Regression Models for Predicting Peak and Continuous Three-Dimensional Spinal Loads during Symmetric and Asymmetric Lifting Tasks

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Most biomechanical assessments of spinal loading during industrial work have focused on estimating peak spinal compressive forces under static and sagittally symmetric conditions. The main objective of this study was to explore the potential of feasibly predicting three-dimensional (3D) spinal loading in industry from various combinations of trunk kinematics, kinetics, and subject-load characteristics. The study used spinal loading, predicted by a validated electromyography-assisted model, from 11 male participants who performed a series of symmetric and asymmetric lifts. Three classes of models were developed: (a) models using workplace, subject, and trunk motion parameters as independent variables (kinematic models); (b) models using workplace, subject, and measured moments variables (kinetic models); and (c) models incorporating workplace, subject, trunk motion, and measured moments variables (combined models). The results showed that peak 3D spinal loading during symmetric and asymmetric lifting were predicted equally well using all three types of regression models. Continuous 3D loading was predicted best using the combined models. When the use of such models is infeasible, the kinematic models can provide adequate predictions. Finally, lateral shear forces (peak and continuous) were consistently underestimated using all three types of models. The study demonstrated the feasibility of predicting 3D loads on the spine under specific symmetric and asymmetric lifting tasks without the need for collecting EMG information. However, further validation and development of the models should be conducted to assess and extend their applicability to lifting conditions other than those presented in this study. Actual or potential applications of this research include exposure assessment in epidemioligical studies, ergonomic intervention, and laboratory task assessment.

INTRODUCTION

Despite numerous attempts to mitigate occupational low-back disorders (LBDs), their prevalence and costs are still alarming (Andersson, 1997; Webster & Snook, 1994). Finding ways to reduce the impact of these disorders would benefit both workers and employers. Most of the existing biomechanical quantification of spinal loading during industrial work has focused on estimating peak spinal compressive force observed during the entire task or job of interest. The use of compressive force as the sole indicator of spinal loading, and the methods and conditions under which these forces are commonly estimated, suffer from several shortcomings.

First, quantifying compressive loads in industrial settings has been limited mainly to simple static and sagittally symmetric lifting situations (Capodaglio, Capodaglio, & Bazzini,

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1997; Keyserling & Chaffin, 1986; Neumann, et al., 1997). However, most industrial manual materials handling (MMH) tasks are dynamic in nature and require motion in multiple planes in addition to the midsagittal plane. Hence this typical mismatch between the actual and assumed situations usually results in underestimation – as much as 30 to 40% – of the spinal forces and moments experienced during dynamic work (Garg, Chaffin, and Freivalds, 1982; Leskinen, Stalhammar, Kuorinka, & Troup, 1983; Marras & Sommerich, 1991b; McGill & Norman, 1985).

Second, most of the biomechanical models applied to industrial settings make extensive assumptions about the muscular system (e.g., single equivalent force generators) in order to simplify the model for practical reasons, such as ease of use and feasibility. These simplifications commonly include ignoring the role of co-contraction of antagonistic muscles, which would lead to underestimating the actual compressive forces (Granata & Marras, 1995; Lavender, Andersson, Tsuang, & Hafezi, 1991).

Third, most of the studies investigating compressive forces during industrial work report only the maximum compressive force without an indication of the time history of this parameter throughout the task. Knowledge of compression at every instant of the task allows an in-depth quantification of other parameters (e.g., average compression, standard deviation, and number of peaks) that would provide a better estimate of the true mechanical risk of the task. Fourth, recent research indicates that the quantification of shear forces in combination with compressive forces provides a more complete assessment of the loading patterns experienced by the spinal structure during work (Fathallah, Marras, & Parnianpour, 1998). Therefore using compressive forces as the sole indicator of spinal loading could also result in underestimation of total loading.

Consequently, it would be desirable to have a biomechanical tool that provides an adequate representation of the behavior of the trunk musculature system and an estimation of continuous dynamic three-dimensional (3D) spinal loading during the performance of industrial work. Electromyography (EMG)-assisted models have been shown to provide such a tool in laboratory settings (Cholewicki, McGill, & Norman, 1995; Fathallah, Marras, & Parnianpour, 1998; Granata & Marras, 1993). However, at this stage use of EMG-assisted models in industrial settings is rather limited. These models require extensive expertise and would not be viable for most practitioners. The time required for setting up the required apparatus and preparing and placing the electrodes on the worker is considerable. In addition most EMG systems require hard-wires that could limit effective work space and hinder the worker's mobility. Given such limitations, it is necessary to find practical ways to obtain information provided by EMG-assisted models without the need for monitoring the EMG response of the trunk muscles (Cholewicki et al., 1995; Mirka & Marras, 1993).

Regression models that predict certain aspects of spinal loading from a set of "simple" (i.e., easier than EMG) independent variables may provide the practical tool of interest. Susnik and Gazvoda (1986) were among the first to demonstrate such a potential. They showed a good agreement between spinal compression (as determined from a simple biomechanical model) and three factors: object weight, trunk angle, and upper body weight. However, the conditions investigated were static (holding weights) and sagittally symmetric, and conditions that are not representative of typical lifting situations. Potvin, Norman, Eckenrath, McGill, and Bennett (1992) successfully extended the use of this approach to dynamic lifting. However, they limited the domain of lifts to the sagittally symmetric plane and investigated only peak compressive loading.

Finally, McGill, Norman, and Cholewicki (1996) demonstrated a strong association between peak compression (as determined from an EMG-assisted model) and the 3D moments about the L5/S1 joint. However, one of the main shortcomings of the study is that it focused only on peak compression with no indication of the continuous performance of the models. Other loading planes – anterior-posterior and lateral planes – were also not assessed. In addition, their results were not validated with a second set of participants and conditions.

Hence the main objective of this study is to explore the potential for using regression models to predict 3D spinal loading during lifting tasks. The regression models include various combinations of equipment and worker characteristics and load characteristics without the need for acquiring trunk muscle EMG information.

METHODS

Participants

A total of 11 healthy men volunteered to participate in this experiment (average age 28.2 years, SD = 4.4; average height 180.7 cm, SD = 3.7; and average weight 78.6 kg, SD = 10.8). A questionnaire was administered to each participant to ensure there was no significant history of back disorders (e.g., surgery, herniated disc, hospitalization), and to screen participants with current back discomforts.

Experimental Design

The experiment was a three-way within-subject design. The dependent variables consisted of continuous 3D spinal loading at the L5/S1 level in terms of compressive, anterior-posterior shear, and lateral shear forces. Independent variables included speed of lift, weight handled, and task symmetry. Speed of lift (heretofore referred to as speed) had three levels: low (2 s/lift), medium (1.5 s/lift) and high (1 s/lift). These speed levels were chosen to represent varying speeds similar to those observed in industry (Marras et al.,1995). Three weight levels were considered: low (22 N), medium (67 N), and high (156 N). The weight levels were determined based on the distribution of weights observed in industrial tasks (Marras et al., 1995). Low weight level corresponded to a value between the 25th and 50th percentile, the medium level between the 50th and 75th, and the high level between the 75th and 100th percentile of weight distribution. Finally, task symmetry had two levels: symmetric and asymmetric lifting.

Apparatus/EMG-Assisted Model

An EMG system collected signals from 10 pairs of bipolar silver-silver/chloride surface electrodes affixed over specific locations of 10 trunk muscles. The 10 muscles included the right and left latissimus dorsi, erector spinae, rectus abdominus, external obliques, and internal obliques. Three-dimensional continuous angular position, velocity, and acceleration of the trunk were determined using the Lumbar Motion Monitor, or LMM (Ohio State University, Columbus, OH; Marras, Fathallah, Miller, Davis, & Mirka, 1992). Three-dimensional external forces and the estimated moments about the L5/S1 joint were monitored by the combination of a Bertec 4060A force plate (Bertec, Worthington, Ohio) and two electrogoniometers used to determine the continuous location and orientation of the L5/S1 joint in 3D space (Fathallah, Marras, Parnianpour, & Granata, 1997). The weight lifted consisted of a 30.5 × 30.5 × 23-cm wooden box with two handles (3.8 cm in diameter and 11.4 cm in length) centered on its sides. All the analog signals were collected at 100 Hz via a 12-bit, 32-channel analog-to-digital (A/D) converter connected to a 386-based microcomputer.

An EMG-assisted model provided estimates of the internal moments required to achieve the balanced equilibrium conditions and the total 3D spinal loads (compression, anterior-posterior shear, and lateral shear) on the L5/S1 joint (Fathallah et al., 1998; Granata & Marras, 1993). The model assumes that in order to achieve dynamic equilibrium during a lifting task, the external moments generated about the L5/S1 joint must be balanced by moments generated internally by the body's musculature system. Forces and moments generated by the 10 major trunk muscles are estimated by activation levels (EMG), muscle cross-section areas, muscle moment arms, and muscle velocities and length modulations (Granata & Marras, 1993; Marras & Sommerich, 1991a). The model combines these internal (muscle) forces with the external (load carried and upper body weight) forces to estimate the total loads generated at the center of the L5/S1 joint.

Experimental Procedure

Initially each participant consented to volunteer for the experiment and answered a "history of low-back disorder" questionnaire. Written instructions were given to each participant detailing the conditions of the experiment. Prior to any testing, the experimenter ensured

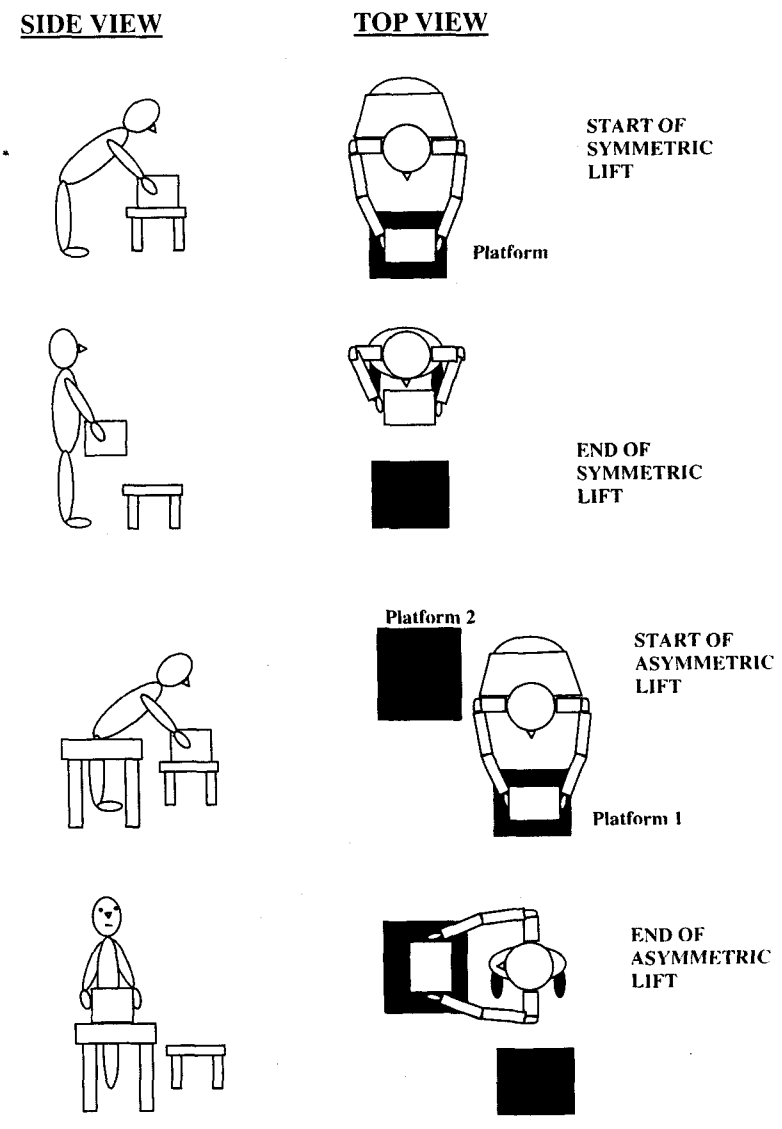


Figure 1. Top and side view illustrations of a symmetric and an asymmetric lift.

that the participant understood the nature of the exertions.

During the experiment, the participant lifted the wooden box weighted as specified for the prescribed condition. Two types of conditions were administered: symmetric and asymmetric lifting. In the symmetric condition, the box (weight) was placed on a platform in front of the participant slightly above knee height, at a horizontal distance from the spine to the center of the load equal to his arm length (distance between the center of the shoulder joint and tip of the middle finger). At the onset of a tone, the participant was asked to lift the box from the platform to a position as close as possible to his body while maintaining straight legs and arms (see Figure 1). A second tone indicated the end of the lift.

For the asymmetric condition, the box was placed in front of the participant in the same manner as the symmetric condition. However, in this case the participant was asked to set the box down on another platform to his right at an angle perpendicular to the midsagittal plane at the start of the lift (see Figure 1). The platform height was set level with the participant's

iliac crest height and was placed about arm's length, horizontally. Similar to the symmetric condition, the participant was provided with tones indicating the start and finish of a given trial. To minimize fatigue, the participant was given at least a 60-s rest period between exertions. Participants were also instructed to take an additional rest period whenever they desired.

Prior to each experimental condition, the task was demonstrated and the participant was allotted time to practice the lift. During the experiment, the experimenter ensured that the participant was performing the task as instructed, especially starting and finishing the task at the onset of the two auditory tones; otherwise, the trial was repeated.

Within a given speed, the type of symmetry was randomized. Also, within a given symmetry level, symmetric or asymmetric, the three weights handled were presented in random order. However, the participant was not asked to alternate either between speeds or between symmetric and asymmetric conditions. This restriction was necessary in order to ensure consistency in lifting and lowering speeds and styles.

Development of Regression Models

The 11 participants were randomly divided into two subgroups. The first group included 6 participants and was used to develop regression models (average age 28.8 years, SD = 5.5; average height 181.9 cm, SD = 8.4; and average weight 83.9 kg, SD = 9.7). Data from the second group (the remaining 5 participants) were used to validate and assess the performance of the regression models (average age 27.4 years, SD = 3.8; average height 179.3 cm, SD = 8.4; and average weight 72.3 kg, SD = 11.7). This approach provides a less biased indication of the overall performance and generalization of the models (Tabachnick & Fidell, 1989).

Three classes of regression models were considered in this study: (a) models using workplace, subject, and trunk kinematic variables as independent variables (kinematic models), (b) models using workplace, subject, and measured moment variables (kinetic models), and (c) models incorporating workplace, subject, Lumbar Motion Monitor (LMM), and measured moment variables (combined models). As mentioned earlier, for each class of models the dependent variables consisted of continuous compression, anterior-posterior (A/P) shear, and lateral shear forces. The structures of the various models and the independent and dependent variables are shown in Table 1.

The nine LMM variables consist of angular position, velocity, and acceleration within each of the three coronal planes (sagittal, lateral, and transverse planes) captured by the device during a given lift. For example, when a participant lifted a box, the device recorded, at 60 Hz sampling frequency, how many degrees the trunk was bent forward or backward (sagittal position), bent side-to-side (lateral position), and twisted (twisting position) with respect to erect posture (0°). The angular velocities and accelerations of the lift in these directions reflect how fast the trunk is moving and the rate of change of that movement, respectively. The measured X, Y, and Z moment variables are directly captured by the force plate and correspond to moments generated about the medial-lateral axis (x axis), the anterior-posterior axis (y axis), and the vertical axis (z axis) during a given lift. The approximated moments about the L5/S1 joint in the X (MXL5S1, extension moment) and Y (MYL5S1, lateral moments) directions were determined from a combination of LMM and subject variables. These estimates were adapted from Mirka and Baker, (1994) as follows:

$$MX_{L5S1} = MT \times g \times R1 \times \sin\theta + MAB \times g \times R2 \times \sin\theta + MAB \times R2^2 \times (\sin\theta)^2 \times a + I_{cm} \times \alpha \quad (1)$$

$$MY_{L5S1} = MT \times g \times R1 \times \sin\rho + MAB \times g \times R2 \times \sin\rho + MAB \times R2^2 \times (\sin\rho)^2 \times \beta + J_{cm} \times \beta \quad (2)$$

where MX_{L5S1} = estimated extension moment about the L5/S1 joint, MY_{L5S1} = estimated lateral moment about the L5/S1 joint, g = gravitational acceleration (9.81 m/s^2), $R1$ = distance from L5/S1 joint to center of gravity (COG) of trunk (m), θ = sagittal angle of the trunk (upright = 0°), ρ = lateral angle of the trunk (upright = 0°), MAB = mass of the arms and mass of the box (kg), $R2$ = distance from L5/S1 joint to the shoulder joint (m), α = angular sagittal acceleration of the trunk

TABLE 1: Dependent Variables and Continuous Independent Variables Available for Inclusion in Three Classes of Models (Kinematic, Kinetic, and Combined Models)

	Kinematic Models		Kinetic Models		Combined Models		
DEPENDENT VARIABLES	LMM Variables	Subject/ Workplace Variables	Moments Variables	Subject/ Workplace Variables	Moments Variables	LMM Variables	Subject/ Workplace Variables
Compression A/P shear Lateral shear	Sagittal, lateral, and twisting position, velocity, and acceleration Approximated X Moment* Approximated Y Moment*	Body weight Box weight	Measured X, Y, Z moments	Body weight Box weight	Measured X, Y, Z moments	Sagittal, lateral, and twisting position, velocity, and acceleration	Body weight Box weight

*Includes a combination of both types of variables.

(rad/s²), β = angular lateral acceleration of the trunk (rad/s²), I_{cm} = sagittal mass moment of inertia of the trunk about center of mass (kg m²), and J_{cm} = lateral mass moment of inertia of the trunk about center of mass (kg m²).

Forward-selection, stepwise linear regression was used to select a subset of the available independent variables. *F*-to-enter was set at a minimum of 10.0, and variable tolerance ($1-R^2$) was set at .25.

Data Analysis

Continuous and maximum predicted spinal loads (using the regression models developed in this study) were generated for the 5-participant validation group and compared with the loads estimated from the EMG-assisted biomechanical model. First, for each Weight × Speed × Symmetry combination, predicted average maximum spinal loads (compression, A/P shear, and lateral shear) were calculated using the three types of regression models (kinematic, kinetic, and combined) and compared with the corresponding average maximum values estimated by the EMG-assisted model. Paired *t*-tests were performed to assess the significance of differences between predicted and estimated (EMG-assisted model) spinal loads.

Second, predicted average continuous profiles of the 5 validation participants were compared with the EMG-assisted model average continuous profiles under each Weight × Symmetry combination. Note that the average continuous profiles were determined based on the percentage of lift. In other words, at each point in time the spinal loads of the 5 validation participants were averaged with respect to the same point in the lift that corresponded to a given percentage of that lift. For each condition, the Pearson correlation coefficient (*r*) and average absolute error (AAE; error = EMG model – predicted) were determined between the predicted and EMG-assisted model average continuous spinal loading profiles.

RESULTS

Table 2 summarizes the results of the three classes of regression models (kinematic, kinetic, and combined) for each of the three continuous spinal loads (compression, A/P shear, and lateral shear). The adjusted R^2 values for the kinematic models were .51, .71, and .72 for compression, A/P shear, and lateral shear, respectively, with corresponding standard errors of 1001, 241, and 136 *N*. The kinetic model adjusted R^2 values were .54, .51, and .54 for compression, A/P shear, and lateral shear, respectively, with corresponding standard errors of 971, 314, and 175 *N*. The adjusted R^2 values for the combined model were .68, .67, and .77 for compression, A/P shear, and lateral shear, respectively, with corresponding standard errors of 808, 257, and 123 *N*. The number of variables in the models ranged from 5 (kinetic model) to 12 (kinematic model) for compression, from 5 (kinematic model) to 8 (combined model) for A/P shear, and from 5 (kinetic model) to 9 (kinematic model) for lateral shear. Note that all the variables included in all models reported in Table 2 were significant at the .0001 level.

Figures 2 through 4 provide comparisons between the EMG model and the predicted average maximum forces under each Weight × Speed × Symmetry condition for compression, A/P shear, and lateral shear, respectively. As mentioned earlier, data in these figures were determined from the 5 participant validation group and not from the participants used in developing the models. For average maximum compression, under all conditions, there was no statistically significant difference between the EMG model values and those predicted by any of the three models (see Figure 2 on page 381). For all three models, the average maximum predicted A/P shear forces were mostly in agreement with the EMG model values. The only significantly underestimated values were for most of the high-weight symmetric conditions (see Figure 3 on page 382). Maximum lateral shear was generally overestimated by the models, especially under the asymmetric conditions. In general, the kinematic model performed better than the other two models under medium- and high-weight conditions (see Figure 4 on page 383). Under the low-weight asymmetric conditions, the kinematic model substantially overestimated the EMG model values.

Figures 5 through 7 show comparisons between the EMG model and predicted average continuous spinal loads under each Weight × Symmetry condition for compression, A/P shear,

TABLE 2: Regression Models for Predicting Continuous Spinal Loading Using Three Sets of Continuous Independent Variables: (a) Motion, Subject and Workplace Variables (Kinematic Models), (b) Kinetic, Subject and Workplace Variables (Kinetic Models), and (c) a Combination of Motion, Moments, Subject and Workplace Variables (Combined Models)

MODELS	Adjusted R^2	Standard Error (SE)
Kinematic Models:		
$COMP = 2946.6 - 2.5 \times MX_{L5S1} - 19.6 \times BDWT - 28.2 \times BXWT + 40.0 \times TVEL - 371.8 \times LPOS - 64.5 \times TPOS + 37.2\ H\ SPOS - 60.4 \times MY_{L5S1} + 24.9 \times LACC - 12.4 \times SVEL - 6.1 \times TACC - 22.6 \times LVEL$	.51	1001
$ASHR = -426.4 - 16.9 \times SPOS + 1.7 \times MX_{L5S1} - 2.0 \times SACC + 7.4 \times TPOS - 9.1 \times MY_{L5S1} - 22.7 \times LPOS$	.71	241
$LSHR = 230.9 + 21.6 \times TPOS + 61.9 \times LPOS + 13.2 \times MX_{L5S1} + 18.6 \times LVEL - 10.4 \times TVEL - 1.5 \times BDWT - 2.2 \times LACC + 1.7 \times BXWT - 0.13 \times MY_{L5S1}$	.72	136
Kinetic Models:		
$COMP = 618.8 - 19.4 \times M_x + 17.7 \times M_y - 4.0 \times BDWT - 1.6 \times BXWT - 0.83 \times M_z$	.54	971
$ASHR = 1208.7 + 7.5 \times M_x + 3.7 \times M_y - 5.1 \times M_z - 5.5 \times BXWT - 10.0 \times BDWT$	.51	314
$PLSHR = -165.1 - 10.2 \times M_y + 7.6 \times M_z - 0.60 \times M_x + 1.1 \times BDWT + 0.87 \times BXWT$	.54	175
Combined (Kinematic/Kinetic) Models:		
$COMP = 1422.6 + 21.5 \times SPOS - 251.0 \times LPOS - 28.8 \times TPOS - 14.6 \times SVEL + 3.4 \times SACC + 14.8 \times LACC - 3.7 \times TACC - 19.4 \times M_x + 26.1 \times M_y - 2.4 \times BXWT - 6.3 \times BDWT$	.68	808
$ASHR = 175.6 - 17.6 \times SPOS + 3.1 \times M_x - 4.2 \times BDWT + 0.70 \times SACC - 9.6 \times LPOS + 1.1 \times M_y + 1.3 \times TACC + 1.1 \times SVEL$	.67	257
$LSHR = -27.3 - 7.0 \times M_y + 39.3 \times LPOS + 15.1 \times TPOS - 9.90 \times TVEL + 3.7 \times M_z + 5.2 \times LVEL + 1.0 \times BXWT$	.77	123

COMP = Compression (N), ASHR = Anterior-posterior shear (N), LSHR = Lateral Shear (N), BXWT = Box weight, BDWT = Body weight, LACC = Lateral Acceleration (deg/s²), LPOS = Lateral Position (deg), LVEL = Lateral Velocity (deg/s), M_x = Moment about X axis (extension moment) (Nm), MX_{L5S1} = Approximated extension moment about L5/S1 joint (Nm; see text), M_y = Moment about Y axis (lateral moment) (Nm), MY_{L5S1} = Approximated lateral moment about L5/S1 joint (Nm; see text), M_z = Moment about Z axis (twisting moment) (Nm), SACC = Sagittal Acceleration (deg/s²), SPOS = Sagittal Position (deg), SVEL = Sagittal Velocity (deg/s), TACC = Twisting Acceleration (deg/s²), TPOS = Twisting Position (deg), TVEL = Twisting Velocity (deg/s).

and lateral shear, respectively. Several observations can be made from these figures. For compression (Figure 5, page 384), the predicted continuous profiles for all three spinal loads had consistently high correlation coefficients and relatively low AAEs under the symmetric conditions. Furthermore, for all three models the compression model's performance under the symmetric conditions seemed to improve as weight increased. For the asymmetric conditions, performance was more varied among the three models. The kinematic model seemed to perform better under low-weight conditions, whereas the kinetic and combined models' performance improved as the weight increased (see Figure 5).

The results for A/P shear (Figure 6, page 385) were similar to those for compression, with the

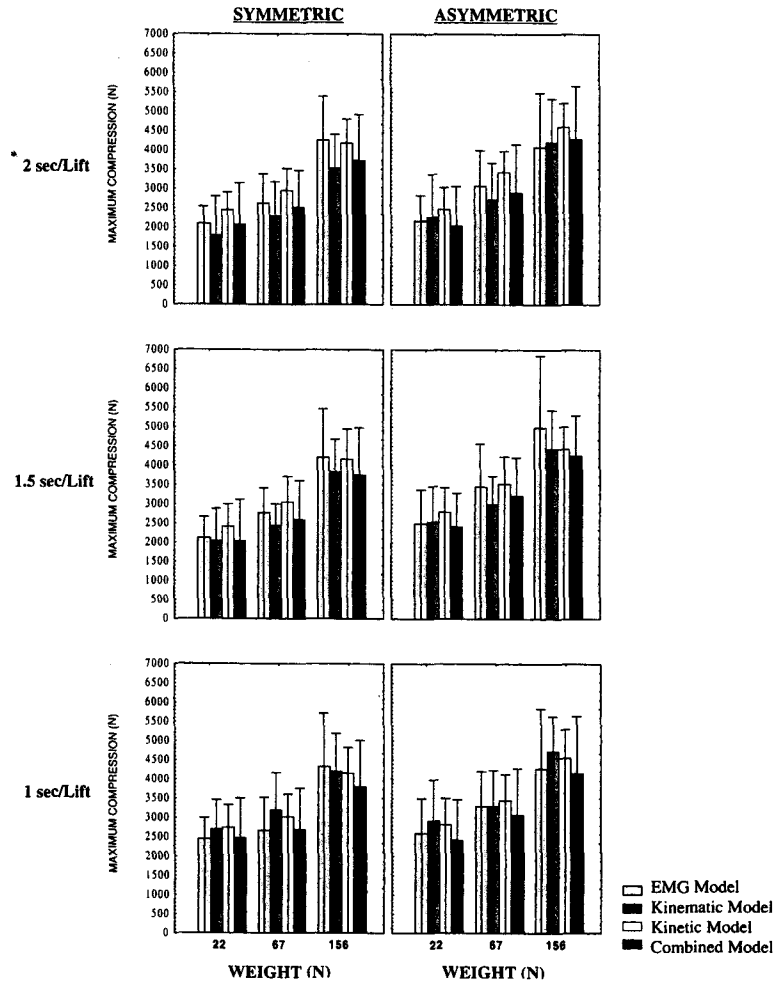


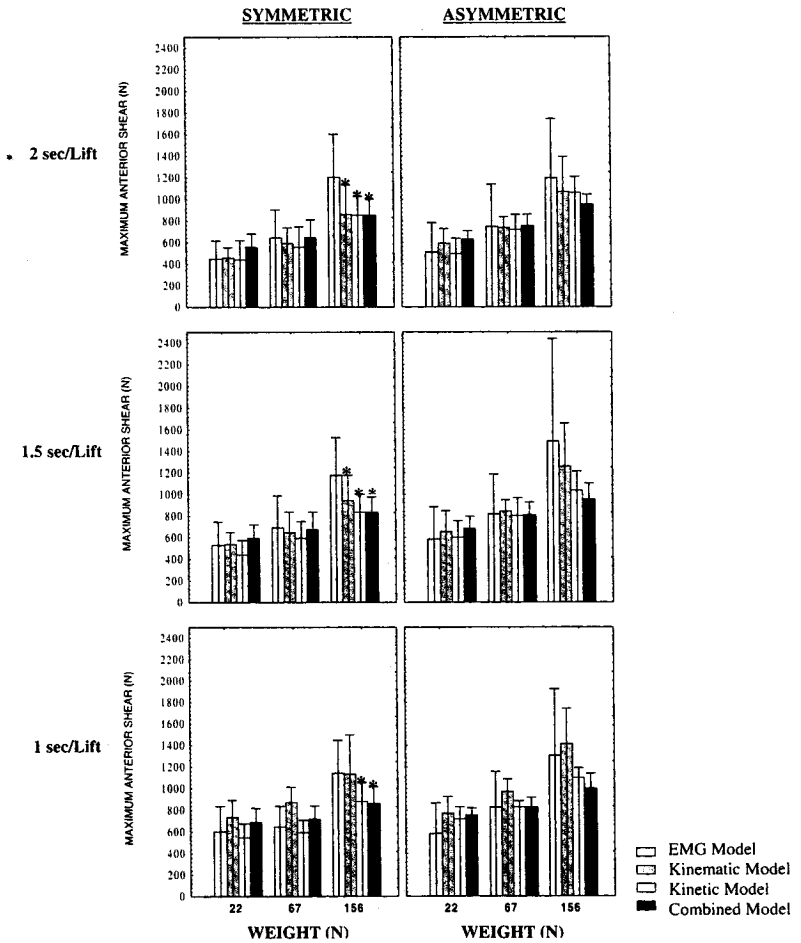
Figure 2. Average maximum compressive force predicted by the kinematic, kinetic, and combined models compared with the EMG model values of the validation group under each Weight × Speed × Symmetry combination. Average + 1 *SD* bars are also indicated.

exception of the kinetic model's performance. Under symmetric conditions, both the kinematic and combined models improved with increased weight, whereas the kinetic model worsened. Under the asymmetric conditions, the kinematic and kinetic models performed better under the low-weight condition when compared with the medium- and high-weight conditions. The combined model had consistently high correlations across the asymmetric conditions and improved in AAE as weight increased (see Figure 6).

As in the case of average maximum loading, the continuous lateral shear results (Figure 7, page 386) showed that for the majority of the lift, all three models consistently overpredicted the EMG model values, especially in the asymmetric conditions. However, correlations between the EMG model and predicted profiles were generally high (i.e., the lowest was .71). Note that under symmetric conditions the lateral shear was, as expected, very low, and hence the results are of little importance.

DISCUSSION

Knowledge of mechanical loading on the spinal structure during work can help identify instances when that structure's tolerance is challenged and placed at a higher risk of injury. In an attempt to mitigate the risk of back injuries,



* Significantly different from EMG-model values at $\alpha < 0.05$

Figure 3. Average maximum anterior/posterior shear force predicted by the kinematic, kinetic, and combined models compared to the EMG model values of the validation group under each Weight × Speed × Symmetry combination. Average + 1 *SD* bars are also indicated. Statistically significant differences are also indicated when appropriate.

ergonomics and safety professionals could redesign the workplace, the task(s), or both, in a manner that assures the workers' spinal structures are not exposed to excessive levels of spinal loading. However, as discussed previously, a comprehensive quantification of spinal loads in industrial settings has been lacking. This study explored the potential for providing a practical way to predict spinal loads during lifting tasks using various combinations of motion, moments, individual factors, and workplace factors.

Compression

All three regression models predicted EMG model average peak compression rather well. For all experimental conditions, the peak compression predictions were statistically equivalent to the EMG model values. This may indicate that peak compressive forces, under conditions similar to those presented in this study, can be well estimated using a combination of kinetic, kinematic, individual factors, and workplace factors. Given that all three models performed equally well, the kinematic model can be considered the more practical choice for predicting peak compression under situations similar to those described in this study because it requires the least instrumentation.

Overall the performance of regression models in predicting continuous compression was

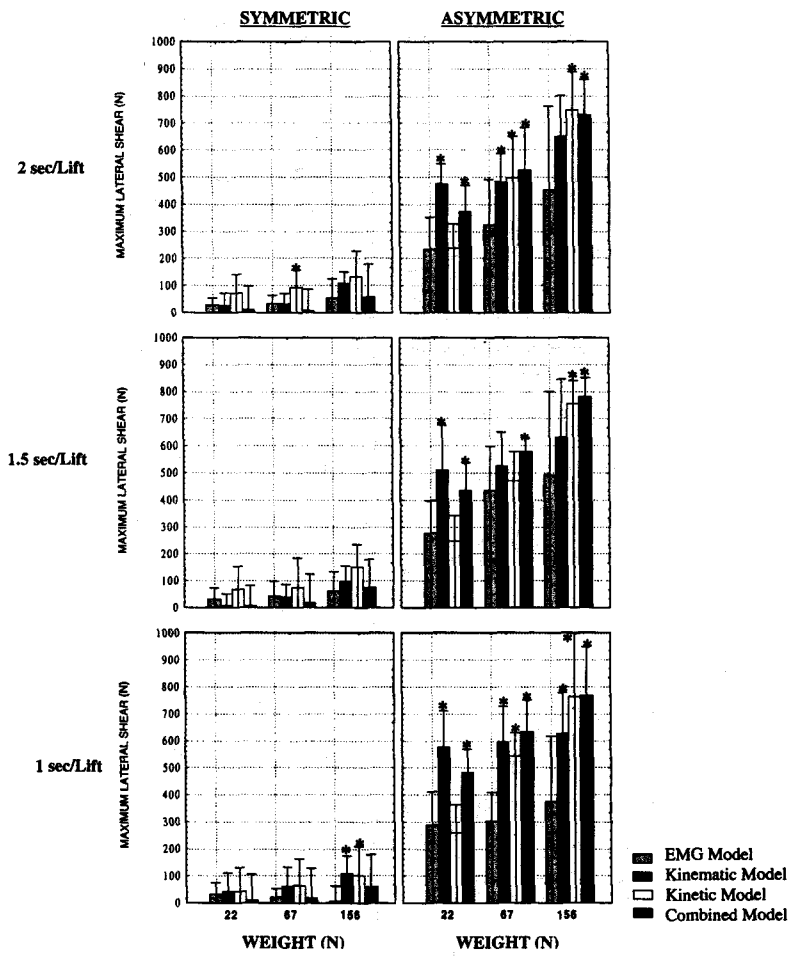


Figure 4. Average maximum lateral shear force predicted by the kinematic, kinetic, and combined models compared with the EMG model values of the validation group under each Weight × Speed × Symmetry combination. Average + 1 *SD* bars are also indicated. Statistically significant differences are also indicated when appropriate.

adequate. Several specific observations can be made regarding these models. First, all three models predicted continuous compression better for symmetric lifts than for asymmetric lifts. This was expected because, unlike symmetric lifting, asymmetric lifting involves several additional factors, such as twisting and lateral motions, which play a role in the development of spinal loads. These additional factors require more complex neuromuscular activation patterns, which may not be well predicted without direct measurement (i.e., EMG models). Second, the kinematic and combined models generally performed better than the kinetic models. This finding emphasizes the need to quantify trunk kinematics during lifting in order to predict spinal loading. Relying solely on moment and worker/workplace parameters may not provide a consistent approach to predicting *continuous* spinal loads.

Furthermore, the combined models seemed to provide the most consistent performance overall. Therefore, combining both kinematic and kinetic information about the lift along with worker/workplace parameters may provide the most accurate predictions of continuous spinal compressive loading. Finally, the performance of the models was affected by the weight handled. In general, the models performed better under higher weight levels, with

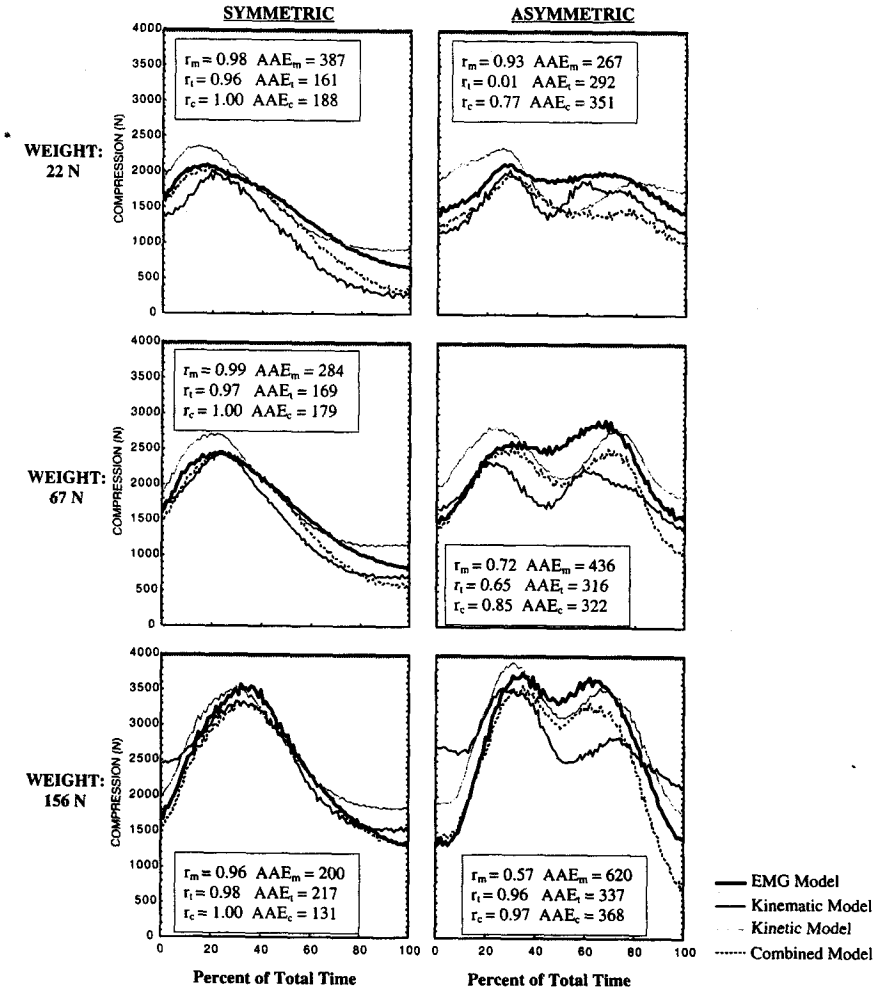


Figure 5. Average compression force predicted by the kinematic (m), kinetic (t), and combined (c) models compared with the EMG model average of the validation group under each Weight × Symmetry combination. Pearson correlation (*r*) and average absolute error (AAE) are also indicated for each combination.

some exceptions. Under asymmetric conditions, the accuracy of the kinematic model decreased as the weight increased.

A/P Shear

The observations for A/P shear were similar to those made previously for compression, with a few exceptions. Overall the regression models predicted peak A/P shear rather well, with the exception of the high-weight symmetric conditions in which the predicted values were significantly underestimated. As in the case of peak compression, the kinematic model seems to provide reasonable estimates for predicting peak A/P shear forces in lifting tasks similar to those described in this paper.

The continuous A/P shear was predicted equally well under both symmetric and asymmetric conditions. In other words, the general decrement in performance observed when comparing the asymmetric conditions with the symmetric conditions under compression was not observed in the case of A/P shear. This may be because under asymmetric conditions, A/P shear was dominant during the early phase of the lift, when lifting conditions resembled those of the symmetric lifts (i.e., the participants were still in sagittally symmetric postures). Conversely,

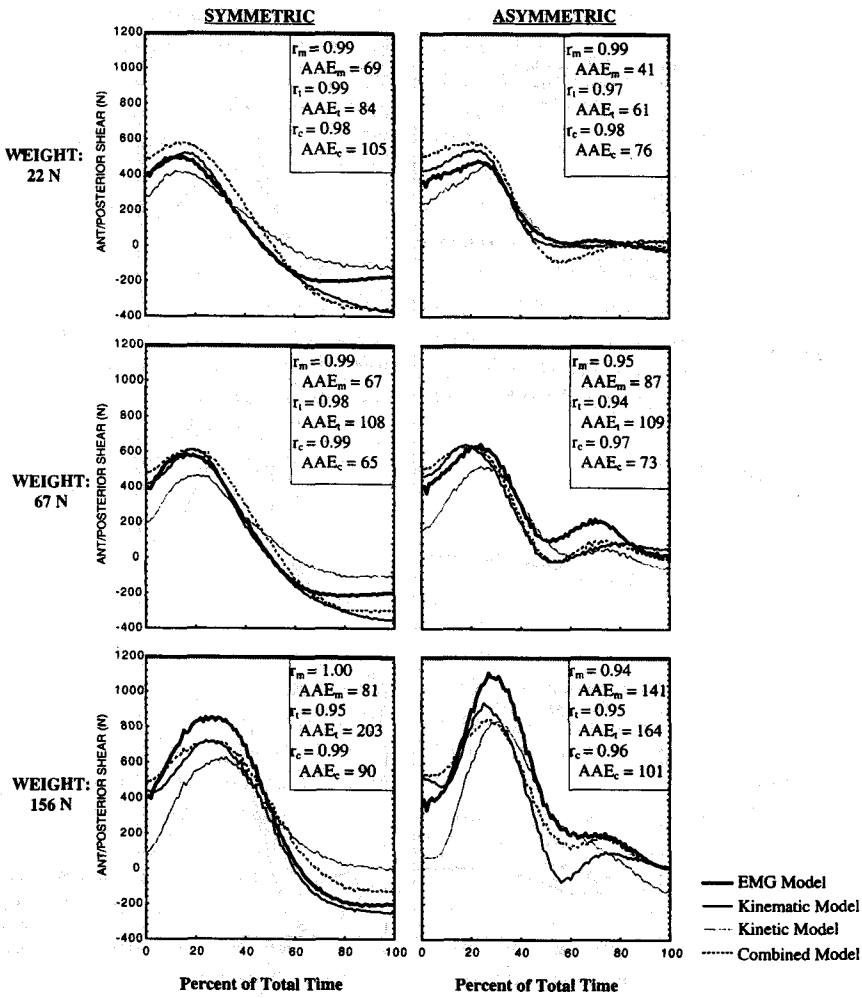


Figure 6. Average anterior/posterior shear force predicted by the kinematic (m), kinetic (t), and combined (c) models compared with the EMG model average of the validation group under each Weight × Symmetry combination. Pearson correlation (r) and average absolute error (AAE) are also indicated for each combination.

compression was observed at increased magnitudes throughout the course of the lift.

Lateral Shear

Under all experimental conditions, all three regression models significantly overpredicted peak and continuous lateral shear forces. It is difficult to ascertain the reasons for such discrepancies between the EMG model and predicted values, but it is likely that characteristics of the two groups of participants (model development and validation groups) may have contributed to such a difference. For example, the average body weight of the validation group was substantially higher than that of the model development group (82 kg for the validation group vs. 72 kg for the model development group). This difference in body weight may have had a larger impact on the lateral shear forces because these forces are lower in magnitude than the compressive and A/P forces. Note that the correlations between predicted and EMG model profiles were consistently high (i.e., average .87). In general, performance of both the kinematic and the combined models was superior to the kinetic model. This finding reemphasizes the need for both kinetic and kinematic information in predicting continuous spinal loads.

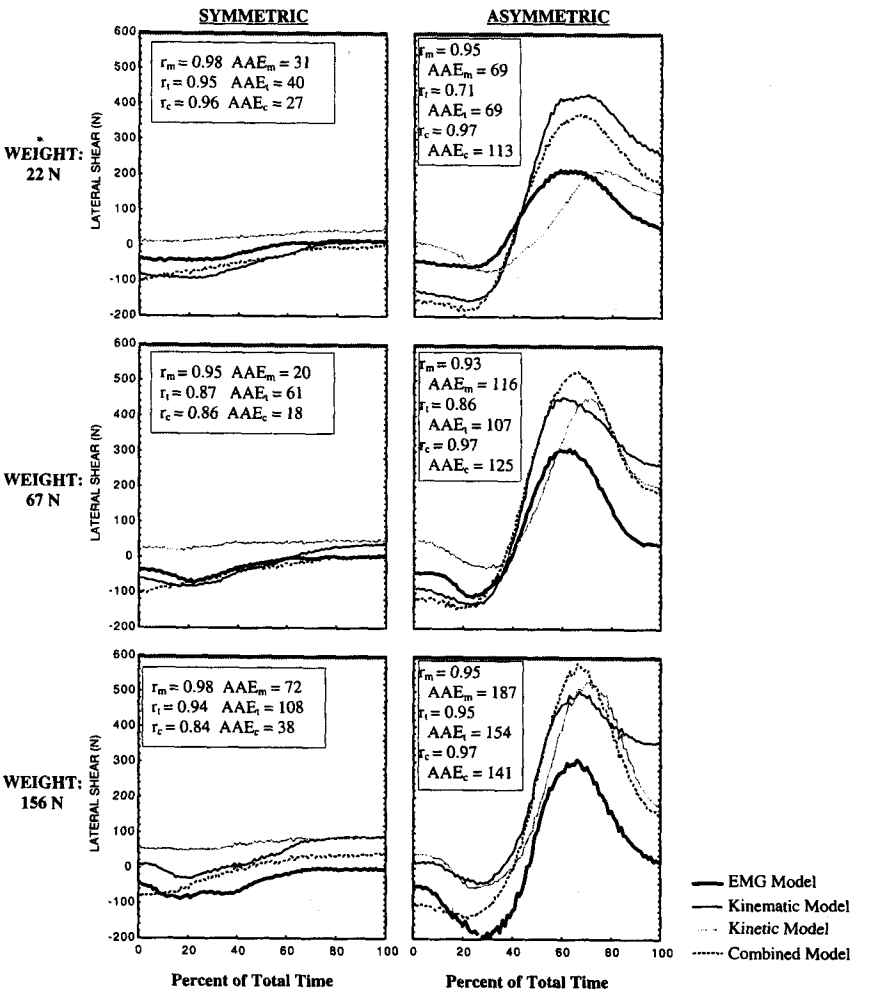


Figure 7. Average lateral shear force predicted by the kinematic (m), kinetic (t), and combined (c) models compared with the EMG model average of the validation group under each Weight × Symmetry combination. Pearson correlation (r) and average absolute error (AAE) are also indicated for each combination.

GENERAL DISCUSSION

The apparently low R values (.51–.77) reported in Table 2 were anticipated because there was an underfitting situation stemming from the fact that the data was used to develop the models were very large (more than 55 000 data points; Tabachnick & Fidell, 1989). We believed that the accuracy of the models was better evaluated through the series of comparisons performed between the EMG model values (regression models input or actual values) and the predicted values (Figures 2–7). It is evident that through the use of kinematic, kinetic, individual, and workplace parameters, it is possible to adequately estimate spinal loading during lifts similar to those described in this study, without the need for EMG information. The models presented in this study appear to predict peak 3D loading very well, especially for symmetric conditions. Given that all three models were equivalent in their prediction performance of peak loading, the kinematic model may be more practical to use since it requires the least instrumentation (only the LMM). For predicting continuous 3D loading, the combined model offered the best and most consistent performance, followed by the kinematic and the kinetic models. Hence when predicting continuous spinal loading, it

is recommended that 3D moments coupled with kinematic and individual and workplace parameters be captured. However, if direct measurement of moments is infeasible, the kinematic model may be appropriate.

It should be reemphasized that this study is an attempt to demonstrate the potential for using kinematic and kinetic information combined with individual and workplace factors to approximate spinal loading. The models presented here are limited to the specific symmetric and asymmetric conditions described previously. Further validation and model refinement may be necessary to obtain comprehensive prediction models that would be appropriate to use in industrial settings. However, the study provided the first step in developing such comprehensive tools.

Limitations

There are several limitations to this study. First, the number of participants used in the model development might be perceived as small (6 participants). However, the models in this study had more than sufficient sample size for model development purposes, because continuous profiles were used (the number of sampled data points was over 55 000). Furthermore, the model performance was tested with a new set of participants (more than 50 000 data points). These participants provided mostly new conditions in terms of the kinematic, kinetic, and individual parameters, because they had different anthropometric and individual characteristics than those of the model development group.

Second, the prediction of both peak and continuous lateral shear was consistently underestimated. However, the models retained the relative relationships among various experimental conditions observed using the EMG model values. Therefore, even though the EMG model magnitudes of lateral shear may be questionable, the use of the models may be applicable for relative comparisons among various lifting conditions. Third, as mentioned earlier, the models presented here are most applicable to the conditions covered in this study. Any extrapolation to other conditions is yet to be assessed, and hence the models should be applied with caution.

Finally, the EMG model used in this study has certain prediction errors associated with it that may affect the source of prediction errors in the regression models. However, note that EMG-assisted models, such as the one used in this study, are expected to offer more accurate estimates of spinal loading during dynamic lifting because they incorporate neuromuscular response in combination with kinematic and kinetic parameters. The regression models presented in this study provide approximations of spinal loads and may suffer from accuracy problems as the complexity of the task increases.

CONCLUSIONS

Knowledge of continuous and peak 3D spinal loading can assist both researchers and practitioners in their efforts to better quantify the risks imposed on the spinal structure during lifting tasks in industrial settings. To date, such a comprehensive assessment of spinal loading in industrial settings has been limited by many practical obstacles, including the need for continuous capture of EMG signals. This study explored the potential for using regression models to predict peak and continuous 3D loading on the spine during specific lifting tasks using kinematic, kinetic, individual, and workplace parameters without the need to capture EMG signals.

In summary, peak 3D loading on the spine during symmetric and asymmetric lifting was predicted equally well using each of the three types of regression models. Continuous 3D loading on the spine was best predicted using models that included kinetic, kinematic, individual, and workplace information (i.e., combined model). Lateral shear forces (peak and continuous) were consistently underestimated using each of the three types of models. Characteristics of the validation group may have been responsible for the observed discrepancies. This study demonstrated that regression models can be used to determine estimates of 3D spinal loading during different symmetric and asymmetric lifting tasks. However, further validation and development of the models should be conducted to assess and extend their applicability to lifting conditions other than those presented in this study.

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