Analysis of Relationships between Body Load and Training, Work Methods, and Work Rate: Overcoming the Novice Mason's Risk Hump

JuHyeong Ryu[1]; Abdullatif Alwasel[2]; Carl T. Haas, F.ASCE[3]; and Eihab Abdel-Rahman[4]

Abstract: Masons regularly perform physically strenuous and demanding duties that may exceed a safe limit. Such activities can contribute to an early retirement for masons, resulting in a shortage of skilled craft workers. Previous ergonomic studies have observed that workers develop safer and more productive work techniques as they gain experience. This study aims to analyze relationships between body loads, experience, and work methods. Specifically, we expanded a previous pilot study by increasing the number of participants from 21 masons to 66 masons. Participants completed a prebuilt standard concrete masonry unit (CMU) lead wall using 45 CMUs. Motion capture suits were used to capture masons' motions, and a combined biomechanical-productivity analysis was carried out to determine the loads experienced by major body joints. Exploiting the larger dataset, this study assessed how different experience groups load their joints and adjust their work techniques as the work height changes. The results suggested that experienced journeymen adopt similar work techniques distinct from those of less experienced workers. Further, training apprentices to adopt these work methods can help reduce occupational injuries and improve productivity. The results show that the journeymen with more than 20 years of experience adopt safer and more productive work techniques distinct from those of less experienced workers. The present study contributes to the body of knowledge on masons' safety and productivity by providing an in-depth understanding of the linkage between body loads, work experience, techniques, and productivity. Additionally, the findings in this study are expected to have a greater impact when they are adopted to apprentice-training methods and applied to other high musculoskeletal-disorders-risk trades. **DOI: 10.1061/(ASCE)CO.1943-7862.0001889.** *© 2020 American Society of Civil Engineers.*

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Introduction

Continued exposure to occupational injury risk in the construction industry, such as work-related musculoskeletal disorders (WMSDs), leads to the early retirement of workers who suffer injuries prematurely in their careers. More importantly, this exposure can cause a shortage of skilled craft workers, resulting in an increase of the aging worker population problem. Contrarily, labor demand in Canada's construction industry continues to escalate. Estimates call for 300,000 new workers to be recruited, trained, and retrained over the next decade (BuildForce Canada 2019). As a result of the rising labor demands, a significant emphasis has been placed on adequate worker training to improve safety performance and efficiency among current and new-hire employees (Teizer et al. 2013).

[1]Ph.D. Candidate, Dept. of Civil and Environmental Engineering, Univ. of Waterloo, 200 University Ave. West, Waterloo, ON, Canada N2M 0A9 (corresponding author). ORCID: https://orcid.org/0000-0001-5836-9968. Email: j4ryu@uwaterloo.ca

[2]Assistant Professor, Dept. of Biomedical Technology, King Saud Univ., Riyadh 13362, Saudi Arabia. Email: alwasel@ksu.edu.sa

[3]Professor, Dept. of Civil and Environmental Engineering, Univ. of Waterloo, 200 University Ave. West, Waterloo, ON, Canada N2M 0A9. Email: chaas@uwaterloo.ca

[4]Professor, Dept. of System Design Engineering, Univ. of Waterloo, 200 University Ave. West, Waterloo, ON, Canada N2M 0A9. ORCID: https://orcid.org/0000-0002-3709-7593. Email: eihab@uwaterloo.ca

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Skilled craft workers are mainly supplied through different sources of craft training, such as apprenticeship programs, community colleges, and firm-sponsored training (Wang et al. 2008). Through these training programs, workers are taught essential work skills (e.g., proper use of tools) and work safety to reduce occupational risks (Albers et al. 1997; Wang et al. 2008). An evaluation of the effectiveness of training programs is usually done qualitatively using subjective means, including manual observation and surveying (Teizer et al. 2013). One limitation is that there is no quantitative score or index for apprentice performance. Furthermore, apprentices lack the necessary training loop feedback on postures and motions that would provide sufficient data to produce the functional adaptation. In particular, qualitative evaluations do not provide a full understanding of proper work methods for apprentices, thereby adding a layer of challenge to proactive injury prevention.

To provide quantitative evaluations of apprentice performance, collecting and analyzing their work motions are essential. Namely, working postures and movement patterns are primary inputs for evaluating ergonomic risks due to their association with joint load (joint force/joint moment) in which there is a vulnerability to WMSDs (NIOSH 2014; Punnett and Wegman 2004). Recent advanced sensing technologies, such as wearable inertial measurement units (IMUs), have enabled the acquisition of a broad range of accurate motion data (Valero et al. 2016; Chen et al. 2017). This data has allowed researchers to look at improving safety performance (Dzeng et al. 2014; Jebelli et al. 2016; Yang et al. 2017; Zhang et al. 2019a, b), work efficiency and productivity (Joshua and Varghese 2014; Ryu et al. 2016, 2019), and ergonomic analyses (Nath et al. 2017; Ryu et al. 2018; Valero et al. 2016, 2017) within the construction industry. Collectively, a great potential for predicting and monitoring worker safety and productivity are in the

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previous motion data studies. Nonetheless, there has been little research into how workers interpret appropriate or inappropriate working methods, as well as how to reduce or eliminate the inappropriate working process.

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

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

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

In the present study, we expand on the previous pilot study to analyze relationships between body loads, work experiences, and work methods by significantly increasing participant numbers from 21 masons to 66 masons. The objective of this study is to evaluate how different work experience groups load their joints and adjust their work postures. Furthermore, we investigate whether journeymen adopt different work techniques that are safer and more efficient than those of apprentices and whether the higher injuries among apprentices can, therefore, be explained. Finally, we exploit the larger sample to investigate differences in masonry work methods and their relationships to joint loads, experience level, and working height.

Background

Prevalence of Occupational Injury Risks in Construction and Masonry Trade

Construction workers perform physically strenuous and demanding tasks repeatedly that lead to physical fatigue and may exceed a safe limit. These tasks also involve significant risk factors of WMSDs, such as overexertion, repetitive motion, and awkward posture. Continued exposure to WMSD risks is associated with workers' injury and loss of workdays, which can cause the deterioration of well-being and economic costs (Cheng et al. 2013; Gatti et al. 2014).

In 2016, the US Department of Labor (BLS 2016) reported that WMSDs accounted for 31% (a total of 349,050 cases) of all injuries requiring days away from work. Notably, laborers and freight, stock, and material movers reported the highest number of cases (24,810). Over the last ten years, sprains and strains were reported as being the leading nature of injuries in Canada, while overexertion was the leading injury event, which accounted for 38% and 18%, respectively, of allowed lost-time claims in 2016 (WSIB 2017). The US Center for Construction Research and Training (CPWR 2013) reported that the number of WMSDs in construction have continuously dropped between 1992 and 2010; however, in 2010, the rate of WMSDs in construction was still 16% higher than for all industry combined (rate of 32.8 per 10,000 full-time workers). Even worse, the overall reported numbers may be underestimated due to the probability of injuries going underreported and the difficulty of estimating work-relatedness of musculoskeletal disorders (CPWR 2013). Because the reports are from both the US and Canada, it is evident that the risks of WMSDs are significantly prevalent in North America.

Among construction trades, the masonry trade has the highest rate of overexertion injuries resulting in days away from work (66.5 per 10,000 full-time equivalent workers), which is even more than double the rate for the construction field overall (28.5 per 10,000 full-time equivalent workers) (CPWR 2013). The high injury rates in masonry are closely related to physically demanding tasks. Particularly, manual block lifting, which is an integral part of masonry work, requires masons to perform frequent deep bending of their trunk to lift heavy materials—such as concrete masonry units (CMU) (Hess et al. 2010; van der Molen et al. 2004). According to Hess et al. (2010), block masons manually lift at least 200 CMUs per day, and considering the standard CMU size and weight ($0.19 \times 0.19 \times 0.38$ m and 16.6 kg) (CCMPA 2013), masons manually typically lift over 3,300 kg per workday. Moreover, masons spend up to 53% of their working time in a bending posture in order to pick up materials at ground or knee level and 38% of working time in aggravating postures (Boschman et al. 2011). Frequent handling of heavy materials with bending postures exposes masons to severe lower back injuries, and in practice, the back injury rate for masons is the second-highest among construction subsectors (CPWR 2013).

WMSD Risk Assessment Methods

Awkward body-postures and motions with external forces tend to create excessive musculoskeletal stresses beyond the internal tolerance of tissues (Kumar 2001). Appropriate work posture is also considered an essential factor for improving productivity on the job (Gilbreth and Gilbreth 1917). Although posture and motion information are considered the primary parameters in different assessment methods, current practices rely heavily on manual observation to acquire the motion data. Furthermore, although manual observation is straightforward and easy to use, it may be prone to inaccuracies and inconsistencies due to human errors (Valero et al. 2016).

To overcome the drawbacks of manual observation, recent motion capture systems have drawn attention. These systems enable the quantitative measurement of human motions. Particularly, wearable IMU motion suites—a 3D sensor platform integrating an accelerometer, gyroscope, and magnetometer—have generated excitement due to their ability to track full-body motion continuously using measured acceleration, angular rate, and magnetic field orientation (Chen et al. 2017; Seel et al. 2012). Moreover, IMUs firmly attached to the major body segment allow direct tracking of worker motions without interrupting ongoing tasks. Accurate estimations for joint kinematics using IMU-based systems have been observed in several studies in comparison to a gold standard (optical motion capture system) (Schall et al. 2016).

Wearable IMUs that are integrated with different assessment methods enable automated and objective investigation of worker-related issues in the construction sector. Valero et al. (2016, 2017) developed a joint-angle based system to detect unsafe working postures of construction workers based on the standardized rules of the ISO. Zhang et al. (2019a, b) assessed the level of physical exertion and fatigue by analyzing jerk, the time derivative of acceleration. Furthermore, the use of ankle-located IMUs have been studied to examine fall-risks caused by balancing failure (Jebelli et al. 2016; Yang et al. 2014, 2015). In addition, IMUs with activity recognition were used to track productivity among masonry workers (Joshua and Varghese 2014; Ryu et al. 2016, 2019).

As such, utilizing motion data obtained from IMU-based systems has a distinct potential for practical assessment of worker safety, health, and productivity issues. Current studies have contributed to the monitoring of ergonomic risks and tracking work performance. Meanwhile, high occupational injuries and low productivity among apprentice-level trade workers remain a critical problem in the construction industry. Nevertheless, such deteriorations can tend to result from a lack of understanding of the correct working methods and procedures that trade workers should be employing.

Injury Rate by Gained Experience

With more working experience, workers earn essential skills and knowledge of safe working procedures that enhance their performance (Ayim Gyekye and Salminen 2010). In the reported occupational injury statistics, many researchers have found that more experienced workers encounter fewer injuries on the job than their less experienced counterparts (Oh and Shin 2003; Keyserling 1983; Siskind 1982). Therefore, a comparison of working methods between expert and novice has been highlighted to identify appropriate working practices in terms of safety and productivity. For instance, Authier et al. (1995, 1996) identified that the strategies of experts differed from those of novices' during manual handling (e.g., straightening back, orienting pelvis, and taking short steps).

Considering the lower injury rates among experts, different experts' strategies are a significant indication for safer and more efficient working methods. These findings have potential as a means of injury prevention and practical training for apprentices (Plamondon et al. 2010). Thus, evaluating the consequences of different strategies is essential to transfer the practical knowledge to apprentices, and a biomechanical analysis can be an effective solution (Gagnon 2005). The biomechanical analysis estimates a load on the body segments using a two-dimensional (2D) or a three-dimensional (3D) biomechanical model (Radwin et al. 2001). An estimation of joint loads can provide a quantitative evaluation of safer working methods. However, only a few studies have been interested in an experience-based biomechanical analysis, and these studies were validated in a limited laboratory environment with restricted conditions (Plamondon et al. 2010, 2012; Gagnon 2005). Therefore, it can be said that a quantitative investigation of the relationship between body loads (biomechanical analysis) and levels of experience, work methods, and productivity have not yet been studied sufficiently (Alwasel et al. 2017a).

Subsequently, we had the opportunity to expand the pilot study (Alwasel et al. 2017a), concentrating on masons who enrolled in different levels of the apprenticeship program and journeymen with 20 years of experience. We thereby utilized the aforementioned IMU-based motion capture systems to collect whole-body kinematics and conducted a combined onsite biomechanical-productivity analysis. As a result, the extension of this study has more than tripled our previous sample size, enabling detailed evaluations of the hypothesis raised by the initial investigation in the pilot study.

Methodology

In our pilot study, we hypothesized and confirmed that experienced masons adopted safer and more productive methods than less experienced masons (Alwasel et al. 2017a). In this study, we firstly evaluated a combined biomechanical-productivity analysis with an increased sample size to improve the confidence in the results. Further, we investigated differences and similarities of adopted working methods between experience groups. The materials and methods have been described in detail in the pilot study conducted by Alwasel et al. (2017a). Only the main points are described in this article.

Participants

In Ontario, Canada, the 3-year masonry apprenticeship program consists of onsite and in-school training. Upon completion, an apprentice can apply to become certified as a journeyman. Sixty-six healthy masons with different work experiences were recruited to collect motion data at two institutions: the Ontario Masonry Training Centre in Waterloo and the Canada Masonry Design Centre in Mississauga, Ontario, Canada. The participants were grouped into four different cohorts based on their experience: (1) novice with no experience, (2) 1-year of experience, (3) 3-years of experience, and (4) journeyman with twenty or more years of experience. The number of participants and their demographics are shown in Table 1. Because participants were only requested to report their work experience categorically, their average age was estimated by taking a weighted measure of their years of work experience and distributing it by the proportion of the number of participants in each group. The estimated average age of each group is (1) 22.63 ± 6.35 years in novice, (2) 25.84 ± 4.79 years in 1-year apprentice, (3) 28.56 ± 3.59 years in 3-year apprentice, and (4) 40.93 ± 3.12 years in journeyman. This study and its protocols were approved by the Institutional Review Board (IRB) of both the University of Waterloo and Conestoga College.

Table 1. Demographics of participants

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

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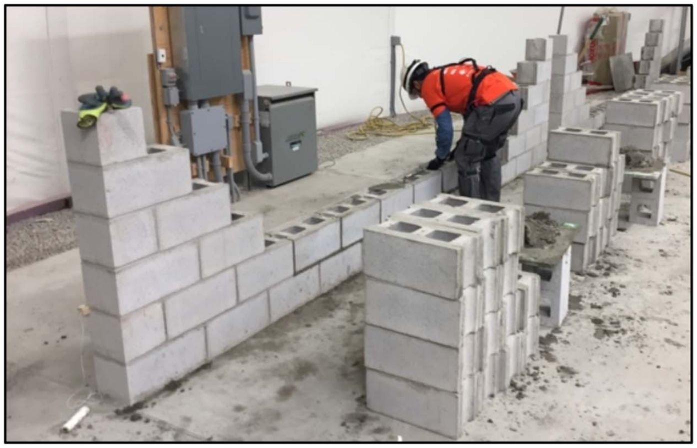

(a)

(b)

Fig. 1. Experiment configuration: (a) placing a CMU at the second course; and (b) sixth course.

Experimental Setup and Protocol

Each participant completed a prebuilt lead wall using 45 CSA-Type A CMUs weighing 16.6 kg with dimensions of $0.19 \times 0.19 \times 0.39$ m (CCMPA 2013). The prebuilt lead wall consisted of 27 CMUs with a six-course height. The participants laid down CMUs from the 2nd course to the 6th course. The CMUs were placed in the three pallets approximately 1 m away from the lead wall, and mixed mortar was provided by helpers in two mortar trays placed between the pallets. The experiment configuration is shown in Fig. 1. A wall might take 30–60 min to build.

Two sets of wireless motion capture suits, namely, MVN Awinda (Xsens 2016) and Perception Neuron (Noitm 2017), were utilized to acquire whole-body motion data during the experiment. Each suit consists of 17 IMUs, while each unit is composed of a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer. Specifically, the IMUs were firmly attached using elastic straps to the head, back, each of the shoulders, upper and lower arms, hands, upper and lower legs, and feet. Moreover, all participants reported that the motion capture suit was comfortable and did not interrupt their work.

At the beginning of the experiment, participants performed a calibration procedure to determine the sensor-to-body alignment and body dimensions as directed by the motion capture software, MVN Studio (Xsens 2016) and Axis Neuron (Noitm 2017), which required the participant to take a T-pose, an A-pose, and an S-pose. The motion data was sampled at a frequency of 125 Hz. The suits' software, MVN Studio version 4.4 and Axis Neuron version 3.8.42.8591, were designed to reconstruct 3D human skeleton models from the collected data. Both systems implement a Kalman filter and a proprietary algorithm, respectively, to counteract sensor drift. Each of the experiments was recorded using camcorders to enable labeling and segmentation during the data processing phase.

Data Processing

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

The obtained motion data was extracted as Biovision Hierarchy (BVH) files that define hierarchical body segments as local rotation and translation information from a root body joint, namely, the hip (Meredith and Maddock 2001). Then, the global position (3D coordinates) of body joints in the BVH file were repeatedly computed from local transformation matrices based on the hierarchical kinematic structure of humans. In this study, a BVH viewer version 1.0 software, which enables the export of 3D joint information from a BVH file to .txt files, was used. Finally, 28 body joint positions in three axes (i.e., X, Y, and Z) were obtained from the processed motion data. As the motion data was segmented into 45 single lifts, the 3D joint center information was also stored into 45 individual files.

Biomechanical Analysis

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

Due to the intensive computation required to estimate the internal loads on 3D whole-body biomechanical models, software packages have been used for biomechanical studies (Seo et al. 2015). Likewise, one software program utilized in our research was the 3D static strength prediction program (3DSSPP), a biomechanical analysis tool to estimate physical demands (e.g., spinal compression force and joint moments) using a static biomechanical model (Center for Ergonomics at the University of Michigan 2016). The biomechanical analysis in this study follows the approach utilized in the pilot study (Alwasel et al. 2017a). The loads experienced by major body joints were examined using IMU-based motion data and 3DSSPP version 6.0.7.

To run the biomechanical analysis in 3DSSPP, the BVH motion files are converted to location files and formatted for a special hierarchical description of the body joint center location (X, Y, and Z coordinates). Therefore, we converted the BVH files to .loc files using developed MATLAB version 9.6 (R2019a) code. Combining the participants' anthropometric parameters (height and weight) with joint location files corresponding to their lifts, along with the external forces (e.g., CMU weight) they experience, we obtained the compression force of the lumbar joint and the moments in the elbow, shoulder, L5/S1 disc, hip, and knee joints. With an estimation frequency of 125 Hz per joint, per mason, the overall data collected totals approximately 2 TB.

In this analysis, the dynamic estimates of joint loads were not analyzed. Alternatively, we treated the masonry motion as a set of static postures, which is the current standard practice in the ergonomic analysis. The analysis finds the most critical posture defined by a peak force or moment registered in the mason's posture. Finally, the peak joint loads were averaged and compared according to different experience groups and course heights.

Productivity

In their typical job environment, masons are expected to complete a predetermined number of CMUs per day. Thus, productivity is an essential part of a mason's career. In this analysis, productivity was measured for all participants by recording the average time taken by

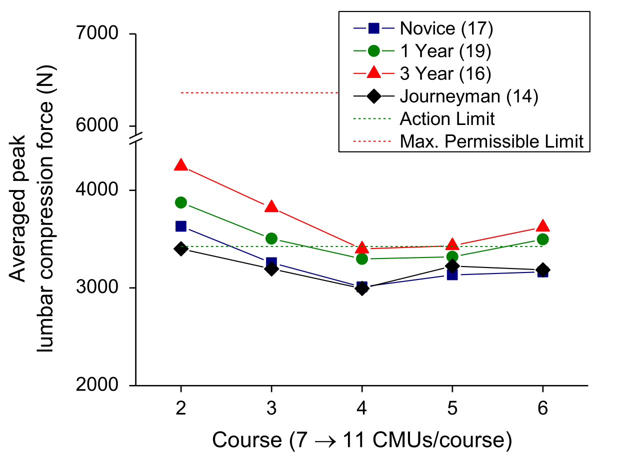

Fig. 2. Averaged peak lumbar compression force by levels of experience to complete each course (analysis of 2 TB of data).

masons to complete the laying of a block. The analysis sheds light on whether work experience enhances productivity substantially more than safety or whether experts gain both safety and productivity skills.

Results

For each lift, we identified the peak joint compression forces and moments, as these are the most critical for posture. The peak joint loads were then grouped according to the participant's levels of experience and course height. Therefore, the averages of the peak joint loads (i.e., most critical working postures) were investigated for each category.

Joint Loads and Work Experience

We concentrated more on the lumbar compression force (L4/L5–L5/S1), as it was found to be the most crucial load point in the trunk and was linked to lower back pain among the estimated loads on different joints (Alwasel et al. 2017a). The lumbar joint load is also considered to encourage the advancement of safe methods (Plamondon et al. 2010).

Fig. 2 shows the lumbar compression force arranged by levels of experience. What is also defined in the figure is the loading threshold defined by the National Institute for Occupational Safety and Health (NIOSH) (i.e., the action limits are 3,433 N, and the maximum permissible limits are 6,376 N). Interestingly, journeyman and novice groups achieved more lower lumbar compression force values than the midexperienced groups. Particularly, the journeyman group achieved a lumbar compression force lower than the action limits through all five courses. On the other hand, all groups experienced the lowest lumbar compression force when working on the 4th course. The statistical significance of the body of observations is explored subsequently in this paper.

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

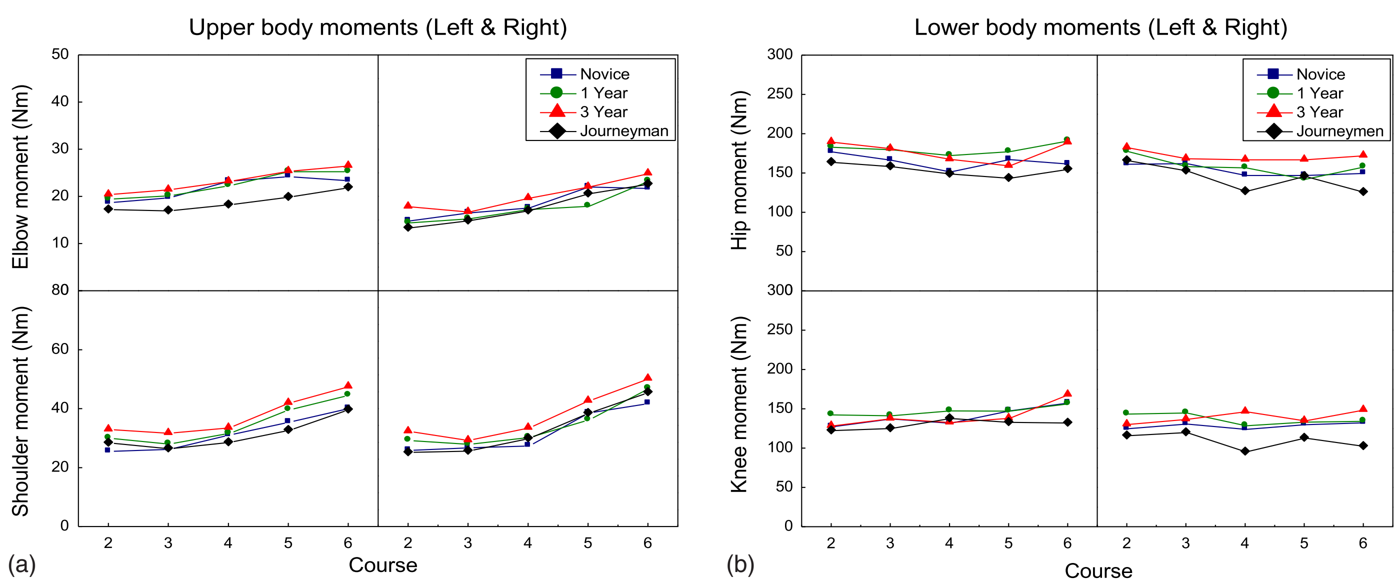

Fig. 3. Averaged peak joint moments by levels of experience to complete each course: (a) upper body; and (b) lower body.

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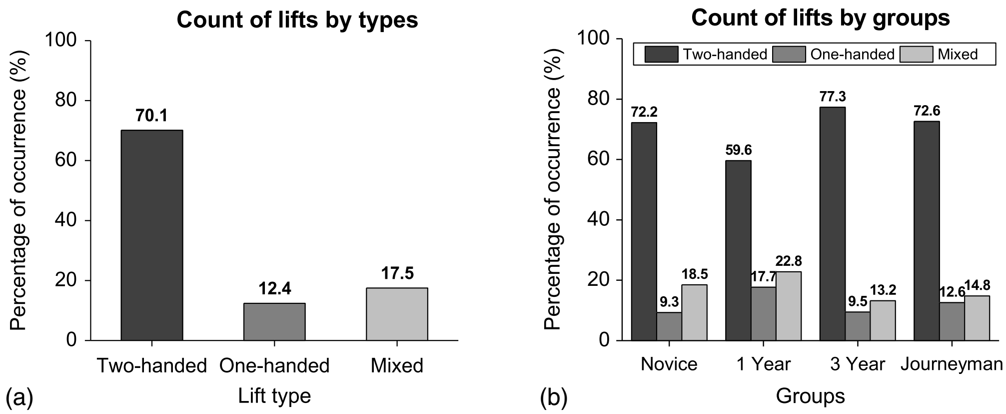

Fig. 4. (a) Count of lift by types; and (b) count of lift type by groups.

increasing joint moments in the upper body by completing higher courses.

Joint Loads with Lift Type

In the current experiment, we observed that participants handled CMUs with different lift types (Fig. 4). While most of the participants handled CMUs using a two-handed lift (70% of all lifting), 12.4% of all lifting was done one-handed, a method using only one hand from picking up to laying down CMUs. The remainder of the tasks involved mixed lifts, such as picking up a CMU with a one-handed lift and then switching to a two-handed lift at the halfway point of the lift. The same proportion of lift types was observed among experience groups, except for 1-year apprentices.

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

Significant asymmetry occurs to the body when handling a CMU with only one hand. Thus, we compared the joint moments between one-handed and two-handed lift types. We examined joint moments on the side of the carried block and free-loading sides because participants have different dominant hands (e.g., right-handed and left-handed). Fig. 6 shows the joint moments at the upper and lower bodies by two lift types and levels of experiences. While all groups experienced symmetric joint moments on the right and left sides of the body during two-handed and one-handed lifts, it was apparent that there were significant asymmetric joint moments present between carrying and free-loading sides.

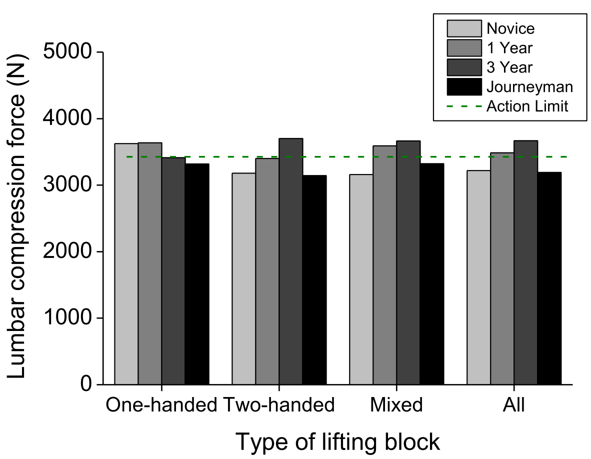

Fig. 5. Lumbar compression force at L4/L5 level by lift type and experience level.

Productivity

While each participant placed the same number of CMUs during the controlled experiment, the completion time varied as per their

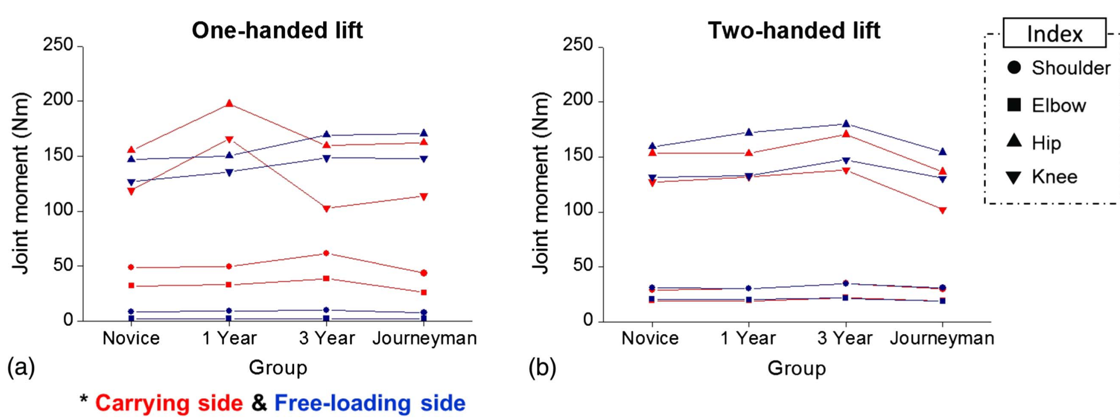

Fig. 6. (a) Joint moments by one-hand lift; and (b) two-hand lift by levels of experience.

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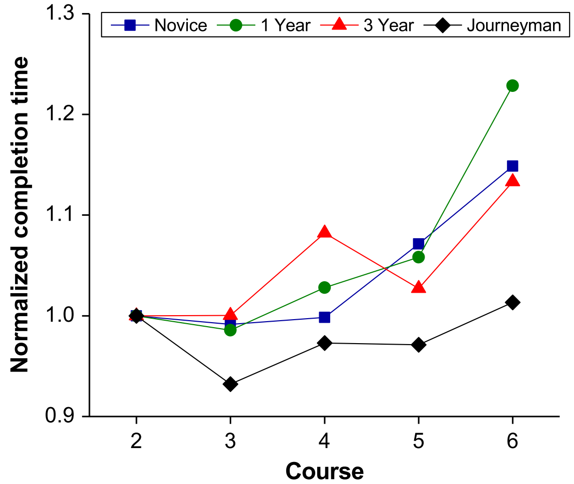

Fig. 7. Normalized completion time per course for four experience groups.

work experiences. Specifically, journeymen completed building the wall with the shortest time, being an average of 28 min, while novices, 1-year, and 3-years apprentices completed an average of 56, 37, and 40 min, respectively. Similarly, when converting the completion time to the number of CMUs laid per minute, journeymen laid about twice as many CMUs as novices (1.63 CMU/min and 0.83 CMU/min). These results follow the same trend shown in the initial report by Alwasel et al. (2017a), which was based on a subset of the data in this study. As discussed in their study, expert masons appeared to adopt safe working methods while maintaining high efficiency as their work experience increased (Alwasel et al. 2017a, b).

We also investigated productivity loss that occurred as the experiment progressed. An average time taken to lay a CMU for each course was found for each experience group from the 2nd course to the 6th course. Then, the averages were normalized with respect to the 2nd course average (Fig. 7). The normalized time taken to lay a CMU for each course indicates changes in pace throughout the task. While novice, 1-year, and 3-years apprentice groups dropped their pace at the end, journeymen maintained an almost constant pace from the 2nd to the 6th course.

Discussion

We carried out a combined biomechanical-productivity analysis on masons with varying levels of experience. This study expands the number of participants from 21 in our previous work (Alwasel et al. 2017a) to 66. Specifically, 3-year apprentices experienced the highest lumbar compression forces, while novices and journeymen experienced relatively lower joint compression forces. Furthermore, the journeymen group achieved the highest productivity, corresponding to the time taken to complete the lead wall, which was shown to be twice as fast as the novice group.

To examine the significance of differences in the mean of peak joint loads among the experience groups, we carried out a one-way Analysis of Variance (ANOVA) using SPSS version 21. The significance level was set to 5%. The name of the joint loads, experience groups, mean and standard deviation, ratio of variability among the groups to the variability within group F, and p-value are listed in Table 2. The analysis confirms that all joint loads of the journeyman group were significantly different from the less experienced groups. Three-year apprentices especially experienced higher joint loads with a significant difference with the journeyman group for all joint loads. We conclude that these results accord with our previous results, which showed that journeymen have distinguishable work postures causing low joint loads.

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

To investigate the dispersion of the dataset between the pilot study and the current study, we measured the normalized standard deviation for the lumbar joint forces, which is defined as the standard deviation for each group divided by the mean for all participants (Fig. 8). For all groups, the overall results were increased compared to the pilot study. Specifically, novice, 1-year apprentice, and journeyman groups increased by 10%, 3%, and 5%, while 3-year apprentice groups showed an increase of 31%. Although the number of participants for each group increased approximately two or three times, the dispersion of the experienced lumbar compression force is similar, except for the 3-year apprentice groups. The finding also indicated that the higher diversity of working methods and motions existed in the 3-year apprentice groups.

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

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

We examined the relationship between the lift type and course height in Fig. 9. We found that journeymen never use one-handed lifts to place a CMU at the 6th course. Instead, they more frequently used mixed lifts than other groups. To place a CMU on the 6th course of the wall, participants needed to pick a CMU near the ground level and lay down the CMU at the height of approximately 120 cm. Therefore, participants moved the CMU a longer distance over a significant height difference. This difference may result in excessive joint stress. Instead, the journeyman group used the momentum to pick up a CMU from the ground level in a one-handed lift, and they switched to a two-handed lift during the swing phase to increase the stability and distribute the load on both sides of the body.

The statistical significance of the differences among the anthropometrics (height and weight) of the four experience groups was

Table 2. Joint loads averaged by levels of experience and corresponding one-way ANOVA results

Joint loads	Experience group	Mean	Std. dev.	F value (*p*-value)	Post hoc tests
Lumbar compression force	Novice (a)	3,217.61	779.01	47.812 (0.00*)	c > a, b, d
	1-year (b)	3,485.06	810.00		b > a, d
	3-years (c)	3,668.19	1,050.69		(Dunnett T3)
	Journeyman (d)	3,190.98	767.54		
Center of hip moment	Novice (a)	186.49	41.28	31.921 (0.00*)	c > a, b, d
	1-year (b)	194.93	38.17		b > a, d
	3-years (c)	203.67	52.29		(Dunnett T3)
	Journeyman (d)	182.42	40.80		
Right elbow	Novice (a)	19.04	8.10	13.107 (0.00*)	c > a, b, d
	1-year (b)	17.88	9.99		(Dunnett T3)
	3-years (c)	20.72	10.44		
	Journeyman (d)	18.34	7.55		
Left elbow	Novice (a)	22.26	9.78	28.787 (0.00*)	c > a, d
	1-year (b)	22.76	9.49		a > d
	3-years (c)	23.84	10.02		b > d
	Journeyman (d)	19.24	8.05		(Dunnett T3)
Right shoulder	Novice (a)	28.99	13.36	14.406 (0.00*)	c > a, b, d
	1-year (b)	30.20	15.55		(Dunnett T3)
	3-years (c)	33.89	17.38		
	Journeyman (d)	30.02	12.60		
Left shoulder	Novice (a)	32.60	14.34	26.873 (0.00*)	c > a, b, d
	1-year (b)	35.22	14.81		b > a, d
	3-years (c)	38.48	16.92		(Dunnett T3)
	Journeyman (d)	31.98	13.20		
Right hip	Novice (a)	153.44	60.80	25.732 (0.00*)	c > a, b, d
	1-year (b)	158.55	59.88		a > d
	3-years (c)	171.69	67.46		b > d
	Journeyman (d)	142.40	59.27		(Dunnett T3)
Left hip	Novice (a)	165.01	56.52	30.916 (0.00*)	c > a, d
	1-year (b)	181.46	50.76		b > a, d
	3-years (c)	177.31	65.53		(Dunnett T3)
	Journeyman (d)	154.02	59.92		
Right knee	Novice (a)	129.51	72.03	24.99 (0.00*)	c > a, d
	1-year (b)	137.45	65.85		a > d
	3-years (c)	140.83	80.38		b > d
	Journeyman (d)	109.44	69.81		(Dunnett T3)
Left knee	Novice (a)	142.47	75.57	6.084 (0.00*)	c > d
	1-year (b)	148.03	65.26		a > d
	3-years (c)	143.10	77.33		b > d
	Journeyman (d)	131.52	74.06		(Dunnett T3)

Note: $*p < 0.05$.

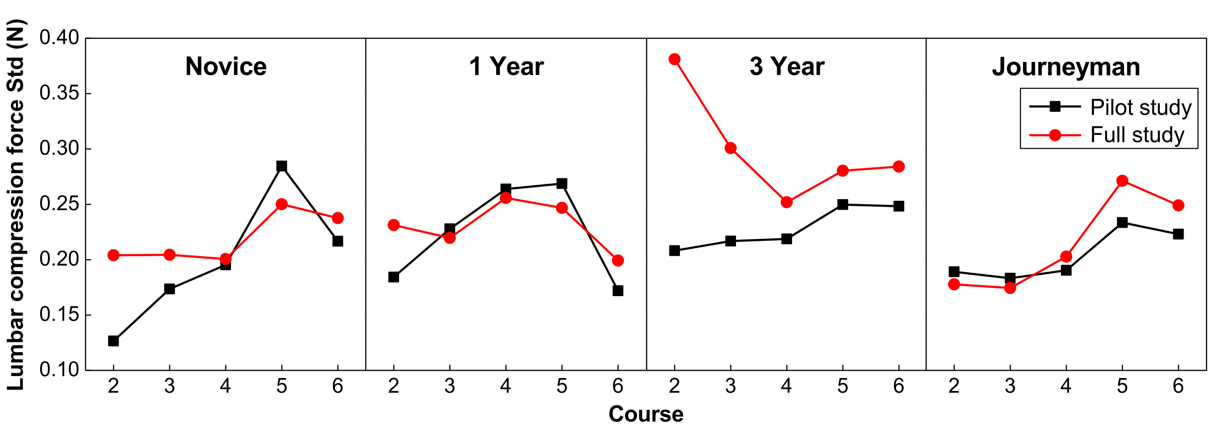

Fig. 8. Normalized standard deviation of lumbar compression force comparison by courses.

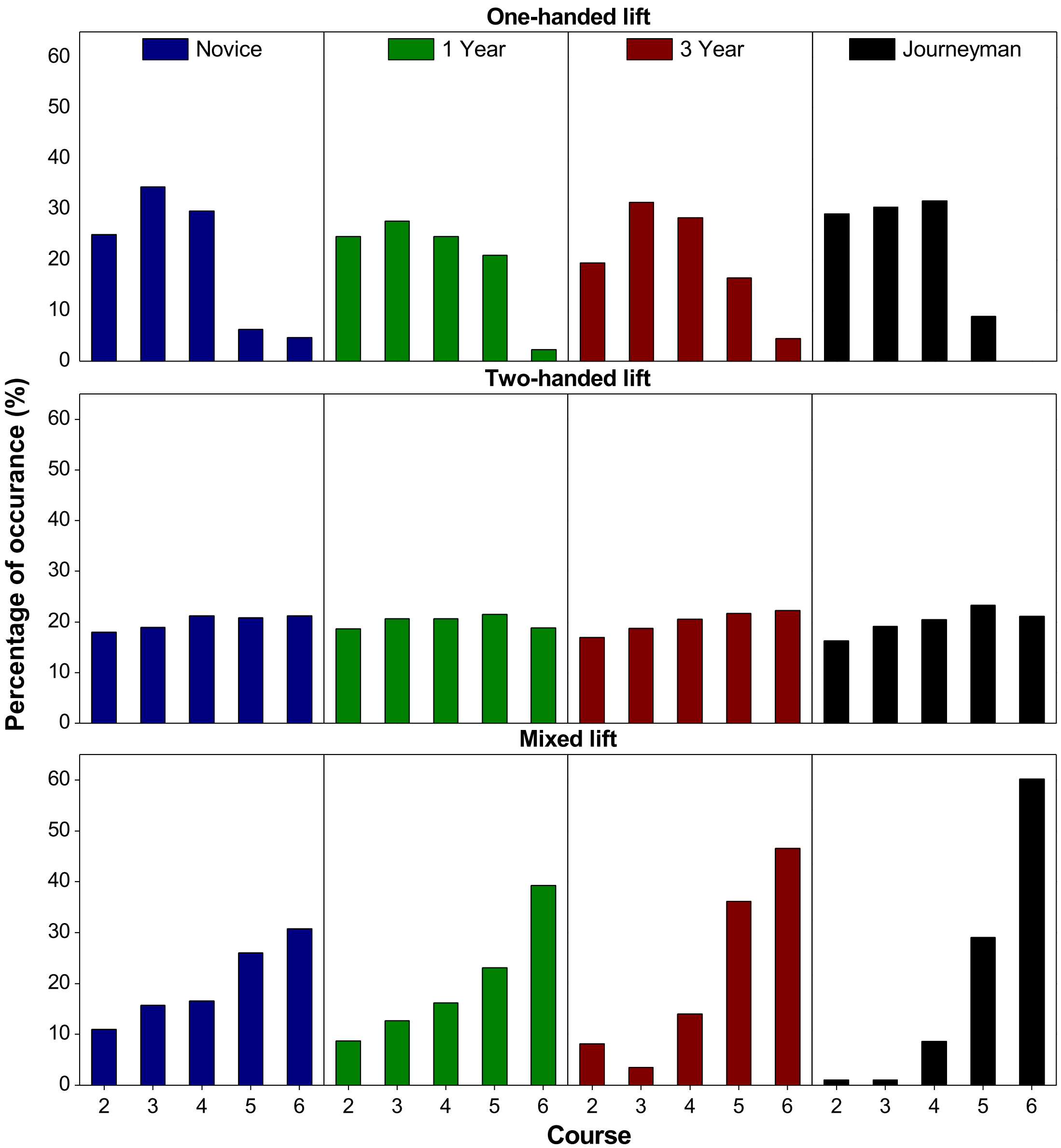

Fig. 9. Percentage of each lift type by course for all experience groups.

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

Regarding the relationship between productivity and levels of experience, journeymen achieved considerably higher productivity rates than less experienced groups. For example, journeymen had a CMU/min approximately two times higher than the novices and 30% more productive than the midexperience groups. Further investigation was focused on determining productivity loss by tracking the working pace to complete each course (Fig. 7). It was found that all novice and apprentice groups decreased their working pace as they progressed through the experiment, while the journeymen maintained theirs. The findings on productivity analysis indicated that journeymen adopted working methods that were not only efficient but also minimized the loss of productivity. The average completion times for 1-year and 3-year apprentices were similar, but the decline in productivity was greater among 1-year apprentices.

Our recent study—which utilized a subset of data of the present study—examined the physical exertion of the bricklaying process by analyzing jerk values, which were used for measuring motor control (Zhang et al. 2019b). Journeymen marked the lowest jerk indicating that they moved with smooth motions and a high degree of motor control while 3-year apprentices performed the lift tasks with the highest jerk values, indicating inferior motor control. Given these findings and the results of the biomechanical and productivity analysis in this study together, journeymen adopted working methods that help control their body properly, resulting in not only minimizing physical exertion but also maximizing productivity. Midexperience groups performed with higher productivity than novices, but their working methods were accompanied by higher joint loads and poor motor control. In our previous studies, we suggested possible explanations to support these findings: (1) midexperience groups appeared to be in competition with their

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peers during the experiment; and also, (2) they perceived peer-pressure to reach their seniors' productivity level.

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

Conclusion

The current study evaluated relationships between body loads, levels of experience, and work methods of masons. This study extends the preliminary work of Alwasel et al. (2017a) by increasing the number of participants from 21 to 66 masons and expanding the analysis to examine variations in work methods and their relationship to work height. All participants completed a prebuilt lead wall using 45 standard CMUs. Their joint loads and productivity were assessed by utilizing a motion capture system to measure their motions and carry out a combined biomechanical-productivity analysis on those motions. Participants were grouped into four different cohorts based on their experience, from novice with no work experience to journeyman with twenty or more years of experience.

This study has shown that the four experience groups adopted different motion patterns, resulting in different degrees of joint loads while they performed the same tasks. The levels of experience are also closely related to production rates. More specifically, journeymen and novices experienced relatively lower joint loads than those of 1-year and 3-year apprentice groups. The productivity rate tended to increase with more cumulative experience, while productivity loss was negatively related to experience. Furthermore, it was found that the various experience groups adopted different CMU handling methods according to working height, namely, one-handed, two-handed, and mixed lifts. Overall, these findings have indicated that journeymen adopt safer and more efficient working methods that are distinct from those of apprentices. The less-experienced groups had either higher joint loads increasing the likelihood of injury, as is the case for 1-year and 3-year apprentices, or lower production rates, as is the case for novices.

The main contribution of this study is a comprehensive understanding of the relationship among body loads, work experience, work methods, and productivity. The results of this study show the experienced journeymen with more than twenty years of experience adopt similar work techniques distinct from those of less experienced workers. This study found that those work techniques were more productive and safer, suggesting their adoption in apprentice training to reduce the prevalence of occupational injuries and to improve productivity. Finally, the methods described in this study suggest an approach that can be applied to other high MSD-risk trades.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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