construction tasks. By comparing the findings to the current study, the difficulties of applying the proposed approach in different ergonomic postures recognition could be revealed. Besides, the possibility of integrating other vision-based technologies data (e.g., Stereo cameras, Kinect) to foot plantar pressure distribution data in future research studies could provide Kinect skeleton models to realize the visualization of the WMSDs risk factors recognized by the wearable insole pressure system. Third, since only student volunteers were recruited in the current laboratory experiments, future research is warranted to compare the findings with experienced construction workers (e.g., rebar workers, masons) on job sites, which may evaluate the feasibility of using the wearable insole pressure system on construction sites. Fourth, the proposed approach classified awkward working postures solely based on plantar pressure distribution data when participants used their feet as the main support for the whole body. Future studies can investigate if the integration of wearable knee pads to capture knee pressure distribution data can distinguish other awkward postures/movements (e.g., kneeling, crawling). Future research studies can also explore the minimal number of embedded pressure sensing units in a wearable insole for accurate classification of awkward working postures. The outcome can simplify the training time for developing classifier models, and also reduce the cost of the wearable insole pressure system.

However, akin to other proprioception studies that examined repetitive lifting tasks (Sparto et al., 1997a; Lin et al., 2012) the current study has some limitations. First, the sample size was relatively small albeit, significant and second, the study was conducted on student participants in a laboratory setting. Future work should, therefore, evaluate the impact of different lifting parameters on a larger sample size experienced construction workers working on on-site. Third, the study results may not be general with respect to repetitive lifting tasks in construction workers. Although designed to evaluate risk factors in relatively realistic conditions, the current study involved only a static controlled repetitive lifting/lowering task. Also, balance control was evaluated during quiet standing tests, while the majority of fall injuries may occur during dynamic tasks that are initiated by slip, trip and loss of balance events. Earlier research has suggested that balance control system utilizes the same control mechanisms under quiet standing and dynamic test conditions (Lauk et al., 1998). However, future research is warranted to evaluate balance control during real dynamic repetitive lifting tasks, and to investigate how they can be translated to fall prevention in real construction sites. Fourth, it remains unknown how a change in specific lifting posture (i.e., either stoop or squat) may affect balance control. How balance may be associated with increased risk of falls among construction workers remains to be seen given that we did not find a significant change in lifting postures across standing balance tests. Future research is needed to examine other index of fatigue in lifting postures such as reduction maximal voluntary contraction and/or relaxation (Davidson et al., 2009; Paillard et al., 2010b), aspects relating to dehydration (Lion et al., 2010) and physiological effects (Nardone et al., 1997; Mello et al., 2010a).

Although the findings of this study showed potentials for detection and classification of loss of balance events in construction workers, there are some limitations that should be addressed in future studies. First, data collection of loss of balance events was conducted in a laboratory setting by a small sample of novice participants. Future research should compare our results to similar studies by conducting loss of balance events using a large sample of experienced construction workers. Second, despite its great potential as a tool for automated fall risk monitoring, this experimental study was conducted to involve workers' exposure to unsafe environmental surface conditions (i.e., extrinsic risk factors) that could exist on construction sites. Future research needs to detect and classify diverse intrinsic risk factors in construction workers (e.g., work experience, age, and fatigue). Also, it would be beneficial to integrate other sensing and localization technologies such as beacons, light sensors, and cameras into the proposed system in order to (1) provide more robust application solutions for construction workers' safety, and (2) analyze the type of activity being conducted by a worker, which may help in a worker's activity recognition and classification. Third, foot plantar pressure distribution data measured by using wearable insole pressure sensors were wirelessly transferred onto a desktop computer during data collection. Future research should conduct similar experiments using the proposed approach with an application running on a smartphone. This could better aid in both indoor and outdoor environmental settings during data collection.

9.5 CHAPTER SUMMARY

This chapter has summarized the major research findings and acknowledged the limitations of this study. Directions for future research have also been proposed. The information reported herein should shed light on how to evaluate biomechanical risk factors of WMSDs and fall injuries among construction workers, and spark further research interest in the topic.

APPENDICES

Appendix A. The search strategy used in the current review

Academic Search Premier (EbscoHost) search strategies:

1. (Prevalen* OR inciden* OR cross-sectional OR cohort OR perspective OR retrospective OR longitudinal OR follow up OR follow-up*).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
2. (Upper trapezius OR shoulder OR arm OR elbow OR forearm OR wrist OR hand* OR fingers OR thumb).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
3. (Neck OR cervical OR thoracic OR back OR thoracolumbar OR low back OR lumbar OR spinal OR spine OR vertebra* OR sacroiliac OR sacrum OR sacral).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
4. (Coccyx OR hip OR buttocks OR leg OR thigh OR knee OR calf OR shin OR ankle OR foot OR heel OR sole OR toes).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
5. (Ache OR pain* OR disorder*).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
6. 2 AND 5
7. 3 AND 5

8. 4 AND 5
9. Musculoskeletal pain OR Musculoskeletal abnormalities OR Musculoskeletal system OR Musculoskeletal OR musculoskeletal diseases
10. 6 OR 7 OR 8 OR 9
11. (Construction OR carpenter* OR floorlayer* OR bricklayer* OR painter* OR electrician* OR plumber* OR scaffolder* OR roofer* OR mason* OR sheet metal worker* OR floor installer* iron worker* OR rebar worker* OR rodbuster* OR reinforcement worker* OR construction laborer* OR drywall installer* OR insulator*).mp.[mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier]
12. 1 AND 10 AND 11

Note: The same search strategy was used on other databases (i.e., CINAHL, Health and Safety Science Abstract, Medline, PsycINFO, Science Direct, Scopus, SportDiscus and Web of Science)

Appendix B. A quality assessment tool
Guidelines for the critical appraisal and methodological scoring system of the prevalence studies:

A. ARE THE STUDY METHODS VALID?

1. Is the study design appropriate for the research question? (1 point)

2. Is the sampling frame appropriate for prevalence studies? (1 point)

3. Is the sample size adequate (> 300 participants)? (1 point)

4. Are and standard criteria used for measurement outcome (e.g. Nordic Musculoskeletal Questionnaire)? (1 point)

5. Is the health outcome measured in an unbiased fashion? Were the results validated via medical checkup? (1 point)

6. Is the response rate adequate (70%)? Are the refusers described? (0.5 point each)

B. WHAT IS THE INTERPRETATION OF THE RESULTS?

7. Are the estimates of prevalence given with confidence intervals? Is sub-group analysis done? (0.5 point each)

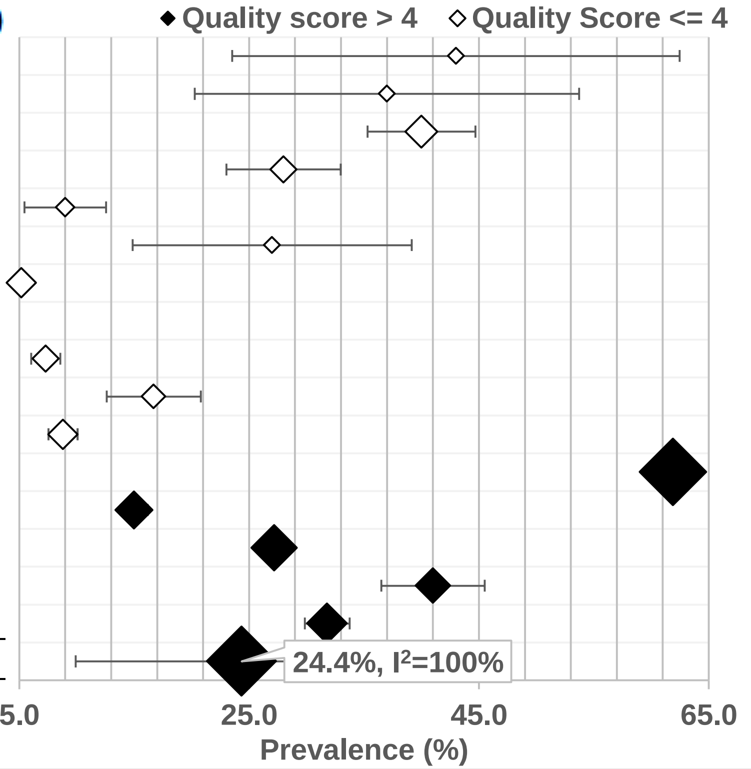
C. WHAT IS THE APPLICABILITY OF THE RESULTS?

8. Are the sociodemographic characteristics and the setting described in detail? (1 point)

Appendix C. 1-year prevalence of different anatomical MSS in construction industry

1-year prevalence of neck MSS in different construction trades

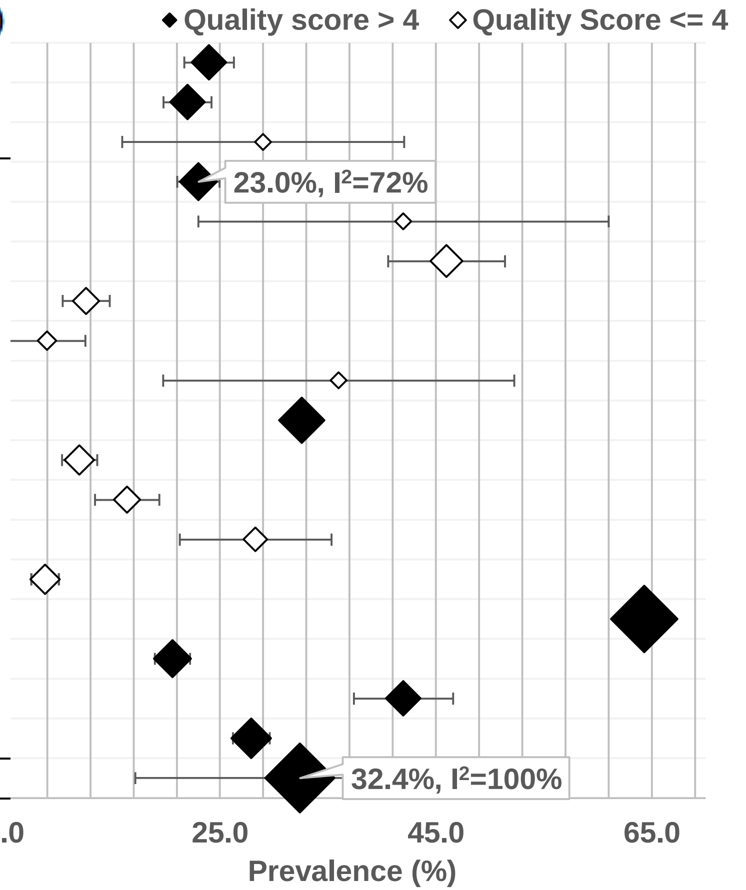
Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Iron-workers	Hanklang et al. (2014)	Thailand	272
Laborers	Telaprolu et al. (2013)	India	118
Managers	Pandey et al. (2012)	India	22
Plumbers	Eaves et al. (2016)	UK	55*
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	82,185
	Guo et al. (2004)	Taiwan	578
	Lee et al. (2005)	Taiwan	2,021
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of shoulder MSS in different construction trades

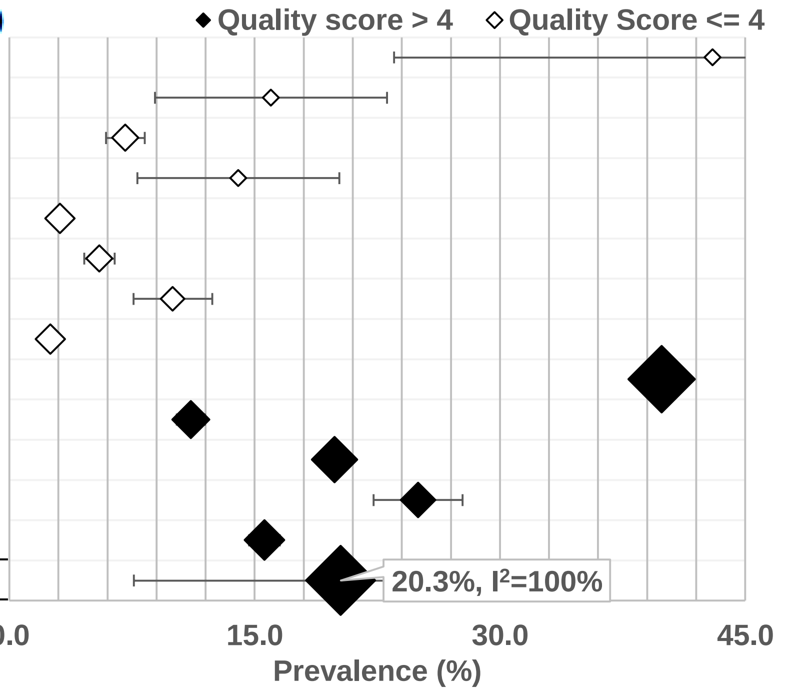
Trade	Study Name	Country	Sample (n)
Carpenters	van der Molen et al. (2009)	Netherlands	401
	(5-year follow-up)		361
	Eaves et al. (2016)	UK	55*
	Mean prevalence (carpenters)		
Electricians	Eaves et al. (2016)	UK	55*
Iron-workers	Hanklang et al. (2014)	Thailand	272
Laborers	Telaprolu et al. (2013)	India	118
Managers	Pandey et al. (2012)	India	22
Plumbers	Eaves et al. (2016)	UK	55*
Scaffolders	Lee et al. (2005)	Taiwan	2,021
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	82,451
	Guo et al. (2004)	Taiwan	578
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of elbow MSS in different construction trades

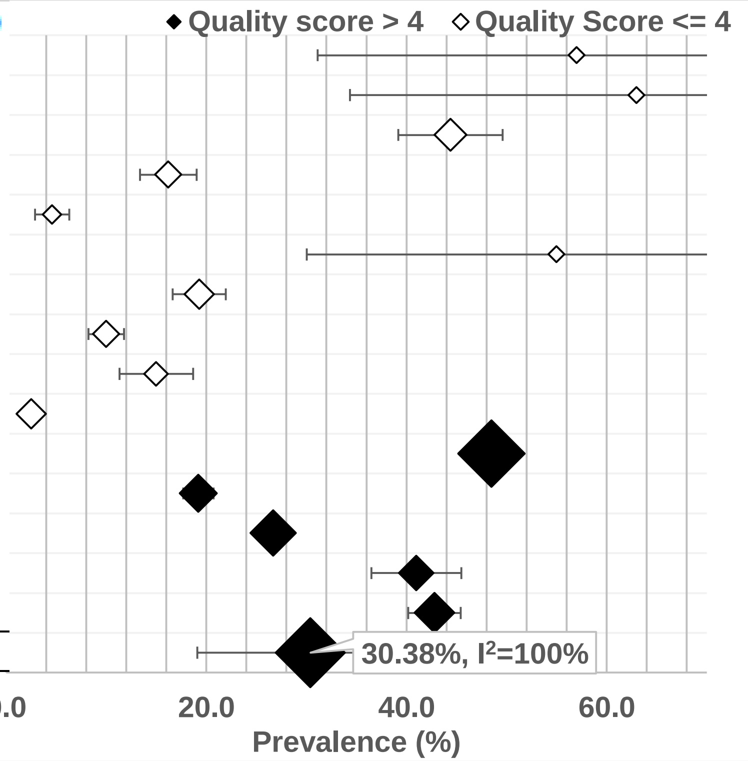
Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Laborers	Telaprolu et al. (2013)	India	118
Plumbers	Eaves et al. (2016)	UK	55*
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	81,615
	Guo et al. (2004)	Taiwan	579
	Lee et al. (2005)	Taiwan	2,021
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of wrist MSS in different construction trades

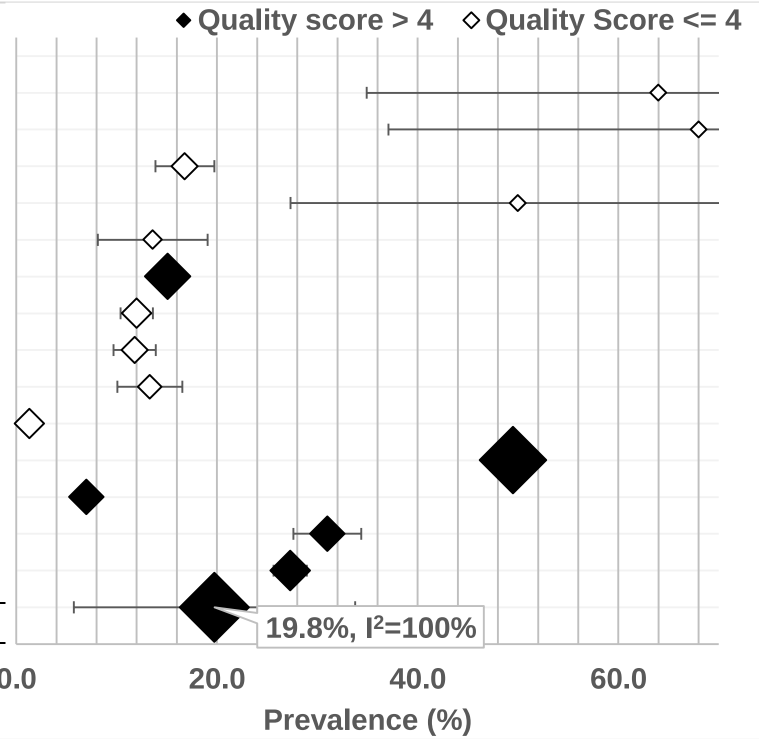
Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Iron-workers	Hanklang et al. (2014)	Thailand	272
Laborers	Telaprolu et al. (2013)	India	118
Managers	Pandey et al. (2012)	India	22
Plumbers	Eaves et al. (2016)	UK	55*
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	81,616
	Guo et al. (2004)	Taiwan	582
	Lee et al. (2005)	Taiwan	2,021
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of upper back MSS in different construction trades

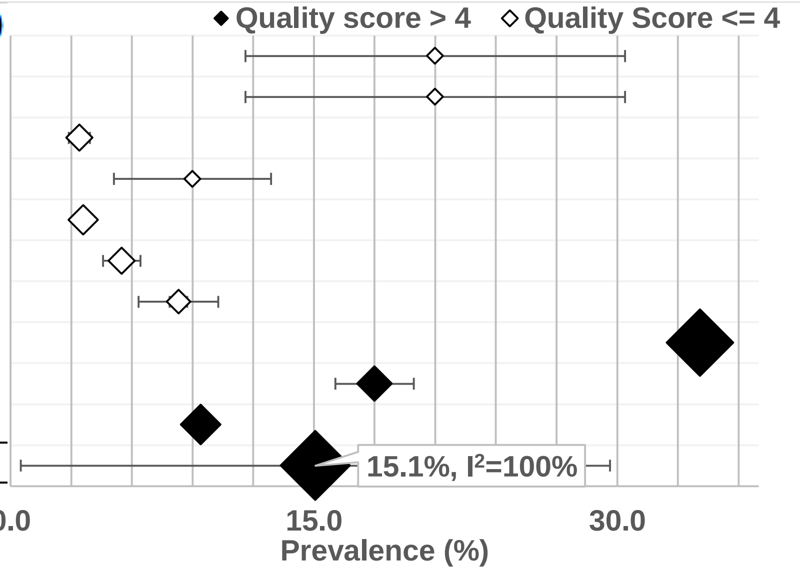
Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Laborers	Telaprolu et al. (2013)	India	118
Plumbers	Eaves et al. (2016)	UK	55*
Managers	Pandey et al. (2012)	India	22
Scaffolders	Lee et al. (2005)	Taiwan	2,021
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	80,836
	Guo et al. (2004)	Taiwan	482
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of hip/thigh MSS in different construction trades

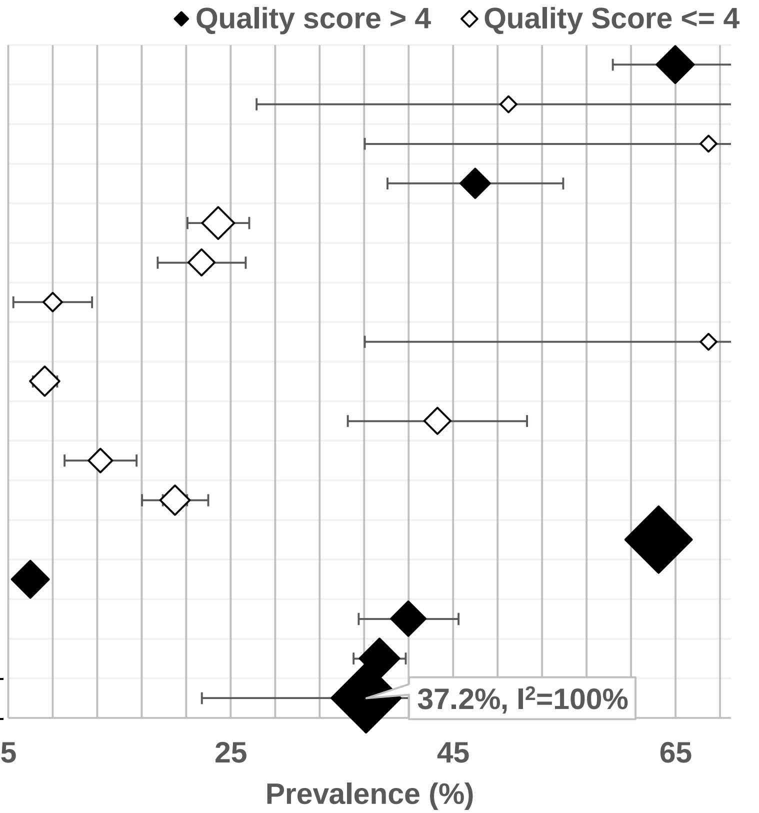
Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Laborers	Telaprolu et al. (2013)	India	118
Plumbers	Eaves et al. (2016)	UK	55*
Multiple	Rosecrance et al. (2001)	Hungary	193
trades	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Engholm and Holmström (2005)	Sweden	81,372
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of knee MSS in different construction trades

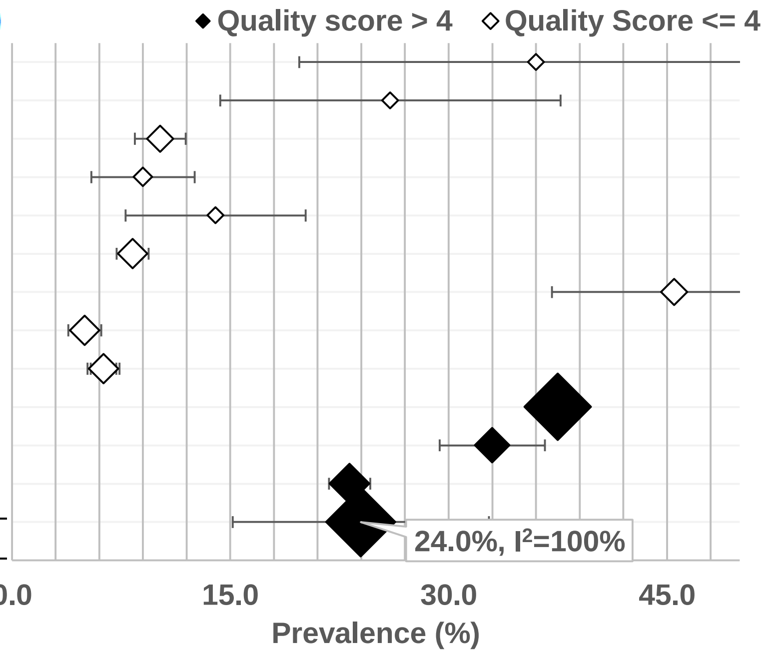
Trade	Study Name	Country	Sample (n)
Carpenters	Jensen et al. (2000)	Denmark	506
	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Floor layers	Jensen et al. (2000)	Denmark	133
Iron-workers	Hanklang et al. (2014)	Thailand	272
Laborers	Telaprolu et al. (2013)	India	118
Managers	Pandey et al. (2012)	India	22
Plumbers	Eaves et al. (2016)	UK	55*
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	82,682
	Guo et al. (2004)	Taiwan	578
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studies.

1-year prevalence of ankle/foot MSS in different construction trades

Trade	Study Name	Country	Sample (n)
Carpenters	Eaves et al. (2016)	UK	55*
Electricians	Eaves et al. (2016)	UK	55*
Laborers	Telaprolu et al. (2013)	India	118
Managers	Pandey et al. (2012)	India	22
Plumbers	Eaves et al. (2016)	UK	55*
Multiple trades	Rosecrance et al. (2001)	Hungary	193
	Gheibi et al. (2009)	Iran	110
	Deros et al. (2014)	Malaysia	60
	Alghadir and Anwer (2015)	Saudi Arabia	165
	Engholm and Holmström (2005)	Sweden	81,766
	Goldsheyder et al. (2002)	US	312
	Merlino et al. (2003)	US	996
Overall	**Mean prevalence**		



Note: MSS = Musculoskeletal symptoms,
The size of ◆ is proportional to the log of the sample size, the bars indicate 95% confidence interval,
* indicates that the sample sizes of individual trades were not available. Therefore, the study was not used in the meta-analysis.
The quality scores ranged from 0 to 8. Studies scored < 4 were classified as low quality, while those scored higher than 4 were classified as high quality.
Some data points do not show the confidence intervals because the sample sizes are so large that they conceal their respective confidence intervals.
Mean prevalence was calculated using data from all relevant studies, excluding the outliers originated from the low-quality studie

Appendix D. Research project informed consent form

RESEARCH PROJECT INFORMED CONSENT FORM

Project title: Evaluation of Risk Factors for Work-Related Musculoskeletal Disorders and Fall Injuries among Construction Workers through Biomechanical Analysis and Postural Control.

Principal investigator: Professor Heng Li, Chair Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Co-investigators: Antwi-Afari Maxwell Fordjour, Ph.D. student, Department of Building and Real Estate, The Hong Kong Polytechnic University;

Dr. Arnold Y.L. Wong, Assistant Professor, Department of Rehabilitation Sciences, The Hong Kong Polytechnic University;

Dr. JoonOh Seo, Assistant Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Project information

The objective of this study is to develop a method that can automatically detect and classify slip, trip, and loss of balance (STL) events based upon a participant's foot plantar pressure distribution data captured from smart wearable insole sensors. This experiment involves a single visit in a laboratory setting.

Possible benefits to you and the society

You will receive a travel allowance of HK$100 if you are not studying at the Hong Kong Polytechnic University. Our results will contribute to providing STL events mechanisms information that can be used for proactive fall-prevention measures of construction workers.

Possible risks

Risk of fall injuries: Participants may fear the risk of fall injuries during the simulated STL events. However, appropriate safety harness and 30cm thick mattress will be fixed to prevent participants from actual falls and recovery steps.

Confidentiality

The personal information related to this study will be subjected to the confidentiality and privacy regulations. If the data will be used for publication in the medical literature or for teaching purposes, no names will be used.

CONSENT TO PARTICIPATE IN RESEARCH

I, ……………………………………………… have been explained the details of this study. I voluntarily consent to participate in this study. I understand that I can withdraw from this study at any time without giving reasons, and my withdrawal will not lead to any punishment or prejudice against me. I am aware of any potential risk in joining this study. I also understand that my personal information will not be disclosed to people who are not related to this study and my name or photograph will not appear on any publication resulted from this study.

I can contact the principal investigator, Professor Heng Li at 2766 5879 for any questions about this study. If I have complaints related to the investigator, I can contact Ms. Chloe Shing, Secretary of Departmental Research Committee, at 2766 5808. I know I will be given a signed copy of this consent form.

…………………………………………..	………..…………………………
Signature of participant	Signature of researcher
……………………………………………	……………………………………
Name of participant	Name of researcher
……………………………………………	……………………………………
Date	Date

Appendix E. Information sheet

INFORMATION SHEET

Project title: Evaluation of Risk Factors for Work-Related Musculoskeletal Disorders and Fall Injuries among Construction Workers through Biomechanical Analysis and Postural Control.

Principal investigator: Professor Heng Li, Chair Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Co-investigators: Antwi-Afari Maxwell Fordjour, Ph.D. student, Department of Building and Real Estate, The Hong Kong Polytechnic University;

Dr. Arnold Y.L. Wong, Assistant Professor, Department of Rehabilitation Sciences, The Hong Kong Polytechnic University;

Dr. JoonOh Seo, Assistant Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Project information

Participants will be invited to participate in a research project aimed to develop a method that can automatically detect and classify slip, trip, and loss of balance (STL) events based upon a participant's foot plantar pressure distribution data captured from smart wearable insole sensors. Prior to participation, it is relevant for the participant to understand the reasons for conducting this study and what it will involve. The researcher will explain the study to you in details. Participants should read the following information carefully and discuss it with the researcher (or other people) if you want. At any time, participants are welcome to ask for more information. Participants should take their time to decide whether or not to participate in this research study.

Falls are the primary cause of construction workers' injuries. Falls on the same level are associated with STL events caused by a disruption of unexpected walking gait. These events may not always lead to falls, but have also potential to cause secondary injuries by workers' sudden reactions (e.g., striking one's arm against a sharp object, uneven surfaces while carrying a load) to recover from imbalance. Preventing falls on the same level should start from understanding how and why they occur at construction sites, which is very challenging. Each STL event that may lead to falls on the same level has a different underlying mechanism of the fall process and are associated with extrinsic risk factor (e.g., site conditions, types of hazardous activities). In this regard, we propose an automated classification of different types of STL events that may lead to falls on the same level by using wearable insole sensors, aiming to understand the causes of falls on the same level in a timely manner. As the wearable insole sensors are light-weight and can be inserted on workers' safety boots, they do not interfere with on-going work.

Objectives

The primary objective of the current study is to identify and classify construction workers' STL events from their foot plantar pressure distribution data. The secondary objective is to evaluate potential fall-preventive measures of construction workers' STL events mechanisms associated with the extrinsic risk factors.

Procedure

1. Recruiting of participants, administration of self-reported demographics questionnaire and providing of written consent form.
2. In all trials, a safety harness and 30cm thick mattress will be provided to reduce the circumstances of actual fall injuries.
3. Prior to the start of the experiment, we will conduct training sessions with each participant; for each type of STL event.

4. We will display a representative video of a real-life STL events experienced by construction workers, and instruct the participant to act in a similar fashion.
5. The sequence of conducting the various types of STL events will be randomized, and each participant will perform 10 trials of each STL event with one minute break between two successive trials.

Measurements

Foot plantar pressure distribution data

During the trials, a pair of wearable insole sensors will be inserted into the participants' safety boots to collect 26 streams of foot plantar pressure distribution data. The sampling frequency of the real-time pressure distribution data will be collected at 50 Hz.

Possible benefits to society

The result from this study will help ergonomist and construction practitioners to identify workers fall on same level risks by predicting extrinsic factors or hazards based upon the detected STL events. Also, the developed method will contribute to providing STL events mechanisms information that can be used for proactive fall-prevention measures of construction workers.

Possible risks

Risk of fall injuries: Participants may fear the risk of fall injuries during the simulated STL events. However, appropriate safety harness and 30cm thick mattress will be fixed to prevent participants from actual falls and recovery steps.

Confidentiality

Your personal information related to this study will be kept confidential. Any research data collected about you during this study will not identify you by name, only by a coded number. Your name will not be disclosed outside the research center. Any report published as a result of this study will not identify you by name.

Voluntary participation

Participants are free to withdraw from the research study at any time. We will update you all the possible new knowledge that may influence your decision to continue in the study.

Termination

If during the study new information suggests that participant should not participate or that the study should be terminated, Dr. Wong can withdraw you from the study without your approval.

Contact name and telephone numbers

If you have any complaints related to the investigator, you can contact Ms. Chloe Shing, secretary of the Department Research Committee on 2766 5808.

Please contact the principal investigator if you have any questions or concerns: Professor Heng Li, Chair Professor in the Department of Building and Real Estate. Tel:2766 5879 or 6017 .

Signature………………………………………… Date ………..05/06/2017…………….

Appendix F. Summary of research project

SUMMARY OF RESEARCH PROJECT

Project title: Evaluation of Risk Factors for Work-Related Musculoskeletal Disorders and Fall Injuries among Construction Workers through Biomechanical Analysis and Postural Control.

Principal investigator: Professor Heng Li, Chair Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Co-investigators: Antwi-Afari Maxwell Fordjour, Ph.D. student, Department of Building and Real Estate, The Hong Kong Polytechnic University;

Dr. Arnold Y.L. Wong, Assistant Professor, Department of Rehabilitation Sciences, The Hong Kong Polytechnic University;

Dr. JoonOh Seo, Assistant Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University.

Abstract

Falls are the primary cause of construction workers' injuries. Falls on the same level are associated with slip, trip, and loss of balance (STL) events caused by a disruption of unexpected gait. Therefore, we propose an automated classification of different types of STL events that may lead to falls on the same level by using wearable insole sensors, aiming to understand the causes of falls on the same level in a timely manner. Ten young healthy participants will participate in experimental trials involving falls on the same level due to STL events experienced by construction workers. Foot plantar pressure distribution data acquired during the STL events were input to supervised machine learning classifiers [e.g., artificial neural network (ANN), support vector machine (SVM)]. As the wearable insole sensors are light-

weight and can be inserted on workers' safety boots, they do not interfere with on-going work. The implications of this study are of value to researchers and practitioners because the method quantitatively measures the type of events and provides a computational tool that records automated foot plantar pressure distributions, which can help to understand fundamental causes of fall-related injuries among construction workers.

Given the above, objectives of the current project are: (1) to identify and classify construction workers' STL events from their foot plantar pressure distribution data; (2) to evaluate potential fall-preventive measures of construction workers' STL events mechanisms associated with the extrinsic risk factors.

Population

Asymptomatic male individuals aged between 18 to 60 years without (1) a history of mechanical upper extremities or back pain or lower extremities injury; and (2) a history of neurological conditions or disabilities or other conditions that affected fall and/or balance will be recruited.

Outcomes

Supervised machine learning classifiers (e.g., artificial neural network, support vector machine) were used to classify the walk, slip, trip, and loss of balance events, using the extracted features from the labeled training data set.

Possible benefits to society

The result from this study will help ergonomist and construction practitioners to identify workers fall on same level risks by predicting extrinsic factors or hazards based upon the detected STL events. Also, the developed method will contribute to providing STL events mechanisms information that can be used for proactive fall-prevention measures of construction workers.

Possible risks

Risk of fall injuries: Participants may fear the risk of fall injuries during the simulated STL events. However, appropriate safety harness and 30cm thick mattress will be fixed to prevent participants from actual falls and recovery steps.

Confidentiality

The personal information related to this study will be kept confidential. Any research data collected about the participant during this study will not identify the participant's name, only by a coded number. The participant's name will not be disclosed outside the research center. Any report published as a result of this study will not identify the participant's name.

Signature……………………………………Date……………..05/06/2017……….

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