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Motor unit behavior of lumbar multifidus during a forward trunk bending task performed under different speeds and loads in asymptomatic participants

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Background The lumbar multifidus (LM) plays a key role in static and dynamic stability; however, studies of LM motor unit behavior have yet to be extensively investigated. This study aimed to assess the test-retest reliability of motor unit behavior measurements using electromyography decomposition (dEMG) and to investigate the motor unit behavior under different speeds and loads in asymptomatic participants. **Methods** In this experimental repeated-measures design, 29 male and female asymptomatic participants were recruited. Motor unit behavior was measured during two sets of 60-second active trunk flexion exercises using dEMG under two speeds (15 and 25 repetitions/minute) and two loads (5% and 10% body weight). The action potential amplitude and motor unit firing rate were derived. Intraclass correlation coefficients (ICC) were used to determine within-session test-retest reliability, and a two-factor repeated-measure ANOVA was used to determine the effects of load and speed. **Results** Findings demonstrated acceptable within-session test-retest reliability (ICC > 0.70) for most parameters. Significantly greater peak and average amplitudes and average firing rates were seen with an increase in speed, while greater average amplitudes and firing rates were seen with an increase in load. **Conclusion** These findings support the use of measures of LM motor unit behavior. Exercises at greater speeds and loads increase LM firing rates and amplitudes. A better understanding of LM motor unit behavior may aid our understanding of rehabilitation protocols for low back pain.

Keywords Electromyography decomposition, Motor unit behavior, Lumbar multifidus, Load, Speed

Abbreviations

LM	Lumbar multifidus muscle
dEMG	Electromyography decomposition
ICC	Intraclass correlation coefficient
ANOVA	Analysis of variance
MU	Motor unit
BMI	Body mass index
IMU	Inertial measurement unit
PeakAP	Peak motor unit action potential
AvgAP	Averaged motor unit action potential
PeakFR	Peak motor unit firing rate
AvgFR	Averaged motor unit firing rate
LL	Low speed and low load
LH	Low speed and high load
HL	High speed and low load

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HH High speed and high load

Efficient stabilization and coordination of the spine depend on the activation capacity of deep trunk muscles, such as the lumbar multifidus muscle (LM)[1,2]. However, contractions of these muscles depend on the recruitment of motor units (MUs)[3,4]. Therefore, studying the MU behavior allows a more detailed analysis of muscle activation, which may be able to provide new insights into muscle function. Specifically, MU recruitment threshold, firing rates, amplitude, and action potentials can indicate how a muscle responds to different physical demands[5], which could provide important information in the development of effective rehabilitation protocols for musculoskeletal disorders[6,7].

The use of surface electromyography decomposition techniques (dEMG) to study MU behavior has been gaining interest owing to its non-invasive nature over intramuscular techniques[7] and enhanced reliability and validity[8–10]. This advancement may be able to provide valuable insights into various MU behavior parameters[11], which in turn may enhance our understanding of how the neuromuscular system orchestrates movement[12]. Unlike traditional surface EMG amplitude, which reflects the summed activity of many units, decomposition allows for analysis of motor unit action potential (MUAP) amplitudes and firing rates. Peak and average MUAPs provide information about the size of motor units contributing to muscle activity, while peak and average firing rates reflect how motor units adjust their firing frequency under different task demands. These measures offer additional insight into muscle function that may not be captured by global EMG signals[9,10].

Several studies using dEMG have documented the MU behavior of various upper and lower limb muscles[12–21], with the majority being performed during isometric contractions[13,15–19]. While these studies provide valuable insights into the physiological function of limb muscles, it is worth noting that research on trunk muscles is generally limited, with the exception of Silva et al.[7] who considered the lumbar erector spinae, with most studies utilizing invasive or intramuscular EMG techniques[22–27].

Although a few studies utilizing dEMG have demonstrated varying MU behavior patterns according to different speeds of movement[12,14], no study has examined simultaneously the effect of different speed and load conditions during a dynamic task. It is anticipated that the MU behavior of a muscle would significantly change as varying the speed and load. Moreover, to the authors' knowledge and at the time when this study was initiated, there is a dearth of studies relating to LM, which is considered a crucial muscle for spinal stability and postural control.

Evaluating the test-retest reliability of dEMG measures is an essential first step to ensure that these parameters are reproducible and suitable for future clinical or interventional research. In addition, examining how MUAPs and firing rates respond to different loads and speeds provides an evaluation of construct validity, as these conditions are known to alter motor unit behavior based on established neuromuscular principles. Thus, this study aimed to assess the test-retest reliability of MU behavior measurements and to explore the effects of different speeds and loads on the MU behavior of LM during a forward trunk bending task in asymptomatic participants. We hypothesized that test-retest reliability would yield an acceptable intraclass correlation coefficient (ICC > 0.70), and that MU amplitudes and firing rates of the LM would be greater with higher loads, and that MU firing rates would be greater with higher speeds. This hypothesis was based on the size principle of motor unit recruitment, whereby increased load leads to the activation of higher-threshold MUs, which exhibit greater action potential amplitudes and higher firing rates[3,4]. Additionally, the expectation that firing rates would increase with speed is grounded in the need for greater temporal summation and rapid force production, consistent with the force-velocity relationship and motor control strategies for dynamic movement[28,29].

Methods
Study design and ethics
This study used an experimental repeated-measures design to evaluate the effects of load and speed on lumbar motor unit behavior and test-retest reliability within the same group of participants. The study was conducted at the Spine Biomechanics Laboratory, Faculty of Physical Therapy, Mahidol University, from March to August 2023. This research followed the principles of the Declaration of Helsinki, and the University Institutional Review Board approved the study (COA No. 2022/118.0711). Informed consent was obtained from all the participants before the beginning of the study. Informed consent for publication of identifying information/images in an online open-access publication has also been obtained.

Participants
A convenience sample of male and female asymptomatic participants was recruited from the University and surrounding areas. Inclusion criteria were age between 20 and 40 years and currently symptom-free. Participants were excluded if they had definitive neurologic signs, including weakness or numbness in the lower extremity, previous spinal surgery, diagnosed osteoporosis, spinal stenosis, inflammatory joint disease, or systemic disease, and a BMI greater than 30 kg/m^2. All participants provided written informed consent before data collection. The sample size was calculated using a G*Power program. Since no study has investigated the effects of speed and load on the MU behavior of LM, we assumed our findings would yield a medium effect size (effect size f = 0.25). We used a two-factor repeated measures ANOVA (four conditions), confidence level 0.05, and 80% power. We found at least 24 participants were required.

Instruments and measures
Three Inertial Measurement Unit (IMU) sensors (Trigno Avanti, Delsys Inc., MA, USA) were attached to the thoracic (T3), lumbar (L1) and sacral (S2) spinous processes to record angular velocity during the active forward trunk bending at 370 Hz, which has been used previously to examine lumbopelvic movements and has

demonstrated excellent consistency in movement patterns during active forward trunk bending (coefficient of multiple determination = 0.85)[30]. These data were further used to ensure that low-speed and high-speeds were correctly performed.

Two dEMG sensors (Trigno Galileo, Delsys Inc., MA, USA) were attached to the skin over the left and right sides of the LM (2 cm lateral to the lower half of the L5 spinous process) with the reference attached over the iliac crests. Each sensor comprises four channels of EMG data from four protruding blunted pins with a 5-mm inter-pin space. This system has been previously utilized to explore the MU behavior of several muscles in healthy individuals and the effect of increased neuromuscular demand by varying speeds and loads during dynamic movements[12,14].

Procedure

Demographic data, including age, sex, weight, height, and BMI, were collected. Then, participants were asked to expose their lumbopelvic area (L1 to S2). The skin was prepared before placing IMU and dEMG sensors (Fig. 1A). The researchers collected data using EMGworks 4.8 (Delsys Inc., MA, USA). Participants were asked to relax in the prone position while dEMG baseline noise was assessed (a value less than 10 microvolts peak to peak was deemed acceptable).

The participants were asked to synchronize their movements with a metronome set at 30 and 50 beats per minute for the downward and upward movements. This resulted in a complete movement rate of 15 and 25 repetitions per minute. These settings have been used before to evaluate the behavior of motor units of the quadriceps muscle[12] and also approximated the mean velocity of participants performing the movement at a self-selected comfortable pace and the maximum pace that participants could consistently keep in time, respectively. Two loads, 5% and 10% of body weight using kettlebells held in front of the body with arms straight were used at the two speeds. The 5% body weight load represented activities of daily living, while the 10% body weight load represented the maximum weight participants could comfortably use for 1 min of repeated forward bending without experiencing fatigue. The participants were asked to perform two sets of forward bends to 45-degree lumbar flexion, which was standardized by adjusting the height of a target bar (Fig. 1B and C), each for 60 s with a 5-minute rest between sets. The order of conditions was randomized for each participant using a computer-generated randomization list. Allocation was concealed by sealed envelopes prepared by a researcher not involved in data collection. Neither participants nor assessors were blinded to load and speed, as these task manipulations were apparent during testing.

Data reduction

Kinematic data were processed using a custom LabVIEW program (National Instruments, Texas, USA). All IMU data were filtered using a second-order lowpass Butterworth filter set at 20 Hz. Start and stop events (neutral position to target position) were marked using 5% of the maximum thoracic angular velocity as a threshold and mean lumbar angular velocity (lumbar motion in sacral reference frame) was calculated and used to ensure that low speed and high speed were correctly performed.

dEMG data processing was performed using NeuroMap software (Delsys Inc., MA, USA), which applies a validated blind source separation algorithm combined with artificial intelligence to identify and extract individual motor unit action potential trains from the raw surface EMG signal[11]. The software decomposes the complex, overlapping EMG signal into its constituent motor unit firings by leveraging differences in spatial and

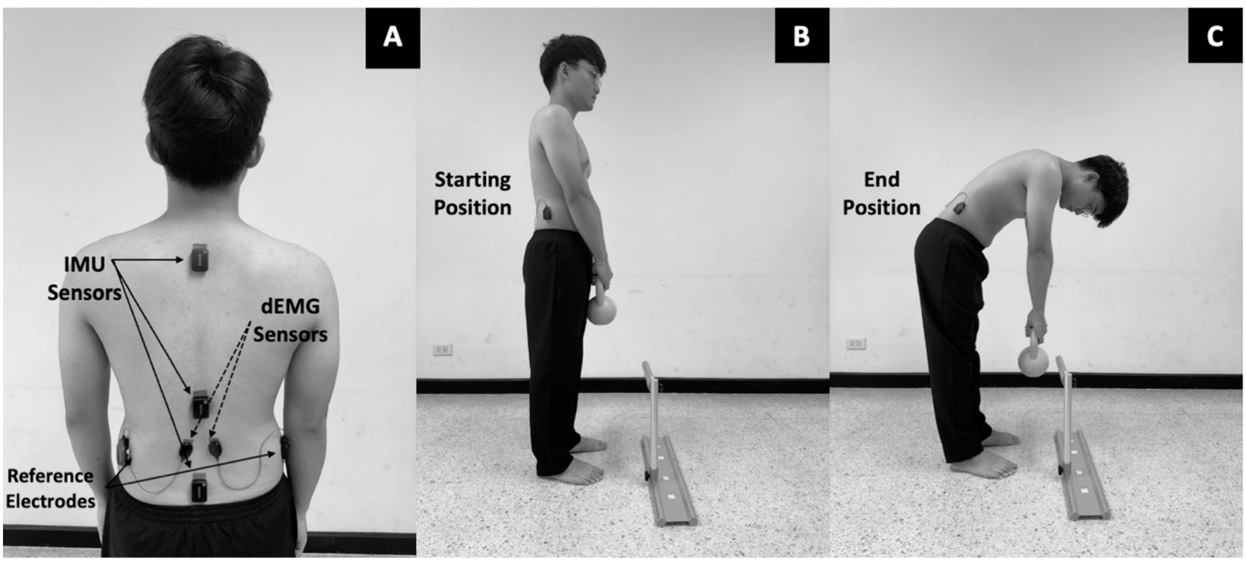

Fig. 1. Inertial measurement unit (IMU) and decomposition electromyography (dEMG) sensor locations (**A**) and task starting (**B**) and end (**C**) positions.

temporal features of action potentials. This process results in the identification of firing instances for each motor unit and the reconstruction of their motor unit action potential shapes.

From the decomposed data (Fig. 2), the following variables were computed for each sensor: (1) peak motor unit action potential (PeakAP): the maximum amplitude of the MU action potentials detected, (2) average motor unit action potential (AvgAP): the mean amplitude across all identified MUAPs during the trial, (3) peak firing rate (PeakFR): the highest instantaneous firing rate among all identified MUs, and (4) average firing rate (AvgFR): the mean firing rate across all MUs during the 60-second trial. Specifically, the raw EMG signals from four channels were decomposed into amplitude and frequency domains to extract individual motor unit action potentials (MUAPs) and their firing rates. From these decomposed signals, we identified both peak and average amplitudes and firing rates for each motor unit for each repetition within each 60-second trial for each condition using the approach from Orantes-Gonzalez et al. (2023)[12]. This quantified the peak and average motor unit amplitudes and firing rates for each individual motor unit seen within each repetition rather than values at a particular time within the muscle activation. These values were then averaged across repetitions and participants to derive the final outcome measures used in our statistical analyses.

Each participant performed two repetitions of 60-second forward trunk bending in each of the four test conditions, including low speed and low load (LL), low speed and high load (LH), high speed and low load (HL), and high speed and high load (HH). The dEMG variables were calculated for each repetition separately. Because the number of movement cycles differed between the fast and slow speed conditions, we did not segment the signal by individual repetitions (i.e., individual bending cycles); instead, we analyzed the entire 60-second trial for each repetition to ensure consistency in the temporal window of MU behavior analysis. The final values used in statistical analyses were the averaged results of the two repetitions for each condition and side.

Statistical analysis

Statistical analysis was performed using SPSS version 21 (IBM Corp., NY, USA). Descriptive statistics were used to present age, sex, weight, height, BMI, and mean angular velocity (for each condition). The data distribution was tested using Shapiro-Wilk tests, and all kinematic and dEMG data were normally distributed.

We used data from 2 sets of 60-second forward bends to calculate within-session test-retest reliability using the intraclass correlation coefficient ($ICC_{3,1}$) for left, right, and combined sensors. A two-way mixed effects model $ICC_{3,1}$ was used to estimate test-retest reliability because the same participants performed two sets of 1-minute forward trunk bending under identical conditions, and the same dEMG system was used in both trials. This model is suitable for evaluating the consistency of repeated measurements when both subjects and testing conditions are held constant. Our dataset demonstrated no significant differences in dEMG parameters between the left and right sides; therefore, we used side-to-side (combined sensors) averaged values for statistical analysis. Accordingly, we also calculated the standard error of measurement (SEM) and minimal detectable change at the 95% confidence level (MDC_{95}) based on the combined sensor data, as this dataset was used for subsequent analysis.

A three-factor mixed model ANOVA was initially performed to explore differences in motor unit behavior between the sexes at the two speeds and loads. Although our primary hypotheses did not involve sex-specific effects, we included sex as a factor in the 3-way ANOVA based on evidence suggesting sex-related differences in lumbar multifidus (LM) EMG activity and muscle morphology[31–33]. However, no significant interactions were seen between sex and speed or load, which is in agreement with a previous study[12]. Therefore, the data analysis was collapsed to a two-factor (speed and load) repeated-measures ANOVA.

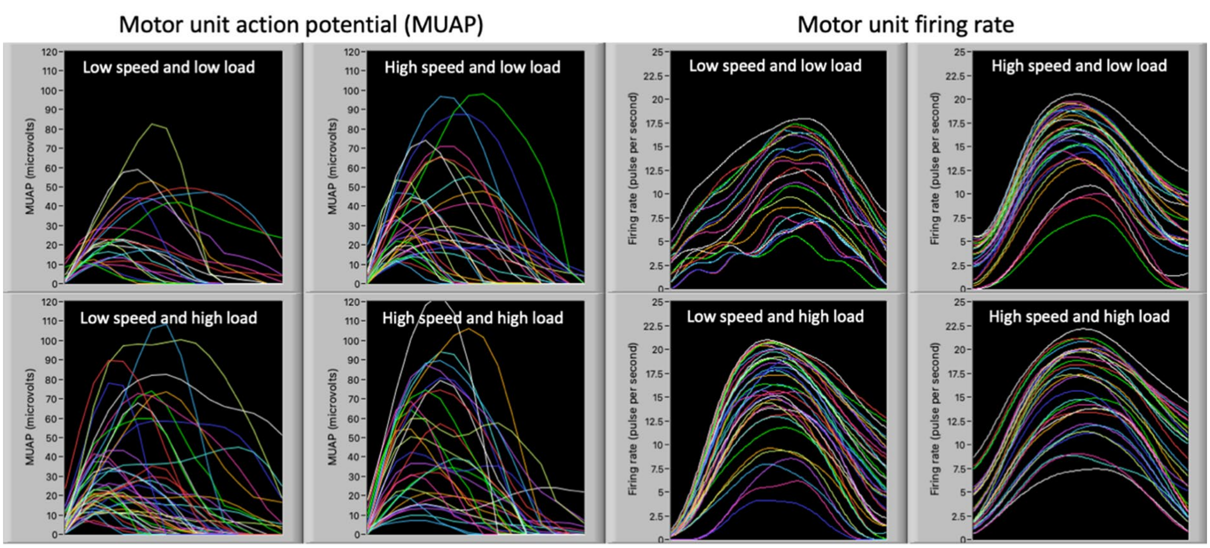

Fig. 2. Decomposed electromyographic data from a single repetition showing individual color-coded motor unit action potentials (left) and their firing rates (right) across conditions.

Effect sizes for repeated-measures ANOVA were reported using partial eta squared, which reflects the proportion of variance explained by each factor, controlling for other variables in the model. Partial eta squared effect sizes were defined according to Cohen's criteria as small (0.01), moderate (0.06), and large (0.14)[34]. The significance level was set at 0.05 for all statistical analyses.

Results

Thirty participants were recruited for this study; however, data from one participant could not be decomposed due to a technical problem. This individual was excluded from the statistical analysis. Therefore, a total of 29 participants were used for data analysis. Figure 3 illustrates the study flowchart. Demographic data are presented in Table 1. The mean age of the participants was 23.4 ± 3.6 years, with slightly more females (51.7%) than males. Significant differences ($P < 0.05$) were found in angular velocity between low speed (53.7 ± 12.0 deg/sec) and high speed (68.4 ± 13.5 deg/sec). No adverse events or participant-reported discomfort occurred during any of the testing conditions.

Table 2 shows the test-retest reliability values ranged between 0.12 and 0.96; however, most ICC values were acceptable ($ICC_{3,1}$>0.7). Table 3 shows no interaction effect of speeds and loads ($P > 0.05$) for all dEMG parameters. However, there were significant main effects of speed ($P < 0.05$), with large effect sizes (partial $\eta^2 > 0.1$) for all dEMG parameters except for PeakFR. Significant main effects of load ($P < 0.05$) were observed in AvgAP, and AvgFR with large effect sizes (partial $\eta^2 > 0.1$).

Discussion

To the best of our knowledge, this is the first study to evaluate the effects of different speed and load conditions on the MU behavior of LM during a dynamic task using dEMG. Studying the MU behavior of this muscle in

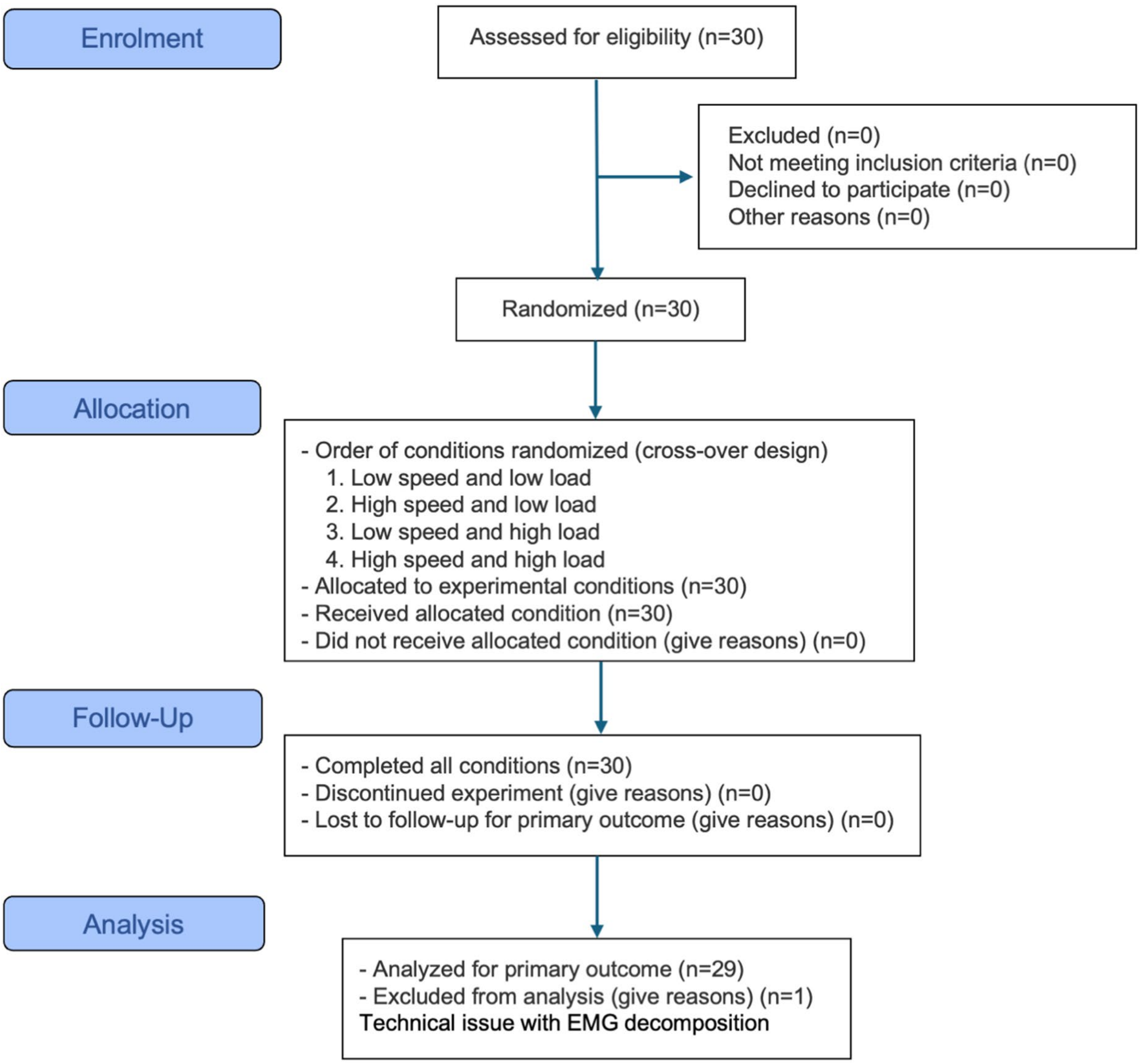

Fig. 3. Study flowchart.

Parameters	Mean ± SD
Age (years)	23.4 ± 3.6
Sex (%female)*	51.7
Weight (kg)	62.0 ± 9.9
Height (m)	1.67 ± 0.08
Body mass index (kg/m^2)	22.21 ± 2.46

Table 1. Demographic data and mean velocity for each condition (n = 29). SD = standard deviation; *=data represented in percentage

Parameter	Sensor 1 (right side)			Sensor 2 (left side)			Combined sensors				
	Repetition 1	Repetition 2	ICC	Repetition 1	Repetition 2	ICC	Repetition 1	Repetition 2	ICC	SEM	MDC$_{95}$
PeakAP_HH (μV)	56.8 ± 22.4	56.1 ± 18.8	0.90[0.79–0.96]	61.5 ± 21.6	65.1 ± 22.6	0.94[0.87–0.97]	57.3 ± 20.6	58.2 ± 20.4	0.94[0.87–0.97]	5.0	13.9
AvgAP_HH (μV)	46.1 ± 18.1	45.8 ± 16.2	0.94[0.86–0.97]	48.1 ± 15.8	51.5 ± 17.1	0.95[0.88–0.98]	45.5 ± 16.1	46.4 ± 16.6	0.94[0.88–0.97]	4.0	11.1
PeakFR_HH (pps)	11.8 ± 2.2	12.5 ± 4.2	0.22[0–0.56.56]	11.9 ± 2.2	11.9 ± 2.3	0.70[0.43–0.85]	11.9 ± 1.9	12.0 ± 3.1	0.36[0–0.64.64]	2.0	5.6
AvgFR_HH (pps)	5.6 ± 1.3	6.0 ± 2.3	0.12[0–0.49.49]	5.4 ± 1.5	5.1 ± 1.2	0.86[0.71–0.93]	5.6 ± 1.2	5.4 ± 1.4	0.41[0.05–0.67]	1.0	2.8
PeakAP_HL (μV)	50.7 ± 20.0	51.2 ± 21.2	0.90[0.78–0.95]	60.6 ± 21.1	58.6 ± 21.3	0.86[0.70–0.93]	54.1 ± 19.1	53.1 ± 20.8	0.89[0.78–0.95]	6.6	18.3
AvgAP_HL (μV)	41.6 ± 16.8	41.1 ± 17.1	0.92[0.84–0.96]	48.2 ± 15.9	46.1 ± 16.6	0.86[0.70–0.93]	43.4 ± 15.4	41.8 ± 16.9	0.92[0.83–0.96]	4.6	12.6
PeakFR_HL (pps)	11.3 ± 2.2	11.6 ± 2.3	0.72[0.47–0.86]	12.4 ± 3.4	12.0 ± 3.2	0.92[0.83–0.96]	11.7 ± 2.4	11.6 ± 2.6	0.89[0.77–0.95]	0.8	2.3
AvgFR_HL (pps)	5.3 ± 1.3	5.3 ± 1.1	0.79[0.59–0.90]	5.2 ± 1.1	5.1 ± 1.1	0.82[0.63–0.91]	5.2 ± 1.0	5.1 ± 1.0	0.83[0.67–0.92]	0.4	1.2
PeakAP_LH (μV)	52.0 ± 20.2	49.1 ± 19.0	0.70[0.43–0.85]	54.2 ± 21.9	52.0 ± 15.3	0.75[0.53–0.88]	52.7 ± 19.7	51.4 ± 15.6	0.75[0.53–0.88]	8.8	24.4
AvgAP_LH (μV)	42.2 ± 16.2	40.1 ± 15.5	0.80[0.61–0.91]	42.4 ± 14.5	41.1 ± 11.3	0.77[0.56–0.89]	42.0 ± 14.6	40.9 ± 12.2	0.81[0.62–0.91]	5.8	16.1
PeakFR_LH (pps)	12.2 ± 1.9	12.2 ± 2.6	0.72[0.47–0.87]	11.9 ± 2.4	12.1 ± 2.5	0.80[0.61–0.90]	12.0 ± 1.9	12.1 ± 2.2	0.83[0.66–0.92]	0.8	2.3
AvgFR_LH (pps)	4.9 ± 0.9	5.1 ± 1.4	0.26[0–0.58.58]	4.6 ± 1.2	4.8 ± 1.3	0.60[0.30–0.79]	4.7 ± 0.9	4.9 ± 1.0	0.46[0.11–0.71]	0.7	1.9
PeakAP_LL (μV)	47.2 ± 17.7	45.2 ± 15.6	0.89[0.78–0.95]	57.5 ± 42.3	52.4 ± 19.1	0.58[0.26–0.78]	52.4 ± 24.6	49.0 ± 15.1	0.68[0.42–0.84]	11.2	31.1
AvgAP_LL (μV)	38.9 ± 15.0	37.1 ± 13.0	0.91[0.81–0.96]	43.6 ± 20.8	40.9 ± 12.2	0.58[0.27–0.79]	41.1 ± 14.9	39.4 ± 12.0	0.79[0.59–0.89]	6.2	17.1
PeakFR_LL (pps)	12.3 ± 4.2	12.3 ± 2.6	0.30[0–0.60.60]	11.3 ± 2.3	11.5 ± 2.5	0.64[0.36–0.82]	11.7 ± 2.7	12.0 ± 2.2	0.35[0–0.63.63]	2.0	5.4
AvgFR_LL (pps)	4.9 ± 2.7	4.8 ± 1.1	0.26[0–0.58.58]	4.3 ± 1.4	4.3 ± 1.6	0.66[0.39–0.83]	4.6 ± 1.7	4.5 ± 1.1	0.34[0–0.62.62]	1.1	3.1

Table 2. Test-retest reliability of motor unit behavior measurement across different conditions (n = 29). LL = low speed and low load; LH = low speed and high load; HL = high speed and low load; HH = high speed and high load; PeakAP = peak action potential across motor units; AvgAP = averaged action potential cross motor units; PeakFR = peak firing rate across motor units; AvgFR = averaged firing rate across motor units; μV = microvolts; pps = pulse per second; ICC = intraclass correlation coefficient; SEM = standard error of measurement; MDC$_{95}$ = minimal detectable change at 95% confidence intervals

Parameter	Condition				Interaction effect		Main effect of speed		Main effect of load	
	LL Mean ± SD	LH Mean ± SD	HL Mean ± SD	HH Mean ± SD	*P*-value	Partial η^2	*P*-value	Partial η^2	*P*-value	Partial η^2
PeakAP (μV)	50.7 ± 18.7	51.2 ± 16.9	53.2 ± 19.2	58.2 ± 20.0	0.228	0.05	0.035*	0.15	0.110	0.09
AvgAP (μV)	40.2 ± 12.8	40.8 ± 12.9	42.4 ± 15.8	46.4 ± 16.0	0.135	0.08	0.015*	0.19	0.013*	0.20
PeakFR (pps)	11.8 ± 2.0	12.0 ± 2.0	11.6 ± 2.4	12.1 ± 2.2	0.472	0.02	0.854	< 0.01	0.117	0.09
AvgFR (pps)	4.5 ± 1.2	4.8 ± 0.8	5.2 ± 1.0	5.5 ± 1.1	0.666	0.01	< 0.001*	0.55	0.014*	0.20

Table 3. Mean and standard deviations and main effects of two-factor repeated measures ANOVA. LL = low speed and low load; LH = low speed and high load; HL = high speed and low load; HH = high speed and high load; PeakAP = peak action potential across motor units; AvgAP = averaged action potential cross motor units; PeakFR = peak firing rate across motor units; AvgFR = averaged firing rate across motor units; μV = microvolts; pps = pulse per second; SD = standard deviation; *=significant difference $P < 0.05$.

asymptomatic healthy individuals can provide insights into its neuromuscular response during dynamic tasks, which may inform the development of rehabilitation protocols aimed at improving spinal stability[35].

The results of our test-retest reliability of MU behavior measurements across different conditions were reproducible, as most ICC values exceeded the acceptable value of 0.70[36]. These findings would allow us to confidently interpret the results as meaningful changes across conditions. In addition to ICC, the standard error of measurement (SEM) and the minimal detectable change at the 95% confidence level (MDC_{95}) were calculated to assess the magnitude of measurement variability and to determine whether observed differences could be interpreted as meaningful changes in response to speed and load conditions. Moreover, the HL condition demonstrated excellent test-retest reliability (ICC > 0.80) of MU behavior measurement in all parameters. Therefore, future research may consider this condition when comparing between groups or pre- and post-intervention since the measurement errors are minimal. Although the majority of parameters demonstrated acceptable test-retest reliability, the parameters representing firing rates in HH and LL conditions and AvgFR in LH conditions were insufficient (ICC < 0.70), which indicate side-specific measurement precision rather than a systematic side effect on the underlying MU behavior. Potential contributors include subtle differences in sensor seating and local tissue interfaces. We therefore emphasized SEM and MDC_{95} to aid interpretation of meaningful change.

It is important to note that one of the drawbacks of the ICC is that it does not reflect measurement error but rather the variability of the participants. To address this limitation, we also reported the SEM and the MDC_{95}. The SEM quantifies the absolute measurement error in the same units as the variable of interest and represents the expected amount of variability due to inherent imprecision in the measurement process, while the MDC_{95} represents the smallest change between repeated measures that can be interpreted as a true change beyond measurement error. Together, SEM and MDC_{95} provide important complementary information to ICC by enabling interpretation of the absolute reliability and the clinical or practical significance of observed changes in motor unit behavior.

Both load and speed showed significant main effects in MU amplitude and firing rates with large effect sizes. The MU behavior of LM showed significantly greater average and peak amplitudes and a greater mean firing rate at the higher speed. Similarly, the higher load was associated with higher averaged amplitudes and firing rates. The substantial rise in these parameters with increases in speed and load conditions indicates that the LM adapts to greater demands by increasing the MU amplitude and firing rates. These adaptations may reflect the neuromuscular strategy to meet increased mechanical demands, suggesting a possible role of the LM in contributing to spinal control during rapid or forceful movements. The implication of our findings is that to achieve greater LM activation during a dynamic task, it is important to consider the speed and load of the activity.

Our study considered MU behavior of LM under different speed and load conditions using dEMG technology for the first time. Though previous studies appear to agree with our findings in terms of the increased MU firing rates and amplitudes at high speeds and loads, most were limited to analyzing the speed of muscle activity only[12,14]. Gonzalez et al.[12] explored the MU behavior of vastus medialis and vastus lateralis muscles during the concentric and eccentric phases of a squat exercise performed at two speeds (15 and 25 repetitions per minute) similar to our speeds. The authors found MU behavior to vary with speed and movement phase, with concentric phase demonstrating higher MU firing rates compared to the eccentric phase. Additionally, faster squatting speeds increase MU firing rates only during the eccentric phase[12]. Similarly, Oliveira and Negro[14] found higher MU firing rates of tibialis anterior muscle during faster contractions compared to slower speeds. Furthermore, increased MU firing rates of the first dorsal interosseous muscle with increasing speed in healthy men was reported when using intramuscular dEMG[37]. Overall, our findings along with previous studies[12,14,37] support the concept that increasing the speed of dynamic tasks is fundamental for enhancing the activation capacity of muscles, including the LM.

When considering the effects of load on motor unit behavior, it is essential to acknowledge that while there is a substantial body of literature demonstrating that surface EMG signals from the back extensors increase proportionally with external load or torque demands, these studies typically reflect the overall EMG amplitude and do not directly capture motor unit behavior responses[38,39]. However, one study investigated how increasing isometric force levels influenced MU parameters in the tibialis anterior muscle and observed that changes in MU firing behavior corresponded with increases in overall EMG amplitude and force production[17]. Although their study did not assess dynamic movement or loading phases, the findings support the concept that greater external load demands are associated with increased MU recruitment and firing rates, which may be extrapolated cautiously to explain the patterns observed in our dynamic trunk bending task. While our study does not directly quantify lumbar force output, the observed changes in MU action potential amplitude and firing rate under higher load conditions may reflect a similar neuromuscular strategy to meet increased mechanical demands.

When considering the load of movement, studies evaluating the direct impact of muscle load on MU behavior are limited. However, the study by Del Vecchio et al. evaluated a linear increase in force contractions which could be directly related to the aspect of load applied during the movement. Although this did not measure directly the load during movement or contraction phase of the tibialis anterior muscle, the authors found that the rate of change in MU variables was associated with the rate of change in global EMG variables with respect to force, which can be compared to our study highlighting the influence of load on the MU behavior.

As in our study focusing on back musculature, Silva et al.[7] investigated the MU behavior of the erector spinae (ES) muscles and determined if differences exist between the dominant and non-dominant sides of the muscles during isometric contraction using dEMG in healthy female participants. The authors found that the mean firing rates between the dominant and non-dominant sides were comparable but the early MUs of the nondominant lumbar were recruited at a lower firing rate suggesting that MU recruited at the same force fire at lower rates on the nondominant side of ES. However, our study examined the MU behavior of the LM during a dynamic task (forward trunk bending) for averaged left and right values as an equal distribution of this muscle on both sides of the lumbar spine has been established in healthy participants[40,41]. Our relatively low firing rates (4.5–14.9 pps) compared to those obtained for dominant (15.8–20.6 pps) and non-dominant (15.8–20.6 pps) obtained by Silva et al.[7] could be explained by the task in which they used isometric test at much greater load as it was during a Sorensen test.

Our findings demonstrated that MUAP amplitudes increased with load, while firing rates increased with speed. This pattern is consistent with neuromuscular adaptations expected under higher mechanical demands and supports the validity of decomposition measures in the lumbar multifidus[5,9,10]. Importantly, these parameters provide complementary information to traditional surface EMG by revealing whether greater activation is achieved through recruiting larger motor units, increasing overall MUAP size, or by adjusting motor unit firing frequency[17].

Despite the strengths of this study, including its unique focus on LM during a dynamic task of varying speed and load, and the inclusion of both male and female participants, some critical limitations need to be considered. Our sample size calculation was based on expected medium effect size which could result in underpowered findings. Future research should aim to replicate our study with a larger sample size. Moreover, it would be interesting to compare MU behavior during static (isometric) versus dynamic (isokinetic) tasks and also integrate muscle force measurements to gain a comprehensive understanding of the role of LM in biomechanical modeling of the lumbar spine in accordance with the different speeds and loads. Although this study focused on average motor unit behavior, future investigations may benefit from analyzing individual MU discharge patterns and recruitment strategies under a variety of tasks and demands to further elucidate neuromechanical control mechanisms. While the electrode placement aimed to specifically target the lumbar multifidus, we acknowledge that there may be some signal cross-talk from nearby extensor muscles (such as the erector spinae), mainly because of their close anatomical location. This limitation is intrinsic to surface EMG techniques and should be considered when interpreting findings.

Conclusion

These findings support the use of measures of LM motor unit behavior. Exercises at greater speeds and loads increase LM firing rates and amplitudes. In addition, this study provides novel insights into the MU behavior of the LM under different speed and load conditions, highlighting the importance of these conditions for enhancing the LM activation. We demonstrated that increased speed and load during a dynamic task are associated with higher MU firing rates and amplitudes which supports the concept that dynamic, speed and load focused exercises are more effective for LM activation. A greater understanding of LM motor unit behavior may aid our understanding of such exercises and the development of more effective rehabilitation protocols for low back pain.

Data availability

The data associated with the paper are not publicly available but are available from the corresponding author on reasonable request.

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Author contributions
PW has significantly contributed to the conceptualization, methodology, formal analysis, funding acquisition, and writing of an original draft. AAI has substantially contributed to writing and editing an original draft. NR has substantially contributed to data curation and formal analysis. SK and KK have considerably contributed to data curation and formal analysis. JR has significantly contributed to the formal analysis, writing, reviewing, and editing of an original draft.

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Declarations

Competing interests
The authors declare no competing interests.

Ethics approval and consent to participate
This study was approved by the Institutional Review Board of Mahidol University (COA No. MU-CIRB 2022/118.0711).

Consent for publication
All participants provided written informed consent. The consent stated that all data collected would be used for publication.

Additional information

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