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The Validity and Inter-Rater Reliability of a Video-Based Posture-Matching Tool to Estimate Cumulative Loads on the Lower Back

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ABSTRACT

Background: Low back pain (LBP) is known as one of the most common work-related musculoskeletal disorders. Spinal cumulative loads (*CLs*) during manual material handling (MMH) tasks are the main risk factors for LBP. However, there is no valid and reliable quantitative lifting analysis tool available for quantifying *CLs* among Iranian workers performing MMH tasks.

Objective: This study aimed to investigate the validity and inter-rater reliability of a posture-matching load assessment tool (PLAT) for estimating the L5-S1 static cumulative compression (*CC*) and shear (*CS*) loads based on predictive regression equations.

Material and Methods: This experimental study was conducted among six participants performing four lifting tasks, each comprised of five trials during which their posture was recorded via a motion capture (Vicon) and simultaneously a three-camera system located at three different angles (0°, 45°, and 90°) to the sagittal plane.

Results: There were no significant differences between the two *CLs* estimated by PLAT from the three-camera system and the gold-standard Vicon. In addition, ten raters estimated *CLs* of the tasks using PLAT in three sessions. The calculated intra-class correlation coefficients for the estimated *CLs* within each task revealed excellent inter-rater reliability (> 0.75), except for *CS* in the first and third tasks, which were good (0.6 to 0.75).

Conclusion: The proposed posture-matching approach provides a valid and reliable ergonomic assessment tool suitable for assessing spinal *CLs* during various lifting activities.

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Keywords

Lifting; Cumulative Spinal Loads; Low Back Pain; Risk Factors; Ergonomic Assessment Tool; Video Analysis; Posture-Matching; Validity; Inter-Rater Reliability

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Introduction

Low back pain (LBP) is known as one of the most common work-related musculoskeletal disorders (WMSDs) [1, 2]. In a survey of ~8000 employees from 20 Iranian industrial settings, Choobineh et al. (2016) found that the most common WMSD among the workers was LBP (48.9%) [3]. Previous studies have shown that the significant risk factors of LBP are activities involving awkward trunk postures [4, 5], repetitive trunk flexion, and lifting [6, 7]. L5-S1 compression and shear peak forces [8, 9], as well as cumulative loads (*CLs*) during manual material handling (MMH) tasks [10, 11], also play a significant causative role. Some studies have attempted to reduce trunk muscle activity as one way to mitigate the LBP [12, 13]. Previous studies assessing the biomechanical risks among Iranian workers performing MMH tasks were either qualitative or did not quantify *CLs* such as Salehi et al. [14]. In epidemiological studies, such quantitative measures are essential to developing exposure-response links between physical exposures and WMSDs [15, 16].

Various objective approaches have been used to quantify *CLs*, such as measuring full-shift lumbar electromyography (EMG) as an indicator of cumulative workload [17], examining the relationship between heart rate-determined physical activity level (HR-PAL) and *CLs* [18], and video analysis [19]. EMG-driven models require a complex and time-consuming procedure to collect and process the data [20]. In addition, these models solely provide estimates for cumulative spinal compression (*CC*) [21]. HR-PAL can predict spinal *CL*, especially *CC* loads (R^2=0.817), through a regression model [18]. However, controlling the confounding factors such as consuming caffeine or cigarettes, altitude, and climate, which influence HR [22, 23], is difficult in the workplace settings. Due to these limitations, the EMG-driven and HR-PAL approaches have not been used in large-scale studies.

Video analysis is the most common approach to determining input variables for estimating *CLs* by a static biomechanical model [24]. The essential advantage of this approach is the use of recorded videos to estimate the spinal shear and compression forces as well as joint moments. However, one of the main disadvantages is the lengthy procedure of manually entering the required information into software [21]. As a remedy, one may use a posture-matching approach [19]. Applying an easy-to-use interface would speed up the video analysis and help to automate *CLs* calculation. Once this issue is resolved, the crucial point is selecting a biomechanical model to estimate spinal loads accurately [25]. Such a model has to consider the main contributing factors in low back loads, including the horizontal distance of the hand-load from the body [26], its asymmetry angle [27, 28] as well as trunk flexion angle [6, 7]. Such an approach may potentially decrease the estimation error associated with the model [20, 29].

The lack of a valid and reliable quantitative lifting analysis tool available to the Iranian health and safety practitioners (HSPs) for quantifying spinal *CLs* during MMH tasks encouraged the authors to develop an interface based on the robust regression model developed by Arjmand et al. [30, 31]. This study aims to assess the validity and inter-rater reliability of the posture-matching load assessment tool (PLAT) user interface developed to estimate spinal *CLs* during MMH at different workplaces for symmetric and asymmetric lifting tasks by the Iranian HSPs.

Material and Methods

PLAT is a tool designed and developed during this experimental study based on the *Predictive Regression Equations* (PRE) [30, 31] to estimate *CC* and *CS* loads at the L5-S1 disc. The outputs obtained from this tool are based only on four postural and load-related inputs. Therefore, a graphical user interface (GUI) was designed based on these input variables (Figure 1). The design of the GUI was centered on the concept of well-defined partitioning (Figure 1a-f) to help users perform a posture-matching task analysis. An operator first took the values of input variables by analyzing the video frames using the PLAT and subsequently entered them manually into the GUI. The videos were recorded by three cameras placed on the ground. The synchronized Vi-

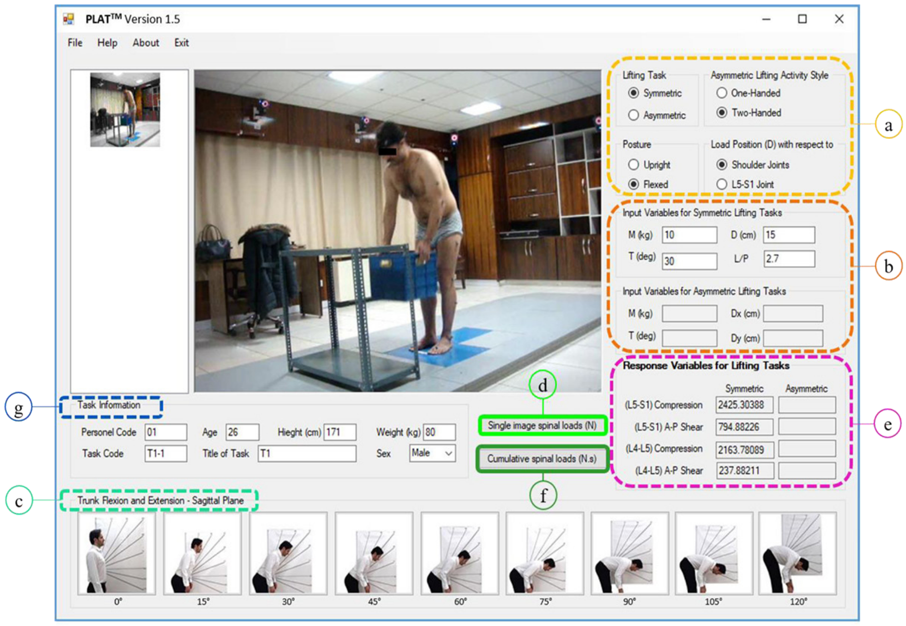

Figure 1: PLAT software GUI for analyzing frames of each task and estimating the loads: (a) The section for defining the worker's task and posture; (b) the room for entering input variables; (c) binned images to help users estimate trunk flexion angle (*T*) concerning to the neutral, upright posture covering a varied range 0°-120°; every line in each gradient represents 15°; (d) push-button to calculate compression and shear forces of each frame; (e) results for spinal loads; (f) cumulative loading estimation button and (g) task and participant information. Note: PLAT: Posture-matching Load Assessment Tool; GUI: Graphical User interface.

con motion (Vicon Motion Systems, Oxford, UK) data were then automatically entered into the *PRE* to calculate the corresponding *CLs*. The obtained *CLs* from the three-camera system were compared to those obtained from the gold-standard Vicon motion capture system for validation purposes. In brief, this study examined the accuracy of PLAT GUI driven by a three-camera system in estimating postures and associated L5-S1 loads while also assessing its inter-rater reliability. Details of the experiment are provided below.

Participants

Two groups of students participated in the study. The first group was comprised of six healthy students (three males and three females; mean ± SD age: 23.4 ± 1.5 years, mean ± SD height: 1.68 ± 0.1 m, and mean ± SD body mass: 66.6 ± 14.6 kg), who participated in performing lifting tasks. The participants had no current or previous history of back pain or spine surgery, no congenital disorder to cause any movement impairment, no history of injury in the musculoskeletal system, and no prior cardiovascular disorders. The second group was comprised of ten student raters (five males and five females; mean ± SD age: 26.7 ± 2 years, and 2.75 ± 0.8 years of postgraduate education). Students with different majors were selected to prevent familiarity with skeletal landmarks and anatomy.

Laboratory simulated lifting tasks

The first group of participants performed five consecutive trials for each of the four lifting tasks (Table 1) using a stoop technique that workers commonly adopt during lifting activities [32]. The protocols performed by each participant are shown in Table 1. Each lifting trial consisted of four phases synchronized with a 6-sec metronome played during the

Table 1: Lifting a 10 kg load placed in a plastic crate (0.31 m × 0.31 m × 0.31 m) in four simulated stoop postures. The participants faced the 0° camera view angle for the entire duration of lifting in T1 and T2. In asymmetric tasks, the 30° of rotation out of the sagittal plane was marked on the ground by drawing a line to the predetermined fixed position.

Task	Description of the task	Type of lift
T1	From the floor to the 0.75 m platform	Symmetric
T2	From 0.75 m to 1.45 m platform	
T3	From the floor to 0.75 m platform on the right side with 30 degrees trunk rotation angle	Asymmetric
T4	From the floor to 0.75 m platform on the left side with 30 degrees trunk rotation angle	

task. The four phases include normal standing to grasping the load (10 kg) on the floor (phase 1), lifting the load and returning to the upright posture (phase 2), lowering the load and placing it on the platform (phase 3), and ending to the same standing position (phase 4).

Participants were required to keep their feet at a fixed position marked by a tape (Figure 2). Two minutes of rest were given between each trial to prevent fatigue. The lifting tasks were recorded using three Vicon Bonita 720c video cameras at the sampling rate of 30 Hz. Video recording was carried out simultaneously at 0°, 45°, and 90° to the sagittal plane (Figure 2) to assess the effect of view angle on the estimation accuracy. For the sake of validation, three-dimensional kinematic data were also simultaneously captured using a synchronized 11-camera Vicon motion capture system at 120 Hz. Data were collected in the gait analysis laboratory of Djavad Mowafaghian Research Center for Intelligent Neurorehabilitation Technologies (Tehran, Iran).

The biomechanical model

The biomechanical model used in this study

Figure 2: The laboratory setting to capture kinematic input data, the Vicon motion capture system, the Vicon Bonita video camera, and two platforms with different heights (top), and a sample frame of each task (T1 through T4 from left to right) from a 45° camera view (bottom).

was based on the *Predictive Regression Equations* (PRE) developed and validated by Arjmand et al. [30-32]. The Posture-matching load assessment tool (PLAT) was developed to be available to the Iranian HSPs thus facilitating the process of estimating spinal loads in lifting tasks using the *PRE* (Figure 1a). The *PRE* input variables are sagittal trunk flexion angle (*T* varying from 0° to 110° for the upright posture), lumbopelvic ratio (*L/P* varying from 0.5 to 3), load mass (*M* varying from 0 to 20 kg), and load position (*D* varying from 0 to 60 cm) (Figure 1b). The magnitudes of parameter *D* are divided into two distinct variables; (*Dx*), which is measured perpendicular from the load to the shoulder joint in the sagittal plane, and (*Dy*), which is measured laterally from the same perspective in the frontal plane (for asymmetric lifting). Parameter *D* can also is calculated based on the horizontal distance of the hand load center of mass to the L5-S1 joint. While both of these measurement approaches are acceptable to PLAT, we used the first approach due to relative ease in recording the location of the shoulder joint. Trunk flexion angle (*T*) is defined as the summation of the pelvis (*P*) and lumbar (*L*) spine rotations, i.e., $T = P + L$. To estimate *T*, nine sagittal trunk posture categories with the size of 15° were accommodated on the bottom of the GUI, which covers the ranges of *T* in the *PRE* from 0° to 120° (Figure 1c). Selecting the size of 15° was made based on two assumptions. First, to decrease the error and the required analysis time when using PLAT, the authors intended to use fewer posture categories [33-35]. Second, the proposed intervals of the range of *T* in *PRE* was 10° [30, 31]. The corresponding *L/P* ratio can automatically be estimated by clicking each posture category that appropriately represents the actual trunk posture in the video frame. *L/P* is considered only for symmetric lifting tasks. Predicted values based on the three-camera video-captured frames as well as those from the Vicon were entered into the GUI (Figure 1) for subsequent comparisons.

Preparation of video and Vicon motion analysis system

The sampling rate of the motion capture system was decimated to 30 Hz to be equal to PLAT inputs. Data were captured based on the Plug-in gait marker placement protocol (Vicon Motion Systems, Oxford, UK). The bony landmarks of the upper/lower limbs and the trunk on both anterior and posterior sides were palpated. According to the Plug-in gait protocol, thirty-nine reflective markers were attached to the skin by the same operator using double-sided adhesive tape (Figure 2). Four additional markers were placed on the upper four corners of the crate and one on one of the lower corners to detect the height of the crate and its horizontal distance from the L5-S1. To ensure that the load is rotated by 30° out of the sagittal plane, the location of shoulder markers was monitored in kinematic data, and trials were repeated when this criterion was not met. The laboratory Cartesian coordinate system was set as follows: *X*-axis to align anteriorly in the sagittal plane, *Y*-axis toward the participant's left side, and the *Z*-axis referring to the upward direction. The location of each skin marker was processed using Nexus 1.4.1 and exported to an Excel sheet (Excel 2016, Microsoft Corp., USA) for subsequent analyses.

The three video cameras and motion capture systems were automatically synchronized to compare the recorded lifting videos directly between the PLAT platform and corresponding Vicon frames. To represent the lifting trial in videos, each participant started and ended the trials when a red light turned on and off. Therefore, a lifting trial was considered to be the time during which the light was on in the video. Simultaneously, the lifting trial in the Vicon data was represented by the time *T* was equal to 0° (relaxed upright posture) to the frame when again *T* became equal to 0° (final return on subject to upright posture). An in-house program code identified every 10° interval (started from the trial's first frame with T equal to 0°) of trunk flexion angles. Once the points were identified, the developed algorithm in the program used five points before and after each point to calculate the mean values of the input variables (see section 2.3). The videos of three camera view angles were transformed to separate clips using a video converter [36]. Each video clip has time duration of 5.33-5.66 seconds. Subsequently, all 360 clips (4 lifts × 3 view angles × 5 repetitions × 6 participants) were converted from 30 to 3 Hz using the same software [36]. This conversion reduced the time required to collect and analyze the data [37]. Afterward, all video clips were converted to image frames in JPG format using Aoao Video to Picture Converter [38]. Each clip consisted of 16-17 frames.

The video frames of each task were imported into the PLAT GUI, and the postures were matched frame by frame by an operator to estimate L5-S1 compression and shear loads (Figures 1d and e). Moreover, the program automatically extracted mean values of the input variables from Vicon kinematic data were entered into PLAT (Figure 1a, b, and c) to calculate the corresponding loads. The *CL* values of the trials were estimated using Eq. (1) after analyzing all frames of each trial.

$$CL_t = \left(\sum_{i=1}^{n} F \right) \times 0.33 \quad (1)$$

where CL_t = cumulative loading of the trial (N.s), t = trial, n = the total number of frames in each trial, i = number of frame, F = the estimated compression or shear load (N) of each frame and 0.33 = 3 Hz = length of each frame (s). Eq. (1) is another form of calculating the area under the force-time curve [19, 21]. PLAT provides the output results, which can be printed or exported to an excel sheet.

For assessing inter-rater reliability, all the raters were asked to analyze the frames of T1, T2, and T3 and estimate the corresponding *CLs* values of each task in three separate sessions with PLAT. Here, only trials (recorded from 90° view) of one of our participants in the validation protocol, who had average anthropometry (26 years, 171.5 cm, and 75 kg) angle were analyzed (3 lifts × 1 view angle × 5 repetitions × 1 participant × 16-17 frames). Each session was approximately one hour in duration. The two first sessions were on two consecutive days, and the third session was in the next week (all in the morning). The aim of the study and how to work with PLAT were reviewed for raters at the beginning of each session. To minimize the effect of learning, the order of frames and the time intervals between them were randomly changed in each session. Before starting this part of the study, a training period was considered to ensure that the raters properly match postures using PLAT GUI (Figure 1) to estimate *CLs*. The criterion was an error of <5% in evaluating 50 sample frames by all ten raters. Each sample frame was uploaded twice, and the raters were asked to evaluate it through GUI (selecting lifting and posture type and estimating corresponding *T* and *D*; Figure 1a-c). Their selections were then compared to the correct answers that one researcher prepared in advance. If their classification was wrong, the correct answer was shown to them, and the next frame was presented. This procedure was continued until the foregoing criterion was achieved.

Data analysis

Validity: The absolute error (Eq. (2)) and the percent error (Eq. (4)) were calculated for *CC* and *CS* estimates in each task and camera view and compared to those obtained from the Vicon motion capture system (as the reference method) as follows:

$$\text{Absolute error} = L_{PLAT} - L_{Vicon} \quad (2)$$

$$\text{Relative error} = \frac{|Absolute\,error|}{L_{Vicon}} \quad (3)$$

$$\text{Percent error} = \text{Relative error} \times 100 \quad (4)$$

Where L = estimated *CC* and *CS* loads, L_{PLAT} represents *CL*-values (N.s) obtained from analyzing the three-camera video frames using the PLAT interface, and L_{Vicon} shows *CL*-values (N.s) obtained from Vicon data inputs.

The three video recording angles' *CC* and *CS* relative error differences were evaluated using the non-parametric Kruskal-Wallis test ($p<0.01$). ANOVA analysis was used to compare the estimated *CC* and *CS* loads from analyzing video frames (by PLAT) and the values obtained from Vicon kinematic data (significance level: $p<0.01$).

Inter-rater reliability: Intra-class Correlation Coefficients (ICCs) and their 95% confidence intervals were calculated to assess the agreement among the raters for the estimation of CC and CS in each of the three lifting tasks. Since the raters were randomly selected from a larger potential population, ICC (2, 1) was adopted [39]. ICCs <0.40, 0.40-0.75, and >0.75 were considered, respectively, poor, good, and excellent [40].

Results

Validity: One-way ANOVA revealed no significant difference between *CLs* obtained from the three-camera view angles and Vicon for *CC* (p=0.999) and *CS* (p=0.969; Table 2). The 90° camera angle had the closest value to the cumulative mean values obtained from Vicon data (i.e. 8857 Ns versus 8842 Ns for *CC* and 3050 Ns versus 3036 Ns for *CS*) (Table 2).

There were no significant differences in *CC* and *CS* mean percent error values across the four different tasks (Table 3). These values ranged from 5.0% (T1) to 8.9% (T2) for *CC* and from 1.2% (T1) to 2.1% (T3) for *CS*. The mean percent error of these values across all four tasks was 6.1% and 1.7% for *CC* and *CS*, respectively. The mean percent error of cumulative variables averaged across the three camera angles ranged from 7.2% for *CC* to 6.6% for *CS* (Table 4). These percent error values ranged from 3.0% for *CS* (0° view) to 9.7%

Table 2: The cumulative loading mean values (SD) in Ns for the three-camera view angles and the Vicon

Variable	Vicon	0°	45°	90°	P-value
CC	8842 (2170)	8890 (2175)	8875 (2172)	8856 (2172)	0.999
CS	3036 (607)	3080 (611)	3068 (611)	3050 (610)	0.969

CC = Cumulative compression, *CS* = Cumulative shear

Table 3: Mean percent error (SD (Standard deviation)) of *CC* (Cumulative compression) and *CS* (Cumulative shear) for each task across all four tasks

Variable	T1	T2	T3	T4	Variable mean
CC	5.0 (4.2)	8.9 (8.2)	6.7 (7.2)	5.6 (3.7)	6.1 (2.2)
CS	1.2 (12.2)	1.8 (11.4)	2.1 (10.4)	1.8 (10.2)	1.7 (0.3)

CC = Cumulative compression, *CS* = Cumulative shear

Table 4: Mean percent error (SD (Standard deviation)) of *CC* (Cumulative compression) and *CS* (Cumulative shear) for each camera view across all three camera angles

Variable	0°	45°	90°	Variable mean
CC	9.7 (9.3)	6.1 (6.4)	5.7 (6.3)	7.2 (2.2)
CS	3.0 (19.8)	8.6 (9.6)	8.3 (9.6)	6.6 (3.1)

CC = Cumulative compression, *CS* = Cumulative shear for *CC* (0° view). Based on Chi-Square test statistics, there were no significant differences in *CC* (p=0.021) and *CS* (p=0.093) relative error between the three video recording angles (Table 5).

Inter-rater Reliability: ICCs for the estimated *CC* and *CS* in each task across the three sessions ranged from good (0.40<ICC<0.75) for *CS* in T1 and T3 (i.e., 0.69 (0.11-0.96) and 0.61 (0.12-0.95), respectively), to excellent (ICC>0.75) for both *CLs* in all tasks (i.e., from 0.78 (0.36-0.97) to 0.83 (0.52-0.98) in T3 and T2, respectively) (Table 6). *CC* was more reliable than *CS* (ranged from 0.78 in T3 to 0.83 in T2). T2 had the largest values (0.83 for *CC* and 0.79 for *CS*), and T3 had the smallest values (0.78 for *CC* and 0.61 for *CS*).

Discussion

A video-based posture-matching assessment tool was developed. Its validity and inter-rater reliability were evaluated to estimate cumulative compression (CC) and cumulative shear (CS) L5-S1 loadings during lifting tasks. In Iran, with 12300 HSPs [41], there is an essential need for a valid and reliable quantitative lifting analysis tool corresponding to the Iranian workforce. ANOVA results revealed no significant differences in the estimated *CC* and *CS* loads between the Vicon input data and PLAT in any of the three camera views (p<0.05). Furthermore, throughout all four tasks, PLAT showed no significant differences in terms of mean percent error when compared to the values obtained from Vicon inputs. Therefore, PLAT was reasonably accurate in predicting *CLs* in all lifting types relative to the reference method. The ICCs and the confidence intervals indicated an excellent agreement between raters on the estimated *CLs* during lifting tasks using PLAT.

Minor *CC* and *CS* loading errors were measured in T1 (Table 3). This might be due to the visibility available to the operator in the symmetric task. A pronounced *T* was observed by the operator over the entire T1 in the sagittal plane, which resulted in an accurate estimation of the *CLs* compared to the reference method. The magnitude of the errors for the *CLs* across all three camera angles was small (Table 4) and had no significant effect on the estimation accuracy (p<0.01) (Table 5). The highest accuracy was obtained for the 90° camera angle (5.7% for *CC* from the reference method). This

Table 5: Kruskal-Wallis test of relative error of *CC* (Cumulative compression) and *CS* (Cumulative shear) grouped by each camera view angle

Variable	0°	45°	90°	Chi-square	df	P-value
CC	201.5	174.3	165.7	7.714	2	0.021
CS	197.0	175.4	169.0	4.747	2	0.093

CC = Cumulative compression, *CS* = Cumulative shear

Table 6: The intra-class correlation coefficients (ICCs) and their 95% confidence interval (CI) for *CC* (Cumulative compression) and *CS* (Cumulative shear) across all tasks and three sessions

Task	*CC*	95% CI		*CS*	95% CI	
		Lower	Upper		Lower	Upper
1	0.81	0.46	0.98	0.69	0.11	0.96
2	0.83	0.52	0.98	0.79	0.38	0.97
3	0.78	0.36	0.97	0.61	0.12	0.95

CC = Cumulative compression, *CS* = Cumulative shear, CI: Confidence interval can be explained by the fact that this angle, as suggested by Norman and McGill [25], gives the operator the most accurate viewing angle for the sagittal plane, thus resulting in smaller errors when estimating input variables.

The ICCs revealed a good to excellent agreement between the raters when estimating L5-S1 *CLs* across three days (Table 6). From an ergonomic standpoint, having higher values of ICC for *CC* compared to *CS* is important and considered an advantage for PLAT in evaluating lifting tasks. Compression force has the strongest relationship with LBP among kinetic parameters and is the most commonly evaluated parameter in biomechanical risk assessment studies for lifting activities [24, 42]. Moreover, the ICC values were higher for T2 in comparison with T1 and T3 (Table 6). This might partially be due to the lesser variability in postures adopted by the participant in T2, which resulted in smaller inter-rater variability in the estimation of *T* and other input variables through matching posture via GUI. The lower ICCs in T3 might be attributed to the task asymmetry, which required estimating *Dx* and *Dy* in addition to *T* thus increasing inter-rater variation, especially when the task was observed from the 90° view angle.

Few studies have investigated the inter-rater reliability of a biomechanical tool for assessing *CLs*. The obtained ICCs in the current study (ranging from 0.61 to 0.83) were in close agreement with those of Sullivan et al. [43], who reported the ICCs of 0.61 to 0.96. In a field study, Cann et al. [44] determined the inter-rater reliability of 3DMatch for predicting *CLs* during selected tasks of 30 food service workers. The calculated ICCs were 0.69 and 0.90 for *CS* and *CC* spinal loadings, respectively.

As recommended by Sutherland et al. [45], trunk sagittal posture categories were considered at the bottom of the PLAT GUI to facilitate the estimation of the T more accurately (Figure 1c). The considered size of these posture categories (15°) was smaller than the optimal value (30°) [35]. Van Wyk et al. [35] stated that selecting a category size smaller than the optimal (30°) is associated with a lower error magnitude but a higher number of errors in posture classification. Training the users of PLAT is therefore suggested to improve the accuracy and precision of outputs [46]. However, because of existing human errors when using video-based posture assessment methods, estimation errors persist despite training the users.

Computing the spinal loads during lifting tasks by only four input variables via a GUI enables our tool to be easily used by any HSPs remotely thereby decreasing the need to be on the site at the workplace physically. This is mainly important in pandemic circumstances such as COVID-19, in which social distancing is required to manage the spread of the virus. The only value that should be taken directly on-site for practical applications is *D*, which can easily be measured by using tape measures in the workplace. Moreover, unlike some previous works that studied the reliability of video-based methods [44, 47, 48], in the present study, the raters with different backgrounds were recruited to minimize the effect of having ergonomics and/or biomechanics background on results. To ensure that they were qualified to participate in the study, a training period was considered regarding working with PLAT for matching postures and estimating the loads. This ensures the generalizability of the results.

Some limitations should also be acknowledged. Similar to the work of Sutherland et al. [45] in validating 3DMatch, validation of our tool was performed with a relatively small sample of six participants repeating the tasks only five times. However, considering a suggested average number of 3-6 cycle times for each task [49], our designed protocol for lifting tasks (6 participants × 4 tasks × 5 repetitions = 120 repetitions; i.e. 30 repeats for each task) yielded meaningful repeatability of the results. For statistical analysis, any repetition of tasks was considered an independent observation. Therefore, 30 observations were included in any of the four independent analysis groups (the three camera views and Vicon; i.e. 30 × 4 = 120). Assumptions of normality and heterogeneity of variances were handled by applying the Kruskal-Wallis test as a non-parametric alternative to one-way ANOVA. However, further analyses with more participants performing more repetitions of tasks are required to confidently generalize our findings to a normal working day.

While demographic and anthropometric factors, and muscle morphology of individuals, are known to affect the spinal loads [50, 51], *PRE* has been developed based on a generic model, thus neglecting the subject-specific variabilities. However, similar to the Lifting Fatigue Failure Tool (LiFFT; [52]), PLAT also represents a faster and computationally less expensive tool in MMH processes evaluation in the workplace. While our primary goal was to examine the *CL* on the lumbar spine as one of the most important risk factors associated with LBP [10, 11], we intend to include different anthropometric data in our future interface by, for instance, adapting anthropometric data from winter [53]. Arjmand et al. [30, 31] have not recommended the use of *PRE* for input variable levels beyond extreme intervals of *T, D,* and *M* (see section 2.3) as it may under or over-estimate the spinal loads in such scenarios. Only one lifting box with one weight and size was applied in all simulated conditions. We believe that heavier loads increase both compression and shear forces on L5-S1. Recent works by Arjmand et al. [30, 31] have shown the accuracy of the *PRE* over a wide range of external loads [54]. This assures us that restricting our experiments to only one load magnitude does not affect the accuracy of PLAT. PLAT uses *PRE*, which is based on a 2D and static sagittally-symmetric model for trunk posture. Therefore, PLAT is applicable for occupational tasks performed symmetrically in the sagittal plane and at a relatively slow movement speed. Moreover, it should be noted that asymmetric tasks in this study (Table 1) had a 30° rotation out of the sagittal plane. Analyzing lifting tasks with a rotation beyond 30° out of the sagittal plane by these equations might underestimate the external moment by 20% [31], thus resulting in unrealistic spinal loads.

Although our study assessed specific static simulated lifting tasks during stoop with both hands on the workload, the *PRE* model has already been tested on various lifting tasks [30, 31, 54]. It may be conceivable that PLAT can be used as a practical tool in different workplace settings, including lifting with one or two hands. Furthermore, wearing fitted underwear to the participants and placing the markers on their bodies (which is not usual in the field) may help the raters to estimate input variables more precisely. Thus, is suggested to conduct this study in the field and compare the results with the present study.

Inter-rater reliability was determined using only video frames captured from a 90° view angle. As it was mentioned earlier, this angle provides the most accurate viewing angle for the sagittal plane [25, 55]. Although 90° is the most common view angle in lifting risk assessment or validation studies, further studies by different view angles are needed to evaluate how inter-rater reliability would be altered. While our primary purpose was to evaluate the validity and inter-rater reliability of the proposed tool, comparing the usability of PLAT with other video-based tools such as 3DMatch [45], which is currently missing, suggests a more comprehensive understanding of its efficiency, ease of use, and required analysis time. We believe that automating the process of selecting the proper variables based on the machine learning algorithm in which the corresponding feature is identified in the image and entered into the program should be applied to the posture-based biomechanical risk assessment methods. This approach may help improve the tool's estimation process, whose accuracy and reliability need to be determined. Therefore, adopting such techniques in the PLAT will be the subject of our future developments.

Conclusion

This paper presents a valid and reliable tool (PLAT) for the Iranian HSPs to assess the lifting biomechanical risk. We found no significant difference between PLAT and the reference gold-standard method, indicating the robustness of PLAT in estimating L5-S1 *CC* and *CS* loads. Inter-rater reliability of the estimated *CLs* was found good to excellent among the raters. Finally, comparative studies between different video-based low back *CLs* analysis tools and PLAT when applied to identical lifting tasks must be carried out to clarify each model's strengths and limitations thereby providing improved guidance to ergonomic practitioners.

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Authors' Contribution

Conceiving the idea and conceptualization was done by S. Ghaneh-Ezabadi, M. Abdoli-Eramaki, and SA. Zakerian. The introduction and manuscript of the paper were written by S. Ghaneh-Ezabadi, M. Abdoli-Eramaki, N. Arjmand and AR. Abouhossein. The method implementation and experimental studies were carried out by S. Ghaneh-Ezabadi. Results and Analysis were carried out by S. Ghaneh-Ezabadi and AR. Abouhossein. The research work was proofread and supervised by M. Abdoli-Eramaki and SA. Zakerian. Laboratory help was provided by SA. Zakerian and N. Arjmand. All the authors read, modified, and approved the final version of the manuscript.

Ethical Approval

All the ethical matters are considered in this study by the authors. This study was approved by the Ethics Review Committee of Tehran University of Medical Sciences, by the ID number of IR.TUMS.SPH.REC.1395.18.67.

Informed consent

Before the study, all participants were informed about the aim of the study and signed the consent form. In addition, the confidentiality of the personal and research data was ensured.

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Conflict of Interest

None

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