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Health and productivity impact of semi-automated work systems in construction

JuHyeong Ryu[a], Tasha McFarland[b], Bennett Banting[c], Carl T. Haas[a,*], Eihab Abdel-Rahman[b]

[a] Department of Civil & Environmental Engineering, Faculty of Engineering, University of Waterloo, 200 University Avenue West, Waterloo, ON N2L 3G1, Canada
[b] Department of Systems Design Engineering, Faculty of Engineering, University of Waterloo, 200 University Avenue West, Waterloo, ON N2L 3G1, Canada
[c] Canada Masonry Design Centre, 360 Superior Blvd, Mississauga, ON L5T 2N7, Canada

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ABSTRACT

Variability of construction sites and tasks make their automation prohibitively complex. Workers continue to carry out physically demanding tasks which adversely affect their health, safety, and productivity. The flexibility of semi-automated work systems, where operators work in conjunction with machines and robots, is an attractive alternative. It is critical to estimate the anticipated effectiveness of these interventions before integrating them into the current work processes. This study proposes a systematic and objective methodology to assess the value of a semi-automated work system in a construction context, as it pertains to reduced exposure to musculoskeletal disorder risks and productivity improvements. Additional assessments are also suggested for a complete analysis of efficacy. The proposed methodology was validated through an experimental evaluation of a force-assist self-leveling pallet in a masonry task. It provides an objective evaluation of impact on the task showing 40% reduction in joint loads and 10% increase in productivity.

1. Introduction

Due to the physically strenuous and demanding tasks in construction fieldwork, work-related musculoskeletal disorders (MSDs) have been widely reported as a considerable challenge in the construction industry [1–6]. The estimated risk of MSDs for construction workers was 50% higher than all other workers [6]. In addition, in 2017, the Bureau of Labor Statistics reported that the incidence rate of MSDs was 31.2 for every 10,000 full-time workers in the construction industry across the U.S. [7].

Despite being one of the oldest industries, the level of automation and robotics in the construction industry has only begun to advance in the past few decades, lagging behind other industries such as automotive and manufacturing [8–10]. Furthermore, continuous changes in construction sites demand manual intervention by laborers, which is a concern due to the high number of injuries and MSDs associated with the trades [11].

Howe [12] states that the automation of manual labor in building processes can be categorized as a robotic system that consists of: (a) independent work cells, which can be integrated into traditional building method techniques; (b) stationary on-site factories; and (c) dynamic on-site factories which move as the building is completed. Modern research developments promote fully automated or near-fully automated building processes—such as the Shimizu Manufacturing System by Advanced Robotics Technology (SMART) system [13], autonomous mobile robots [14], contour crafting [15], and other 3D printing techniques [16]. However, full automation is not yet feasible based on the available technologies and the current challenges of the industry [12,14,16]. These limitations have led to the emergence of semi-automated work systems in construction where human operators work in conjunction with automation and robotics [8,17–20].

In particular, semi-automated force-assist systems have the potential to mitigate MSD risk exposure from physically demanding tasks by directly targeting task demands and biomechanical exposures for operators. For example, robotic arms that externally support weight and maneuver tools on construction sites offload physical demands from the operator onto the mounting system, thereby reducing the associated risk [21]. Furthermore, Warszawski and Navon [22] suggested that robotics could generate economic value by performing the most physically demanding tasks (e.g., heavy lifting, reaching to the ceiling and/or floors) to reduce costs caused by injuries and time loss, leaving the more complex finishing tasks to humans. As such, several streams of semi-automation research in construction have been targeted towards improving the safety of operators concerning MSDs [8,22–24].

The primary goal and driving factor for the development of automation in construction has been the production and economic value

* Corresponding author.
E-mail address: chaas@uwaterloo.ca (C.T. Haas).

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[8,22,23]. A market research questionnaire about the importance of various attributes when implementing automation into construction revealed that the number one priority was increased productivity, followed by improved quality control and reliability, with safety being listed as the third most important attribute [25–27]. Nevertheless, well-designed and implemented ergonomic interventions often have economic value as well, either through the reduction of injuries, worker compensation, lost days or other associated indirect and direct costs of MSDs, or through increased productivity [28–31]. According to the National Safety Council (NSC) [32], estimated industrial work injury costs were $161.5 billion in 2017, including wage and productivity losses, medical expenses, and administrative expenses. Therefore, integrating automation into the work system could reduce exposures to injury risks, and consequently save billions of dollars annually by reducing industrial work injuries.

For effective MSD risk control in construction, most current practices rely on “briefly and generally” written safety guidelines or expert assessments [33]. However, these methods are limited for providing quantitative assessments and can result in subjective evaluation consequences. Therefore, quantitative and objective assessment of MSD risk exposure as well as work productivity of operators is critical to evaluate the impact of implementing automation work systems into traditional work processes.

In this paper, semi-automated work systems are defined as construction equipment which automates a component of a task and is designed to be used in conjunction with manual laborers to complete the task, with a focus on force-assist systems. This study targets the implementation and integration of semi-automated systems with traditional working processes. Previous methodologies have been proposed to assess the value of integrating new work systems into traditional systems in a construction context. Those methodologies focused on either project-level evaluation of full automation [23,34] or were limited to worker productivity [35,36]. This work proposes a systematic and objective methodology to assess the value of semi-automated work systems in a construction context, where value is assessed in terms of both reduction in risk exposure to MSDs and improvements in productivity. A broader and more complete assessment of value prior to implementing such a system would also include analysis of: (1) net present value, (2) safety impact, (3) morale impact, (4) quality effects, (5) competitiveness impacts, and (6) process changers required. Validation of this methodology is demonstrated through an experimental evaluation of a force-assist self-leveling pallet in a masonry task.

2. Methodology

The flowchart of the methodology to evaluate semi-automated work systems is outlined in Fig. 1. The general steps of the methodology involve the following components: the identification of at-risk tasks within the job, a quantitative assessment of biomechanical demands and productivity, a proposal of semi-automated work systems and their integration into current work processes, experimental evaluation of the proposed equipment, and a final implementation decision and plan. Expanding the system boundaries of this type of evaluation is possible by carefully aggregating the basic health and productivity elements of the methodology in a way that accounts for all tasks and activities within the bounded system. An early perspective on this was published by Skibniewski [37].

2.1. Identify at-risk tasks or activities

The first step is to identify which tasks should be prioritized for the introduction of automation in the workplace. The presence of risk factors such as force, repetition, duration, awkward posture, contact stress or vibration can point to at-risk tasks [33,38]. Furthermore, reported occupational injury data (e.g., the incidence rate of nonfatal occupational injury and illness cases reported by the U.S. Bureau of Labor Statistics) may indicate high-risk areas for MSDs. Lastly, critical bottlenecks that affect productivity are also areas where automation can be introduced. Production bottlenecks may be caused by undesirable ergonomic standpoints [39], therefore, the introduction of automation has the potential to mitigate the adverse effects that impact health and productivity concurrently.

2.2. Objective assessments

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

2.2.1. Types of assessment

To evaluate biomechanical exposures in the field of construction, practitioners and researchers have developed different assessment methods and tools. The approaches can be divided into four groups according to the data measurement techniques: self-reports, observational assessments, direct measurements [40], and simulation-based methods. In addition, due to several benefits—such as low-cost and its ease of use—both self-reports (e.g., checklists and diaries) and observational assessments (e.g., direct observation through ergonomic experts) are widely used in most worksites [41]. However, self-reports can be subjective and unreliable [42] and observational assessments can be prone to inaccuracies and inconsistencies due to human error and missing information [43].

Simulation-based methods can also be used to evaluate task demands such as joint loads and internal forces without directly measuring a worker. In simulation-based methods, a digital human model can be incorporated into a virtually reconstructed environment to estimate the biomechanical loads that an operator might face during a prescribed task [44,45]. This is useful for evaluating the potential impacts of workplace redesign without the costs and time for changing the physical environment. However, the accuracy of the simulation can vary according to the accuracy of inputs and the assumptions made by the model. Furthermore, humans have large variability in movement decisions and simulations cannot always accurately predict the way an individual may move in a complex environment or task [46]. An example of this is showcased in a study carried out by Alwasel et al. [47,48], in which they found that expert masons moved in significantly different ways than apprentice masons while performing the same task (e.g., building a concrete masonry block wall). Consequently, experienced masons suffer fewer joint loads and injury risks than the apprentices as they have fewer wasted motions, which also leads to higher productivity than apprentice masons [48]. Therefore, direct measurements may facilitate the capture of more detailed and nuanced information with respect to the real scenario, whereas a simulation may disregard these crucial elements.

2.2.2. Types of data

The quantification of injury risk is a complex challenge due to the many factors which influence injury, such as individual traits (e.g., genetics, morphology, and psychosocial factors), biomechanical risk factors (e.g., force, repetition, duration, and posture), and the integration of these factors acting on the tissues of the body [38]. Since individual risk factors will vary between workers, the best estimate of occupational demands will stem from the analysis of biomechanical exposures, namely force, posture and time (i.e. repetition or duration). While repetition and external loads can be easily measured, internal demands (e.g. joint forces or muscle requirements) and postures are harder to quantify without the appropriate tools. Injury rates are typically easier to track and have a direct relationship with worker

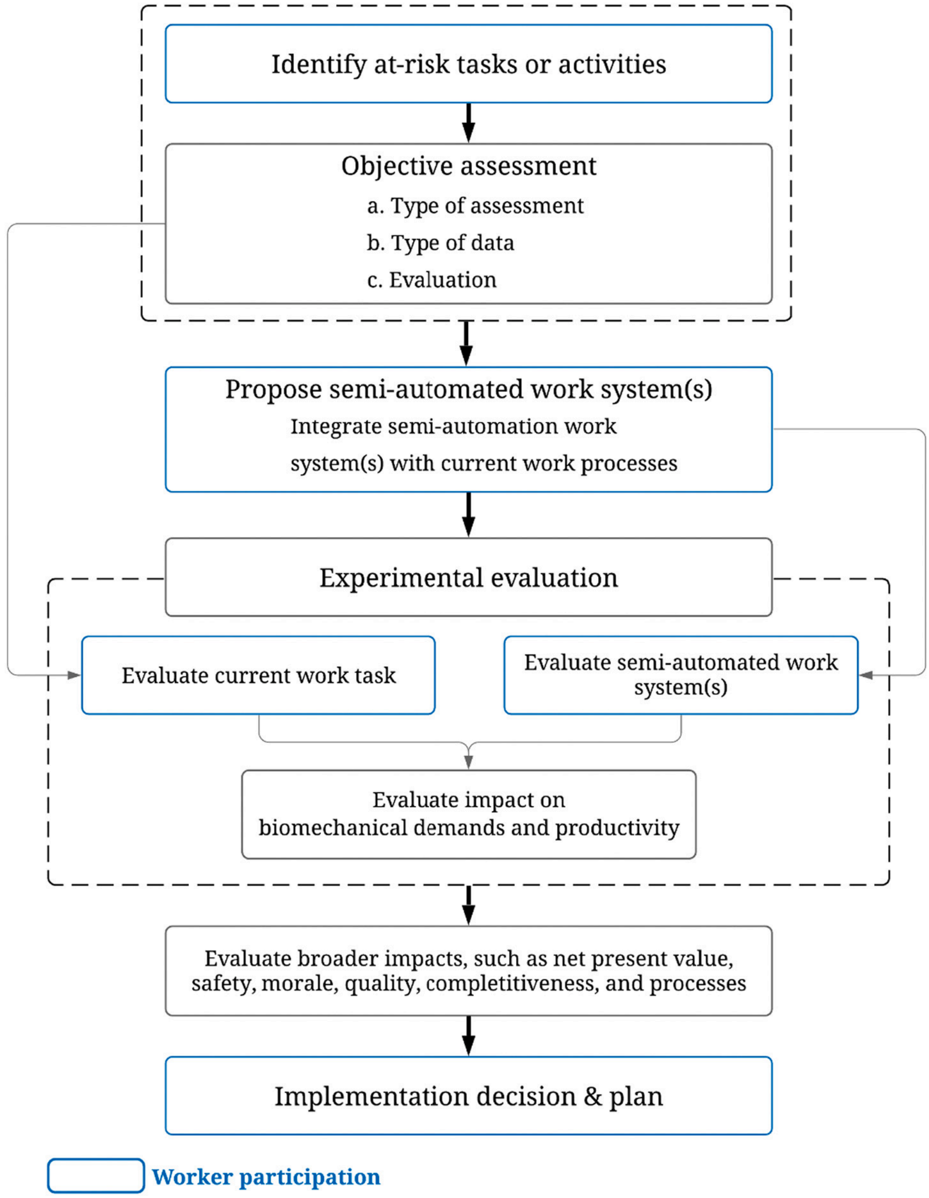

Fig. 1. Flowchart of methodology to evaluate semi-automated work systems.

compensation. However, they are less useful for collecting data on the immediate impact of the intervention, raise research ethics issues, and may not be sensitive enough to evaluate smaller task changes. They are, therefore, not recommended for this methodology. Expected quantitative data collection and analysis is preferable.

Quantitative data collection methods include the direct measurement of forces, body motion (kinematic data), and muscle activity. Force plates, scales and force transducers can be used to determine external forces acting on the body or applied by the body. In construction, there are two main methods for motion capture: optical systems (camera or video-based systems) or inertial measurement units (IMUs). In laboratory studies, optoelectronic motion capture systems are considered the 'gold standard' for kinematic data collection [49]. However, these systems are often impractical for use in field studies, because they have specific illumination requirements which can be sensitive to outdoor conditions or they require a clear line of sight to the individual and are restricted to collection within a bounded area [50].

Another type of camera-based system uses remote-sensing or computer vision algorithms to detect 2D and 3D kinematics [50]. These systems have already been tested in construction settings for posture recognition and ergonomic analysis of workers [51,52]. While these systems can have the advantage of using marker-less tracking, since they rely on cameras, they are limited by line of sight requirements and can be adversely affected by lighting conditions and occlusions [53]. Compared to camera-based systems, motion capture systems based on IMUs are more advantageous for use in working environments because they are portable, lightweight, low-cost, adept in various illumination conditions, and do not require a line of sight [47,50,54–56]. An acceptable level of accuracy and validity has been reported for the measurement of kinematics with IMUs [54–56]. Recent research in construction has presented methods to automate the classification of postures and the assessment of MSD risk using data from IMU systems [43,57–63] or similarly, smartphone sensors [64,65].

2.2.3. Evaluation

Quantitative and objective evaluation is required to assess the value of a semi-automation work system(s) into the current process. Biomechanical analysis can be an effective solution, because it estimates a quantitative load on the body segments (e.g., inertial forces and moments) using a 2D or a 3D biomechanical model [66]. Furthermore, several loading thresholds exist to evaluate the risk of MSD, such as the action limit for lower back compression force defined by the National Institute for Occupational Safety and Health (NIOSH) [67]. In terms of productivity, the best measure of productivity will vary by construction discipline and be unique to both the job site and its management values. Nevertheless, quantitative productivity measures will often take the form of either completion rates (labor productivity) or task completion times, since this information can be included in broader analysis of the business value proposition represented by substituting a semi-automated work system for a manual system.

2.3. Propose semi-automated work system

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

2.4. Experimental evaluation

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

2.5. Implementation design and plan

The value and effectiveness of the semi-automated work system(s) should be determined and compared against alternative solutions based on the impact of biomechanical demands and productivity. Management should make a final decision on whether the system fits their needs and budget, among other factors. Skibniewski [37] suggested that the final implementation decision for the employment of robotics in construction should be based upon the consideration of a wide number of elements such as the type of future projects and location, labor costs, availability and projections, market volume estimations, tax advantages, and other preferences to determine the desirability of the robot [37].

Where management decides not to implement the work system, alternative solutions should be explored, and the process can be repeated from Step 3: Propose semi-automation work system(s) until an acceptable solution has been found. Once management decides to move forward with a solution, a comprehensive implementation plan should be formulated. The implementation plan should be specific and systematic and include the following components: policy changes (where applicable), maintenance guidelines, appropriate training of both management and workers, effective communication and knowledge dissemination, adequate time and resources, and management support and commitment [68,69]

Worker participation is implicated in Step 1: Identify at-risk tasks or activities; Step 3: Propose semi-automated work systems; Step 4.1: Evaluate semi-automated work systems; and Step 5: Implementation decision & plan of the proposed methodology. A systematic review of participatory ergonomic (PE) interventions, in which worker participation is involved heavily in the evaluation, problem-solving and decision-making process of ergonomic improvements, found partial to moderate evidence that PE interventions were successful in reducing MSD symptoms, injuries, compensation claims and lost work days [68,70]. Worker participation and feedback are also noted by several studies as critical in increasing the effectiveness of MSD interventions [69,71,72]. Worker feedback provides an important insight into the practical implementation of the proposed work system through its usability and compatibility with current work processes, which will influence the adoption of the work system by workers and its consequent successfulness.

3. Validation of the methodology

The authors evaluated a semi-automated work system in a masonry task to experimentally validate the methodology. The study protocols were approved by the Research Ethics Committee at the University of Waterloo. In this case, a self-leveling pallet was used both for force assistance and improved positioning while building a standard wall out of 20 cm concrete masonry units (CMUs).

3.1. Identify at-risk tasks

Masonry work requires masons to perform physically demanding and repetitive tasks that may exceed safe limits. Particularly, manual block lifting—which is an integral part of masonry work—requires masons to frequently bend their back to lift CMUs. Previous studies reported that masons manually lift at least 200 CMUs—which corresponds to about 3300 kg—per workday [73,74]. Furthermore, masons spend up to 53% of their working time in a bent posture to pick up materials at ground or knee level and 38% of working time in aggravating postures [1]. As a result, masonry was ranked as having the highest rate of overexertion injuries and the second-highest back injury rate among construction sub-sectors [75]. Therefore, manual CMU lifting was selected as the at-risk task for the following evaluation.

3.2. Quantitative assessment

The biomechanical analysis based on the mathematical models provides a quantitative estimation of physical demands on the body (i.e., joint forces and joint moments). In this study, the 3D Static Strength Prediction Program (3DSSPP) developed by the Center for Ergonomics at the University of Michigan is used for biomechanical analysis. 3DSSPP requires a special hierarchical description of a body joint center location with X, Y, and Z coordinates. Therefore, the wearable IMU-based motion capture suit—with the Perception neuron from Noitom Ltd. [76]—were selected to collect whole-body kinematic data. The suit contains 17 IMUs and each unit is composed of a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer.

3.3. Propose semi-automated work system

To reduce the lifting demands on the operator while building the standard wall, a self-leveling pallet was suggested as an intervention. The self-leveling pallet is an automatic load leveler that uses a mechanical spring system to adjust its height based on the weight of the materials placed on the pallet, allowing the pick-up height of the CMUs to remain at waist height as the number of CMUs, and consequently the weight of the load, decreases. In this study, the self-leveling pallet—manufactured by Southworth Products Corp. (Southworth, Portland, USA)—had a 2041.17 kg (4500 lb.) load capacity with a rotating platform measuring 1.11 m in diameter (Fig. 2). The goal of this equipment was to reduce the height and reach distance while unloading CMUs from the pallet, thereby reducing the arm movement and movement of the lower back as well as reducing wasted motions during lifting to reduce task completion time.

Fig. 2. Self-leveling pallet utilized in the experiment (Southworth, Portland, USA).

3.4. Experimental evaluation

3.4.1. Evaluate semi-automated work system

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

3.4.1.1. Protocol. The study was comprised of control wall sessions and self-leveling pallet sessions. Participants took part in one session per day. In day one, they were randomly assigned to either the control wall session or the self-leveling pallet session. In day two, they completed whichever session they had not yet completed. This randomization was meant to minimize the impact of a learning curve on the results. Each participant was instructed to complete a pre-built lead wall using 45 CSA – Type “A” CMUs weighing 16.6 kg with actual dimensions of 0.19 × 0.19 × 0.39 m [77]. The pre-built lead wall consisted of 27 CMUs with a 6-course height (height of blocks on the wall) in which participants laid down CMUs from the second course to the sixth course.

During the control wall construction session, the materials were arranged to simulate a typical job site set up; the CMUs were stacked in three piles approximately one meter away from the pre-built lead wall, and mixed mortar was provided by helpers in two mortar boards placed between the stacked block (Fig. 3, left). Each pile of CMUs consisted of 16 CMUs, which were stacked with 4 layers of 4 CMUs each.

In the self-leveling pallet construction session, the CMUs were placed on a self-leveling pallet approximately one-meter distance from the lead wall and the two mortar boards were placed beside the self-leveling pallet (Fig. 3, right). During the self-leveling pallet construction session, CMUs were stacked on the self-leveling pallet in stacks of 3 layers of 16 CMUs each.

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

3.4.1.2. Data collection & processing. During the experiment, participants wore a wireless motion capture suit; each IMU was firmly attached using elastic straps to the head, back, each of the shoulders, upper and lower arms, hands, upper and lower legs, and feet. Fig. 5 shows a mason wearing the motion capture suit and highlights the IMU locations with blue dots. The motion capture software, Axis Neuron [76], reconstructed 3D human skeleton models from data collected through the suit. To determine the sensor-to-body alignment and body dimensions, each participant performed a calibration procedure (T-pose, A-pose, and S-pose) directed by the software. The sampling rate was 125 Hz. The motion capture system implemented a Kalman filter and a proprietary filter to counteract sensor drift. Lastly, all participants reported that the motion capture suit was comfortable and did not distract them from the task at hand.

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 [78]. Then, the global position (3D coordinates) of the 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 software, which enables the export of 3D joint information from a BVH file to .txt file, was used. Finally, 28 body joint positions in three axes (i.e., X, Y, and Z) were obtained from the processed motion data.

As described in Section 3.2, a special hierarchical description of a body joint center location was required to run the biomechanical analysis in 3DSSPP. The authors converted 3D joint information into .loc files using an in-house MATLAB code. In this process, the data was segmented into 45 single CMU lift files for each participant. A “lift” was defined as sequence of three motions: picking up a CMU from the pile, moving the CMU to the wall, and laying the CMU within the wall. Each of the experimental trials were also recorded using camcorders for lift segmentation during data analysis. The interval of spreading mortar on the wall was not part of the biomechanical analysis.

3.4.1.3. Analysis. For the biomechanical analysis, the peak lumbar compression force and associated posture was identified for each lifting motion and averaged by course height for both experimental sessions (with and without the pallet). Since the self-leveling pallet maintained pick-up height, the peak lumbar compression forces at pick-up of the CMU were also averaged and compared.

In the typical job environment of masonry work, 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 time to complete the lead wall using 45 CMUs. Furthermore, the average time to complete a single lift was also analyzed to investigate how participants' lift trajectory changed.

3.4.2. Evaluate impact on biomechanical demand

Peak lumbar compression force at the L4/L5 - L5/S1 joint was the primary focus in this study due to the direct representation of the physical demands on the back. In this section, peak lumbar compression force was compared during the 1) lifting and 2) pick-up phase.

Fig. 6 shows the average peak lumbar compression force, at pick-up and during the lift, for all 13 participants. While using the self-leveling pallet, the overall average peak lumbar compression force was reduced by approximately 20% during the lifting phase, and 40% at pick-up (Fig. 6). NIOSH defines the action limit (3433 N) as the threshold below which 99% of male workers and 75% of female workers have the strength capability to perform the task with nominal risk [67,79]. While completing the task manually (without the self-leveling pallet), participants were exposed to lumbar compression forces close to the action limit during lifting. However, significantly lower lumbar compression

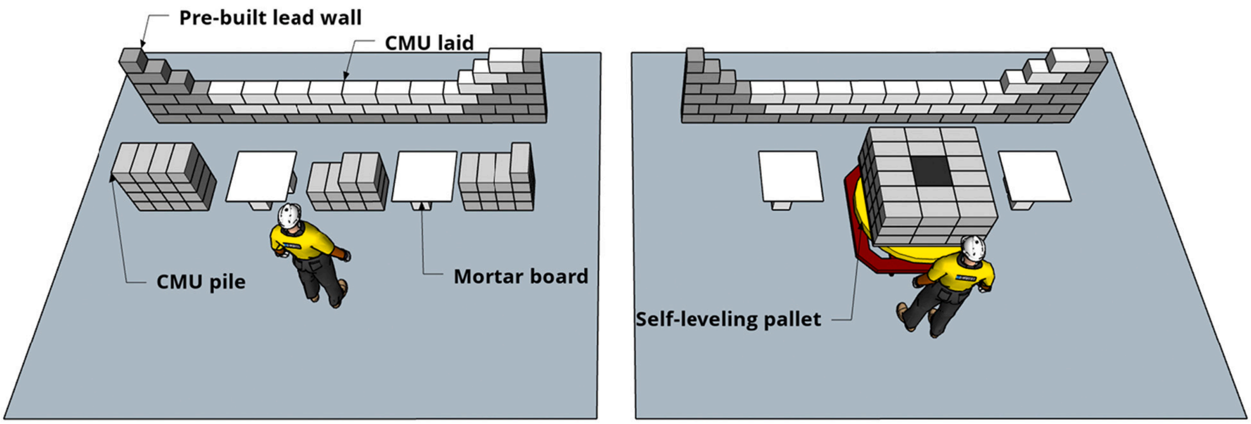

Fig. 3. Experimental setup layout: conventional work set up (left) and semi-automation job site (right).

forces were found when using the self-leveling pallet both during lifting and at pick-up. Notably, participants were only exposed to lumbar compression forces that were ~ 50% of the action limit during the pick-up phase with the self-leveling pallet. The authors determined that the differences in lumbar compression forces between the two work conditions were significant by conducting an independent sample *t*-test ($p < 0.05$).

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

The difference in lumbar load due to the presence or absence of the self-leveling pallet was most significant during the CMU pick-up phase of the "lift". Fig. 8 compares lumbar compression forces by course at pick-up only. In the control wall construction session, the CMUs were picked up from a decreasing height as participants removed CMUs from the stacked piles to complete the wall. As a result, the lumbar compression force increased as they worked on higher courses. On the contrary, with the use of the self-leveling pallet, participants were able to maintain similar CMU pick-up height regardless of the course of the wall, so their lumbar loads remained consistent throughout.

Significant posture variations were observed during the pick-up phase of the CMUs. Fig. 9 shows the postural differences when a participant picked up a CMU manually (left) and with the self-leveling pallet (right). To examine significant differences of postures occurring between the use and non-use of the self-leveling pallet, an independent sample *t*-test was conducted. Mean body joint angle (trunk, right and left shoulder, right and left knee), its standard deviation, t and *p* values are listed in Table 1 ($p < 0.05$). Significant differences were found for all five joint angles between the use and non-use of the self-leveling pallet. Both mean and standard devotion of all five joint angles were lower when using the self-leveling pallet than when using traditional methods. One interesting finding is that the mean and standard deviation of trunk angle without using the self-leveling pallet were

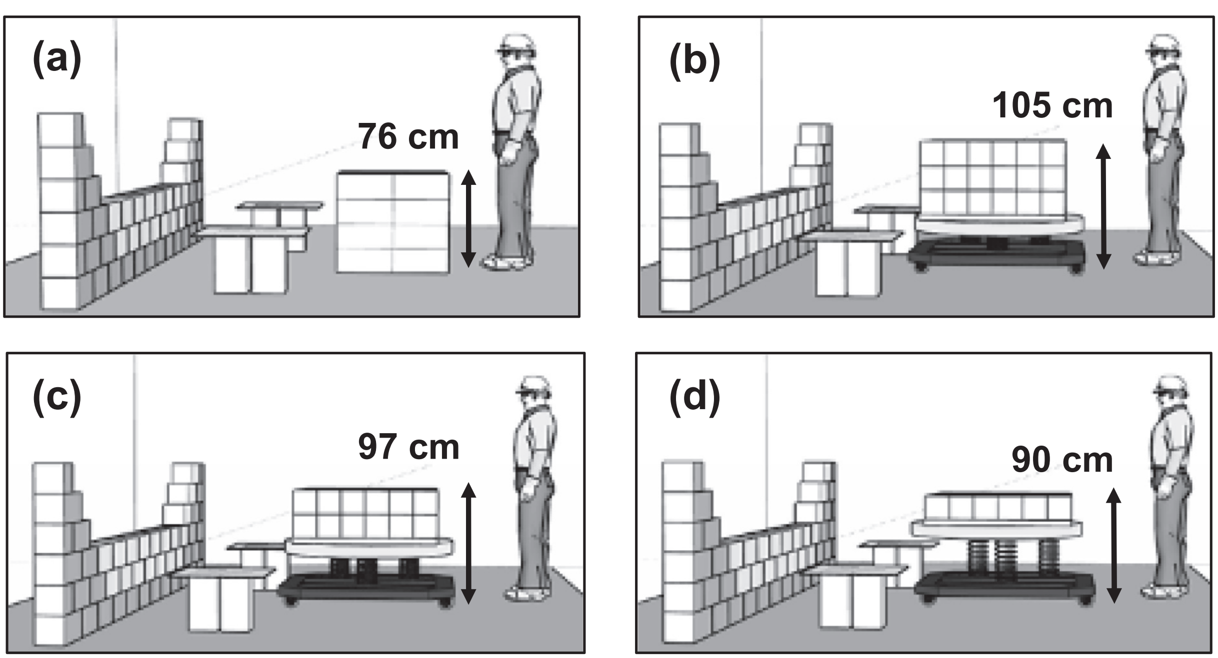

Fig. 4. Pick-up height of the CMUs (a) resting on a pile on the floor, (b) on top of the self-leveling pallet stacked 3 blocks, (c) 2 blocks, (d) and 1 block high.

Fig. 5. Photo of a mason wearing Axis Neuron [76] motion capture suit; IMU locations are marked with blue dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

approximately seven- and ten times larger than the angles using a pallet, respectively. These results indicated that participants can create safer posture patterns at the pick-up phase with the self-leveling pallet.

3.4.3. Evaluation impact on productivity

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

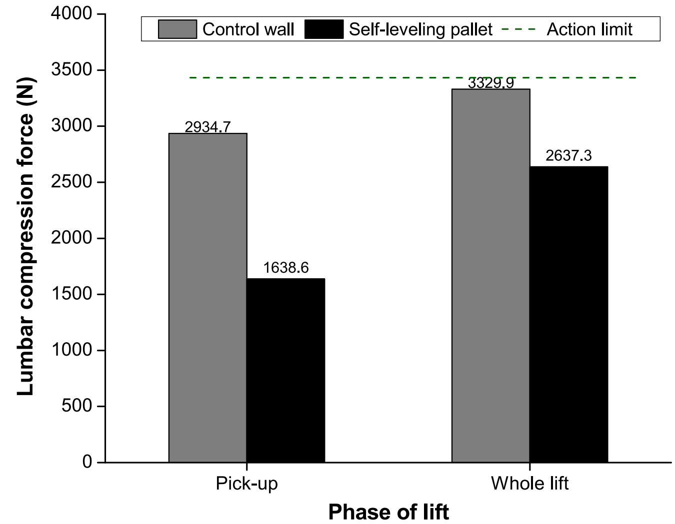

Fig. 6. Peak lumbar compression force (N) during lifting and at pick-up with and without the self-leveling pallet.

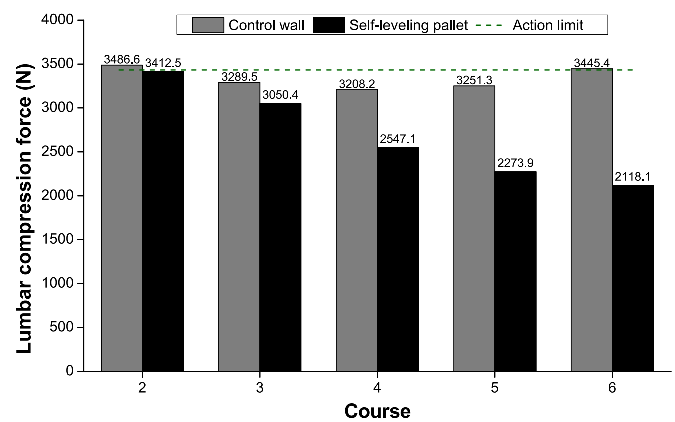

Fig. 7. Average peak lumbar compression force (N) during whole lift for the control wall and the self-leveling pallet by course.

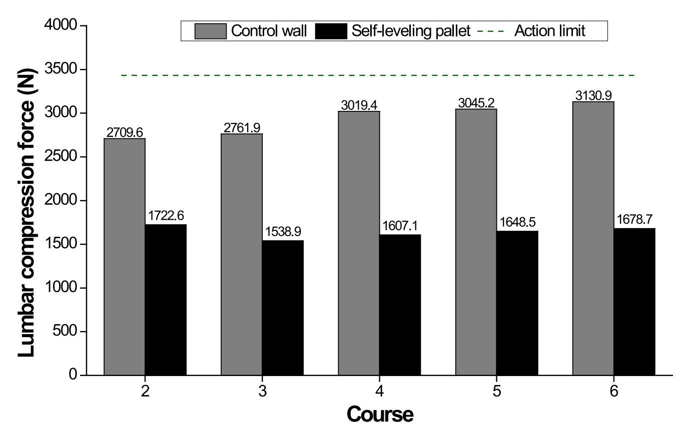

Fig. 8. Average peak lumbar compression force (N) during pick-up phase for the control wall and the self-leveling pallet wall by course.

Fig. 9. Postural differences: picking up a CMU manually (left) and with the self-leveling pallet (right).

Table 1
Means and standard deviations for joint angles at pick-up with and without the self-leveling pallet (significant *p*-values denoted in bold with an asterisk).

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

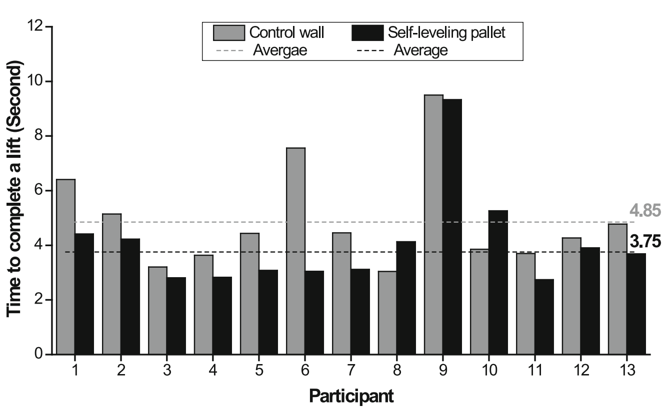

Fig. 10. Average time to complete a CMU lift by participant.

motions and paths resulting in shorter completion times.

3.5. Implementation decision & plan

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

Due to the cost-driven nature of the industry, demonstration of the economic value of the work system is critical for management consideration. For the cost-justification of ergonomic intervention, the potential impact on injury risks must be considered with regard to costs and productivity measures. For example, the National Safety Council reported that the average total incurred medical costs per injuries to the lower back for the years 2016–2017 was $17,583 [32]. In addition to the medical expenses, indirect costs (e.g., time loss on the day of injuries and reduced output of replacement employee(s)) can also be incurred, estimated at four times the direct cost in the U.S. [80]. Connecting with the current study, the self-leveling pallet effectively reduced risk factors related to lower back injuries (i.e., excessive back bending). Furthermore, productivity increased. As a result, significant financial benefits, can be expected from the implementation of the semi-automated work system. The data from the comparative analysis can be used to evaluate the expenses associated with the intervention (e.g. training, maintenance, purchase costs etc.) with cost-savings from increased productivity, reduction in injuries, workers' compensation, turnover and training costs to estimate the payback period and help support the case for adoption of the semi-automated work system [81]. Factors identified in the introduction would also need to be considered in the overall business value proposition.

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

4. Discussion and conclusions

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

The current study has shown that the proposed methodology provided an objective evaluation of semi-automation showing a 40% reduction in lumbar compression force and 22% increase in lift motion speed. Labor productivity was improved by 10%. Therefore, it offered a quantitative evaluation of the semi-automated work system's contribution to reducing exposure to MSD risk factors associated with lower back injuries and increasing CMU pickup speed. This evaluation process also provides much of the quantitative basis necessary to carry out an objective cost-benefit analysis to estimate the potential financial benefits of ergonomic interventions [81,82].

The adoption of full automation in construction is an active area of research. Particularly, in masonry, bricklaying robots, SAM 100 [83] and In-situ-Fabricator [84], are currently being introduced. Such masonry automation promises improvements of masons' health and productivity by taking over physically demanding and repetitive tasks. Full automation is still challenging in many situations because of limitations such as intrinsic dynamic changes in worksites, the need for continued worker interventions, and regulations. Therefore, until construction sites are fully automated, collaboration among robots, machines and workers is inevitable. As such, semi-automation is a feasible alternative for the foreseeable future. In fact, a recent surge in the popularity of exoskeletons has introduced this technology to the construction industry, such as robotic exoskeletons (FRACO) [85] designed to augment masons' physical capabilities. As the popularity of these systems grow and they are adopted onto worksites, management increasingly needs resources to systematically evaluate their impact on health and productivity. Consequently, the methods proposed in this study play an important role in bridging the gap between traditional and fully automated work systems.

The proposed methodology can also be integrated into broader continuous improvement frameworks within organizations, such as MSD prevention programs, occupational health and safety frameworks and integrated management systems, which follow a common framework for continuous improvement e.g. Deming's Plan-Do-Check-Act cycle [86–89]. This allows the evaluation process to integrate seamlessly into previously established internal organizational tools. The compatibility of this methodology with existing processes increases its value and applicability as a pathway for management to undertake health risk reduction activities while promoting a continuous improvement model for MSD prevention and productivity enhancement.

The proposed methodology emphasizes the importance of evaluating not only productivity increments incurred from the implementation of a semi-automated work system, but also the impact on workers' physical exposures as an equally important component. Often, ergonomic principles are neglected in workplace design or the planning phase of new projects, such as the installation of semi-automated work systems, due to a lack of consideration or a deficit in knowledge [90–92]. The introduction of robotics and automation into a workplace may introduce new risks, if human factors and ergonomics principles are not integrated in the design, work processes, and operation and maintenance requirements [93]. This methodology presents a proactive approach to the evaluation of both health and productivity of semi-automated work systems, which fill this deficit.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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