Research Article

Predicting Trunk Muscle Activity in Chronic Low Back Pain: Development of a Supervised Machine Learning Model

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Running Title: Prediting muscle activity using machine learning algorithm

Abstract

Background: Recently the adoption of machine learning has significantly increased across various applications, including prediction of diseases based on person's clinical profile. This study aimed to develop and evaluate a supervised machine learning to predict trunk muscle's activity in people with chronic low back pain.

Methods: This was a secondary analysis of data from a subgroup of people with nonspecific chronic low back pain. The correlation between labeled data and the output data of muscle activity level was measured through surface electromyography. The result showed a good correlation, suggesting the potential utility of this approach in distinguishing individuals with low back pain from pain-free controls.

Results: to validate the performance of the developed machine learning, the results were compared with SPSS. The model's predictive performance was further assessed using various evaluation methods including area under the receiver operating characteristics curve. The study's findings indicate that the model achieved Area Under the Curve (AUC) values ranging from 0.5

to 0.9 across all muscles and different tasks for people with back pain. In contrast, the pain-free group exhibited AUC values between 0.4 and 0.8.
Conclusion: The findings suggest that the supervised machine learning approach using logistic regression may offer clinically meaningful predictions in defining the differences in trunk muscle activity between individuals with non-specific chronic low back pain and pain-free controls. While the obtained results demonstrate promise, further studies need to enhance the model's performance and achieve a more accurate estimation of muscle activity levels.
Keywords: Chronic low back pain; artificial intelligence; machine learning; trunk muscle activity

Introduction

Low back pain (LBP) is a major global health leading to ongoing symptoms, poor quality of life, work performance, and social engagement with an average lifetime prevalence of 30% among adults(1). While most individuals with low back pain experience spontaneous improvement or respond to treatments within a few weeks(2), a subset of people may develop chronic low back pain (CLBP) and despite recovery few people still experience recurring episodes of LBP(3). Only 15% of LBP cases have been identified to have specific underlying causes(4) and in the remaining 85% the cause is unknown and LBP in non-specific(5).

One possible physical factor that can contribute to LBP is the alteration in the level of activity of trunk muscles during daily functions(6). This variability changes the load distributions on spinal structures, leading to continuation and exacerbation of pain. Trunk muscles particularly back extensors, play a critical role in various spinal functions and postures. Previous studies indicate that surface electromyography can differentiate between individuals with CLBP and those without pain(7). It helps to understand muscles' functions by recording their electrical activity during contractions and different tasks.

Subgrouping of people with non-specific chronic low back pain (NSCLBP) based on common features provides a promising approach for tailoring personalized treatments(8). Classification systems have shown that people with NSCLBP have different muscle's activity among subgroups. For instance, results of previous studies based on O'Sullivan classification system have shown that those with active extension related NSCLBP display higher superficial trunk muscles' activity compared to other sub groups such as Flexion-related or multidirectional back pain(7).

In the last decade, there has been a significant rise in the adoption of artificial intelligence (AI) specially machine learning (ML) technologies, across various applications(9-11).ML promise in diagnosis and outcome prediction(12), which is increasingly being utilized for the early prediction of several diseases based on the clinical profile of patients. It also seems to play vital role in developing healthcare systems that integrate various elements such as science, motivation, data science and culture to promote improvement. Practically, by integrating various data sources with advanced ML algorithms to generate data-driven insights aimed at improving biomedical research, public health, and the quality of healthcare services, these systems can be deployed in small clinics as well as major healthcare organizations(12). The growing volume of data in the field of medical science now enables more precise and insightful analyses, leading to higher diagnosis accuracy(13), pattern detection and treatment. Compared to traditional statistical methods, the predictive capabilities of ML methodologies in conjunction with professional insights can enhance the accuracy of clinical decision makings and consequently boost treatment outcomes. Among different ML methods, multivariate logistic regression (LR) is widely used to identify risk factors that predict the development of complications. While ML techniques have been successful in classifying conditions like liver disease, heart failure(14, 15), and lung diseases(16) their application in low back pain research has been limited.

To our knowledge no study has examined ML algorithm in a specific sub-groups of people with NSCLBP and during different dynamic tasks, therefore, the primary aim of the present study was

to develop and evaluate the predictive performance of a supervised ML (SML) algorithm to distinguish differences between trunk muscle's activity of a subgroup of people with NSLBP (active extension related LBP) and pain-free controls both before and after physiotherapy intervention using some clinical data as predictor gathered in some functional tasks.

Methods

Primary information

The raw material for this study was the previous EMG data of 5 trunk muscles collected from 120 people with and without nonspecific chronic low back pain before and after 4-week exercise (stabilization vs movement control sexercises) therapy(17). In brief, the study included a sub group of people with back pain that met the following criteria: pain associated with lower lumbar extension or postures, persistent back pain for more than 3 months, Tampa scale of kinesiophobia (TSK) scores< 41, Oswestry Disability Index (ODI) < 13, and STarT Back scores < 4. Those excluded from the study were individuals with specific low back pain conditions such as fractures, infections, and spondylolisthesis, a history of previous low back pain with radiating pain to the legs, and individuals who were currently pregnancy. Pain-free people were excluded if they had pain during the last 2 years. The study was approved by the ethics committee of Smart Virtual University (ethic number:IR.SMUMS.REC.1402.025)

The EMG activity of lumbar multifidus (LM), iliocostalis lumborum pars thoracis (ICL), rectus abdominis (RA), external oblique (EO), and internal oblique (IO)(7) was evaluated using channel Data link electromyography system (Biometrics) at 1 kHz and bandwidth between20-40 Hz, common mode rejection ratio>96 at 60 Hz and input impedance>10^{12} Ω.

The raw data were full-wave rectified and smoothed with 50 milliseconds and Surface EMG data were normalized with 2 submaximal voluntary isometric contractions described elsewhere(18).

measured tasks were standing with open and closed eyes, sit to stand, flexion relaxation ratio, and forward flexion. EMG activity of 10 ms of standing with eyes closed, 15 ms of double lg and single leg standing with eyes opened, and the transfer time between sit to stand was analyzed.

Machine learning model:

The logistic regression supervised machine learning (LR-SML) model was employed to predict the EMG changes in the mentioned tasks.

Due to its interpretability and low computational cost, logistic regression is considered a suitable classification algorithm for high dimensional data. It is a statistical method that predicts the probability of an outcome based on one or more predictor variables(19). In supervised learning, the algorithm is trained on a labeled dataset where the input data and corresponding output are known, allowing the algorithm to learn the relationship between the input and output variables. In this study, the labeled/input data were ODI scores, pain scores, age, weight, height and BMI. the predicted/ output data were 5 trunk muscles' activity during standing, sit to stand (STS), Forward flexion (FF), and flexion relaxation ratio (FRR) functions before and after the intervention.

Correlation between labeled data (pain and questionnaire scores, age, weight, height, BMI) and output data (EMG activity) was evaluated and the results showed a good correlation between clinical scores and muscles' activity (primary output data).

The labeled data were used to create a training set for model development. During training the labeled data were arranged according to their priority and weight. The erroneous data was excluded and the machine learning software was trained until the error reached a sufficiently minimized state. After establishing a specific controlled matrix, an algorithm to determine the best estimate between inputs and outputs was developed. The SML was employed using data from 80 people with NSCLBP (stabilization group and movement control group) and 40 pain-free controls.

The accuracy percentage was calculated with the following equation(20):

$$\text{Accuracy}=\frac{\text{number of correct classifications}}{\text{number of total classification}}\times 100$$

The detection performance of the model was evaluated using two metrics sensitivity and specificity which are indicative of model's ability to correctly reject negative false instances and avoiding false positive detections respectively(21). The equations of the metrics are:

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$
$$\text{Specificity}=\frac{TN}{TN+FP}$$

Where the TP (true positive) indicates the number of correct predicted event values, TN (true negative) indicates the number of correct predicted non-event values, FP (false positive) indicates incorrectly predicted event values and FN (false negative) indicates numbers of incorrect predicted non-events values.
The model's classification performance was evaluated using F1score. This metric combines precision (sensitivity) and recall (ability of the model to identify true positives) to assess the overall classification performance. F1score ranges between 0 and 1, with 1 represents perfect classification and 0 indicating no correct classification(22). The equation is:

$$\text{F1score}=2\times\frac{Presicion\times Recall}{Precision+Recall}$$

The model's ability to predict outcomes was then evaluated by analyzing the area under the receiver operating characteristic curve (AUC-ROC). The AUC value ranges between 0 and 1, and serves as a measure of discrimination capability in models, where a higher AUC value signifies enhanced discriminatory power(23).

Statistical analysis

The normality of variable distributions was evaluated using the Shapiro-Wilk test. For correlation analysis, Pearson correlation coefficients were used and mean comparisons were conducted using the student's t-test, with a significance level set at $p < 0.05$. The statistical analysis was performed using SPSS17 (SPSS Inc., Chicago, IL, USA) and excel software.

Results

Before writing the algorithm the correlation between primary inputs and outputs was calculated and the results revealed a moderate to strong correlation between them (Table1),(Table S1).

Table 1: correlation between input and primary output layers (muscle activity) for supervised machine learning

	Muscle	Age	Weight	BMI	Pain before	ODI before
Double leg open Stabilization group	RA	-.59**	-.516**	-.483**	-.942**	-.908**
	IO	-.555**	-.504**	-.459**	-.947**	-.929**
	EO	-.566**	-.494**	-.450**	-.959**	-.906**
	ML	-.684**	-.511**	-.509**	-.933**	-.790**

	IC	-.671**	-.527**	-.525**	-.937**	-.821**
Double leg open Movement group	RA IO EO ML IC	-.597** -.563** -.556** -.643** -.690**	-.516** -.496** -.486** -0.233 -.324*	-.483** -.439** -.260 -.351* -.516**	-.942** -.961** -.963** -.690** -.776**	-.908** -.905** -.905** -.282 -.422**
Double leg open Pain-free group	RA IO EO ML IC	-.811** -.839** -.719** -.920** -.731**	-.825** -.784** -.848** -.208 -.156	-.715** -.697** -.648** -.350* -.114		
Transition phase open Stabilization group	RA IO EO ML IC	-.565** -.528** -.539** -.590** -.623**	-.492** -.483** -.473** -.457** -.498**	-.441** -.422** -.415** -.412** -.471**	-.965** -.968** -.974** -.965** -.958**	-.893** -.913** -.891** -.774** -.813**
Transition phase open Movement group	RA IO EO ML IC	-.552** -.544** -.520** -.554** -.600**	-.483** -.482** -.459** -.244 -.313*	-.426** -.428** -.393* -0.216 -0.293	-.971** -.972** -.981** -.794** -.843**	-.888** -.894** -.884** -.395* -.488**
Transition phase open Pain-free group	RA IO EO ML IC	-.739** -.858** -.791** -.862** -.650**	-.831** -.754** -.772** -.332* -.335*	-.644** -.671** -.617** -.311 -.121		

Correlation coefficient (pearson).RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb,external oblique before; EOa,external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; BMI, body mass index; ODI, oswestry disability index

Then the algorithm was written using supervised machine learning methods. In the results section, different metrics for verification and validation of this algorithm are used and discussed.
Initially, a comparative analysis was conducted between the Radial Basis Function Network machine learning algorithm and logistic multi regression in SPSS using labeled data for training and testing (Figure 1).

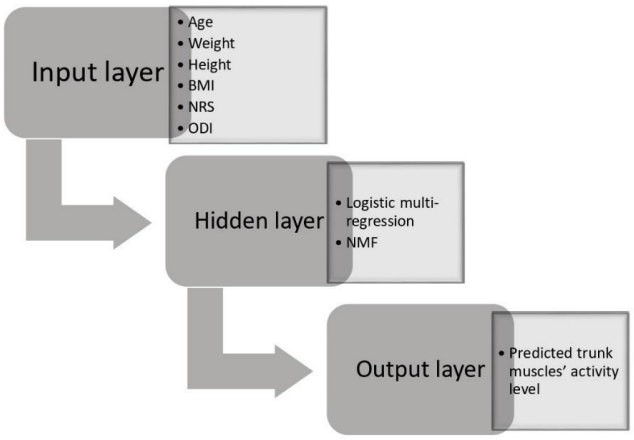

Figure 1: input layer (age, weight, height, body mass index, Numeric rating scale, Oswestry disability index), hidden layer (equation of logistic multi-regression, NMF), output layer (predicted

The results indicated a close correspondence between the actual data from SPSS and the predictive outputs generated by the algorithms. Subsequently, to evaluate the predictive performance of the algorithm, the receiver operating characteristic (ROC) curve was employed. This graphical representation illustrates the trade-off between sensitivity and specificity of a diagnostic test at various threshold levels, allowing assessment of the performance of a binary classification model without the need to select a specific threshold(24). The ROC curve compares the diagnostic ability of a test to random chance, with a diagonal line indicating random guessing (Table2).

Table2: AUC_ROC of both software during double leg standing with eye open and closed, flexion relaxation ratio, forward flexion, and sit to stand before and after exercise in people with AENSLBP and pain-free controls

		AUC LR	**AUC SPSS**		**AUC LR**	**AUC SPSS**
Eyes closed transition phase				**Eyes open transition phase**		
Stabilization group	RAb	0.56	0.51	**Stabilization group**	0.55	0.54
	RAa	0.53	0.52		0.56	0.55
	IOb	0.57	0.57		0.58	0.57
	IOa	0.56	0.57		0.57	0.58
	EOb	0.53	0.52		0.56	0.54
	EOa	0.53	0.52		0.49	0.48
	MLb	0.47	0.47		0.5	0.5

	MLa	0.46	0.47		0.5	0.5
	ICb	0.5	0.5		0.49	0.5
	Ica	0.5	0.5		0.49	0.5
Movement group	RAb	0.53	0.52	**Movement group**	0.6	0.6
	RAa	0.53	0.52		0.6	0.6
	IOb	0.53	0.52		0.6	0.6
	IOa	0.54	0.52		0.6	0.6
	EOb	0.53	0.52		0.6	0.6
	EOa	0.57	0.57		0.6	0.6
	MLb	0.56	0.58		0.46	0.5
	MLa	0.56	0.58		0.52	0.78
	ICb	0.56	0.58		0.5	0.5
	ICa	0.56	0.58		0.5	0.5
Pain-free group	RA	0.57	0.56	**Pain-free group**	0.65	0.65
	IO	0.74	0.74		0.53	0.65
	EO	0.43	0.43		0.5	0.5
	ML	0.52	0.5		0.65	0.49
	IC	0.46	0.46		0.71	0.96

AUC-LR, area under curve- logistic regression; RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb,external oblique before; EOa,external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; FF, forward flexion

The Area Under the Curve (AUC) is a measure employed to encapsulate the comprehensive diagnostic accuracy of a test within binary classification tasks. It ranges from 0 to 1, with 0 indicating a test that is completely inaccurate and 1 signifying an entirely accurate test .
For both Sit-to-Stand (STS) and FRR assessments, the Area Under the Curve (AUC) ranged from 0.4 to 0.9 across all muscles and groups, particularly notable in the healthy group. When comparing different standing positions (open vs. closed and one leg vs. double leg), the AUC values ranged from 0.5 to 0.88 in the stabilization and movement group. In contrast, the healthy group exhibited AUC values ranging between 0.6 to 1, especially during one-leg standing with open eyes, indicating that the classifier demonstrated good predictive performance overall and remains under clinical relevance in some other tasks (Table S2).
The average predicted trunk muscles' activity was assessed and compared with the mean activity of the actual primary output in the test session of the LR-SML algorithm (Table3).

Table 3: Performance parameters of LRS-ML for predicting trunk muscles activity

	Muscle	**Sensitivity**	**Specificity**	**Acuracy%**	**F1-score**
Stabilization group Double leg close	RAb	0.9	0.91	90	0.92
	Raa	0.95	0.92	95	0.96
	Iob	0.93	0.92	92	0.94
	Ioa	0.96	0.92	95	0.96
	Eob	0.96	0.92	95	0.96
	Eoa	0.93	0.92	92	0.94
	MLb	0.96	1	97	0.93

	Mla	1	1	100	1
	ICLb	09	1	92	0.92
	ICLa	0.9	1	92	0.93
Movement group Double leg close	Rab	0.96	0.92	95	0.96
	Raa	0.96	0.92	95	0.96
	Iob	0.96	0.92	95	0.96
	Ioa	0.93	0.92	92	0.94
	Eob	0.96	0.92	90	0.96
	Eoa	0.93	0.92	95	0.94
	MLb	0.90	0.91	92	0.93
	Mla	0.90	0.90	90	0.93
	ICLb	1	0.93	97	0.97
	ICLa	0.90	0.90	90	0.93
Pain-free group Double leg close	Ra	0.45	0.42	50	0.6
	Io	0.5	0.5	44	0.48
	Eo	0.44	0.4	55	0.53
	ML	0.37	0.35	44	0.34
	IC	0.45	0.42	48	0.43

Rab, rectus abdominis before; Raa, rectus abdominis after; Iob, internal oblique before; Ioa, internal oblique after; Eob, external oblique before; Eoa, external oblique after; MLb, multifidus before; Mla, multifidus after; Icb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; FF, forward flexion

The result demonstrated high sensitivity (precision) and accuracy in predicting muscle activity in all tasks in three groups and during all tasks (Table S3).

To construct the predictive algorithm, we first calculated the correlation between pain and disability scores, age, weight, height, BMI, and trunk muscles' activity. This calculation revealed a moderate to strong relationship. Then, logistic regression supervised machine learning (LR-SML) was utilized which is simple and widely used in the medical field. In supervised machine learning, which is the most prevalent for training neural networks and decision trees, different algorithms are used to establish a function that links inputs (subjective scores) to the desired outcomes (SEMG). Concerning this, to confirm the accuracy and validate the model, two distinct methodologies on statistical analysis platforms were implemented. Initially, the algorithms within SPSS were utilized to replicate the entire set of operations executed by the proposed model. Average values and the standard deviations for the absolute prediction errors and the differences was calculated. Additionally, the correlation between the predicted outcomes and the primary outcomes were assessed. Subsequently, the correlation of the predicted values from SPSS with the original dataset, as well as the correlation of predicted values from the LR-SML software with the same dataset was constructed and determined. The analysis revealed a strong correlation between the two software programs. The findings also suggest that the performance of LR-SML and SPSS varied among individuals with LBP, and LR-SML showed a higher error rate across most parameters, while in the pain-free group, there was not a significant difference between the two software in most tasks (Table 4), (Table S4).

Table 4: mean error of two software:

	Muscle	**Mean difference**	**P value**		**Muscle**	**Mean difference**	**P value**
Stabilization group	Rab	2.03	0.00	**Stabilization group**	Rab	2.27	0.00
	Raa	2.82	0.00		Raa	0.93	0.00

double leg close	Iob	2.25	0.00	**Double leg open**	Iob	2.18	0.00
	Ioa	0.98	0.00		Ioa	1.57	0.001
	Eob	2	0.00		Eob	1.96	0.00
	Eoa	2.95	0.00		Eoa	2.92	0.00
	MLb	4.86	0.00		MLb	1.53	0.00
	Mla	3.3	0.00		Mla	1.99	0.00
	Icb	3.31	0.00		Icb	2.99	0.00
	Ica	2.85	0.00		Ica	2.88	0.00
Movement group Double leg close	Rab	2.63	٠,٠٠	**Movement group Double leg open**	Rab	1.1	0.00
	Raa	3.72	٠,٠٠		Raa	1.1	0.04
	Iob	2.33	٠,٠٠		Iob	1.7	0.02
	Ioa	1.1	٠,٠٠		Ioa	0.8	0.11
	Eob	2.35	٠,٠٠		Eob	0.53	0.18
	Eoa	3.74	٠,٠٠		Eoa	0.6	0.02
	MLb	2.21	٠,٠٤		MLb	2.94	0.00
	Mla	1.4	٠,٠٢		Mla	1.71	0.00
	Icb	2.04	٠,٠٤		Icb	3.22	0.00
	Ica	3.24	٠,٠٠		Ica	2.4	0.00
Pain-free group Double leg close	RA	1.17	0.6	**Pain-free group Double leg open**	RA	-1.4	0.32
	IO	1.29	0.06		IO	-2.39	0.14
	EO	5.45	0.02		EO	-0.74	0.36
	ML	1.43	0.10		ML	-0.28	0.49
	IC	2.86	0.10		IC	-0.36	0.56

Rab, rectus abdominis before; Raa, rectus abdominis after; Iob, internal oblique before; Ioa, internal oblique after; Eob, external oblique before; Eoa, external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; FF, forward flexion

F1-score was employed as a statistical measure to evaluate the accuracy of our model. The outcomes revealed F1-scores ranging from 0.4 to 1 across all parameters and all groups, signifying the mode's proficiency in accurately classifying true positive cases and actual positive cases.

Discussion

In this study, a machine learning approach was employed to create a predictive model for estimating the activity level of trunk muscles in individuals with AENSCLB and pain-free groups using information from pain and disability scores, age, weight, height and BMI. In the previous study (25), the LR-SML was employed for individuals with tinnitus to forecast brainwave patterns. The study demonstrated that the model was simple and effective in predicting the functional profile of tinnitus using subjective scales and EEG data. In the present study, a similar model was applied.

Sensitivity and specificity metrics indicate how correctly the model identifies positive (true positive) and negative (true negative) classes, respectively. In this study, the values of sensitivity and specificity were high in testing dataset indicating that LR-SML has a good ability to accurately classify instances with a low rate of error.

Moreover, the results of F1-scores observed for all tasks indicates the model's well performance in accurately predict positive instances while minimizing both false positives and false negatives

In line with the findings of Kyzet et al. (25), which showed higher accuracy during isometric contractions compared to dynamic tasks, our results revealed lower prediction accuracy in more challenging tasks such as one-leg standing with closed eyes. This suggests that additional input data may be necessary to enhance the performance. Previous research has highlighted that predicting pain incidence is challenging because of the intricate interplay between various factors(26).

Similarly, muscles within musculoskeletal system are complex and challenging to model, and the static. Thus, Using the model in clinical devices presents a significant challenge(27). The primary objective of this study was to provide clinicians with a means of estimating EMG activity without an electrode setup. This study aimed to find a method for accurately and efficiently predicting muscle activation using a machine learning model. Recently, machine learning models have been developed to estimate skeletal muscle activity without explicit modeling of the physical characteristics of muscles. However, an inverse muscle model has yet to be developed using a machine learning model. The LR-SML model can offer the ability to predict muscle activity via subjective information.

The estimated EMG signals and real data showed that the designed model in some cases had slight differences; however, the pattern of the estimated signals was sufficiently similar to allow the students and clinicians to avoid EMG electrode setups in the laboratory and use LR-SML instead. However, the model is task specific and may require extensive data for a more generalized model.

Notably, most computational techniques for calculating muscle variables have inherent limitations in their analytical expressions and suffer from unrealistic assumptions in muscle models. The model parameters identified with measurements that are subject to error, such as relative location between muscles and electrodes(28), variability in individuals' biological characteristics, and activation pattern of muscles, require a continual optimization loop, and result in estimated muscle activations that may not be entirely accurate(29). The complex behaviors of muscles during dynamic tasks make them difficult especially for static models.

Results of the present study revealed that despite the higher error of the LR-SML in LBP group compared with SPSS, it stands out for its simplicity and feasibility. Because an integral part of a machine learning algorithm is to be user-friendly and be easily integrated into existing clinical procedures(30), the model's architecture was designed to be robust and stable, even when processing large data despite its accuracy, SPSS showed inconsistency in handling increased data volume and complexity.

The present study has several limitations. First, a specific dataset was used in this study, which may increase the risk that the results are population-specific and the prognostic factors may decrease generalizability in other populations. Second the model is task-based and it is not certain that the model can be used for other tasks. For a general model, a large amount of data is required. In addition, homogenous subgroup of people with low back pain limits the generalizability of our findings; however, acceptable results during most tasks are promising.

Therefore, further research is needed to determine the generalizability of our findings to different populations and to explore the impact of these conditions on treatment outcomes.

Conclusion

Results of the present study suggest that LR_SML may provide slight but clinically relevant, predictions for defining trunk muscle activity of people with AENSCLBP and pain- free controls. Despite the promising results obtained, further studies are necessary to improve model's performance and have a better estimation of muscle activity level.

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Authors contributions:
Each author was involved in data analysis and contributed equally to the writing of the manuscript.

Conflict of interest:
Authors declare that they have no conflicts of interest

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References

1. Andersson GB. Epidemiological features of chronic low-back pain. The lancet. 1999;354(9178):581-5.
2. Cho KH, Beom JW, Lee TS, Lim JH, Lee TH, Yuk JH. Trunk muscles strength as a risk factor for nonspecific low back pain: a pilot study. Ann Rehabil Med. 2014;38(2):234.
3. Shim J-G, Ryu K-H, Cho E-A, Ahn JH, Kim HK, Lee Y-J, et al. Machine learning approaches to predict chronic lower back pain in people aged over 50 years. Medicina. 2021;57(11):1230.
4. O'Sullivan P. It's time for change with the management of non-specific chronic low back pain. BMJ sport Med; 2012. p. 224-7.
5. Gordon R, Bloxham S, editors. A systematic review of the effects of exercise and physical activity on non-specific chronic low back pain. Healthcare; 2016: MDPI.
6. van Dieën JH, Selen LP, Cholewicki J. Trunk muscle activation in low-back pain patients, an analysis of the literature. J EMG Kinesiol. 2003;13(4):333-51.
7. Salamat S, Talebian S, Maroufi N, Kalbassi G, Salamat D, O'Sullivan K. People With Low Back Pain Exhibit Higher Trunk Muscle Activity and Impaired Postural Control During Static and Dynamic Functional Tasks: A Cross-Sectional Study. J App Biomech. 2023;40(1):1-8.
8. Tagliaferri SD, Owen PJ, Miller CT, Angelova M, Fitzgibbon BM, Wilkin T, et al. Towards data-driven biopsychosocial classification of non-specific chronic low back pain: a pilot study. Scie Reports. 2023;13(1):13112.
9. Hartley T, Hicks Y, Davies JL, Cazzola D, Sheeran L. BACK-to-MOVE: Machine learning and computer vision model automating clinical classification of non-specific low back pain for personalised management. Plos one. 2024;19(5):e0302899.
10. Kadhim MA. FNDSB: A fuzzy-neuro decision support system for back pain diagnosis. Cogn Syst Res. 2018;52:691-700.
11. Amorim P, Paulo JR, Silva PA, Peixoto P, Castelo-Branco M, Martins H. Machine learning applied to low back pain rehabilitation–a systematic review. Int J Digit Health. 2021;1(1):10.
12. Sidey-Gibbons JA, Sidey-Gibbons CJ. Machine learning in medicine: a practical introduction. BMC medical research methodology. 2019;19:1-18.
13. Caldo D, Bologna S, Conte L, Amin MS, Anselma L, Basile V, et al. Machine learning algorithms distinguish discrete digital emotional fingerprints for web pages related to back pain. Sci Rep. 2023;13(1):4654.
14. Mizuguchi Y, Nakao M, Nagai T, Takahashi Y, Abe T, Kakinoki S, et al. Machine learning–based gait analysis to predict clinical frailty scale in elderly patients with heart failure. Europ Heart J Digit Health. 2024;5(2):152-62.

15. Yoon M, Park JJ, Hur T, Hua C-H, Hussain M, Lee S, et al. Application and Potential of Artificial Intelligence in Heart Failure: Past, Present, and Future. IntJ Heart Fail. 2024;6(1):11.
16. Hartman DJ. Applications of Artificial Intelligence in Lung Pathology. Surg Pathol Clin. 2023.
17. Salamat S, Talebian S, Bagheri H, Maroufi N, Shaterzadeh MJ, Kalbasi G, et al. Effect of movement control and stabilization exercises in people with extension related non-specific low back pain-a pilot study. J Bodyw Mov Ther. 2017;21(4):860-5.
18. Dankaerts W, O'Sullivan P, Burnett A, Straker L. Altered patterns of superficial trunk muscle activation during sitting in nonspecific chronic low back pain patients: importance of subclassification. Spine. 2006;31(17):2017-23.
19. Chen B. From Logistic Regression to Deep Learning: Machine Learning Advances for Credit Card Churn. IJERMCA. 2024;13(2).
20. Rescio G, Leone A, Siciliano P. Supervised machine learning scheme for electromyography-based pre-fall detection system. Expert Syst Appl. 2018;100:95-105.
21. Kutrani H, Eltalhi S, Ashleik N, editors. Predicting factors influencing survival of breast cancer patients using logistic regression of machine learning. The 7th International Conference on Engineering & MIS 2021; 2021.
22. Jinjri WM, Keikhosrokiani P, Abdullah NL, editors. Machine learning algorithms for the classification of cardiovascular disease-A comparative study. 2021 International Conference on Information Technology (ICIT); 2021: IEEE.
23. Barbosa VP, Said dos Reis JLM, von Zuben de Valega Negrão C, Barboza VR, Simoes Marcondes KCB, Rezende EP, et al. Machine Learning Model to Predict Allocation of Patients with Chronic Back Pain for Integrated Practice Units in a System of Value-based Health Care. medRxiv. 2023:2023.11. 05.23298111.
24. Rahman MM, Hossain MB, Sayed A, Thakur S. ASSESSMENT OF LIQUEFACTION POTENTIAL BASED ON THE LOGISTIC REGRESSION MACHINE LEARNING ALGORITHM.
25. Mohsen S, Sadeghijam M, Talebian S, Pourbakht A. Use of Some Relevant Parameters for Primary Prediction of Brain Activity in Idiopathic Tinnitus Based on a Machine Learning Application. Audiol Neurotol. 2023;28(6):446-57.
26. Joensuu L, Rautiainen I, Hautala A, Siekkinen K, Pirnes K, Tammelin TH. Prediction of multisite pain incidence in adolescence using a machine learning approach. medRxiv. 2023:2023.07. 04.23292222.
27. Nasr A, Inkol KA, Bell S, McPhee J. InverseMuscleNET: alternative machine learning solution to static optimization and inverse muscle modeling. Front Comput Neuroscie. 2021;15:759489.
28. Kizyte A, Lei Y, Wang R. Influence of Input Features and EMG Type on Ankle Joint Torque Prediction With Support Vector Regression. IEEE Trans Neural Syst Rehabil Eng. 2023.
29. Wu D, Yang J, Sawan M. Transfer learning on electromyography (EMG) tasks: approaches and beyond. IEEE Trans Neural Syst Rehabil Eng. 2023.
30. Michelsen C, Jørgensen CC, Heltberg M, Jensen MH, Lucchetti A, Petersen PB, et al. Machine-learning vs. logistic regression for preoperative prediction of medical morbidity after fast-track hip and knee arthroplasty—a comparative study. BMC anesthesiol. 2023;23(1):391.

Supplementary files

Table S1: correlation between input and primary output layers (muscle activity) for supervised machine learning

	Muscle	Age	Weight	BMI	Pain before	ODI before
Double leg close Stabilization group	RA IO EO ML IC	-.591** -.562** -.566** -.684** -.562** -.671**	-.518** -.512** -.494** -.511** -0.517**	-.493** -.462** -.450** -.509** -0.525**	-.936** -.945** -.959** -.933** -0.927**	-.921** -.923** -.906** -.790** -0.821**
Double leg close Movement group	RA IO EO ML IC	-.597** -.574** -.569** -.654** -.645**	-.516** -.503** -.496** -.532** -.530**	-.483** -.464** -.453** -.527** -.531**	-.942** -.955** -.957** -.941** -.942**	-.908** -.906** -.907** -.842** -.844**
Double leg close Pain-free group	RA IO EO ML IC	-.847** -.785** -.838** -.919** -.859**	-.790** -.825** -.784** -.722** -.807**	-.714** -.690** -.691** -.734** -.762**		
Transition phase close Stabilization group	RA IO EO ML IC	-.709** -.528** -.539** -.649** -.623**	-.474** -.483** -.473** -.491** -.498**	-.401* -.422** -.415** -.472** -.471**	-.894** -.968** -.974** -.948** -.958**	-.745** -.914** -.892** -.787** -.815**
Transition phase close Movement group	RA IO EO ML IC	-.568** -.549** -.544** -.615** -.606**	-.495** -.484** -.477** -.507** -.518**	-.445** -.430** -.421** -.480** -.492**	-.963** -.970** -.972** -.960** -.960**	-.896** -.894** -.894** -.840** -.856**
Transition phase close Pain-free group	RA IO EO ML IC	-.836** -.900** -.811** -.898** -.849**	-.783** -.698** -.775** -.721** -.800**	-.686** -.658** -.645** -.683** -.728**		
one leg open Stabilization group	RA IO EO ML IC	-.535** -.504** -.514** -.525** -.583**	-.471** -.463** -.455** -.418** -.472**	-.405** -.390* -.384* -.346* -.427**	-.978** -.980** -.984** -.975** -.970**	-.877** -.897** -.875** -.755** -.802**

One leg open Movement group	RA	-.504**	-.447**	-.367*	-.987**	-.859**
	IO	-.530**	-.471**	-.410**	-.978**	-.886**
	EO	-.494**	-.440**	-.362*	-.988**	-.867**
	ML	-.501**	-.247	-.191	-.837**	-.448**
	IC	-.549**	-.305	-.260	-.871**	-.518**
One leg open Pain-free group	RA	-.907**	-.669**	-.633**		
	IO	-.849**	-.745**	-.645**		
	EO	-.730**	-.751**	-.527**		
	ML	-.766**	-.405**	-.250		
	IC	-.494**	-.232	.046		
one leg close Stabilization group	RA	-.535**	-.471**	-.405**	-.978**	-.877**
	IO	-.504**	-.463**	-.390*	-.978**	-.897**
	EO	-.681**	-.463**	-.389*	-.904**	-.742**
	ML	-.617**	-.474**	-.440**	-.958**	-.780**
	IC	-.617**	-.473**	-.440**	-.958**	-.780**
one leg close Movement group	RA	-.541**	-.475**	-.412**	-.976**	-.882**
	IO	-.526**	-.467**	-.401*	-.980**	-.880**
	EO	-.517**	-.457**	-.387*	-.983**	-.877**
	ML	-.582**	-.485**	-.441**	-.972**	-.829**
	IC	-.567**	-.489**	-.442**	-.975**	-.845**
One leg close Pain-free group	RA	-.873**	-.740**	-.674**		
	IO	-.858**	-.687**	-.582**		
	EO	-.817**	-.769**	-.640**		
	ML	-.872**	-.718**	-.637**		
	IC	-.839**	-.792**	-.696**		
STS Stabilization group	RA	-.597**	-.516**	-.483**	-.942**	-.908**
	IO	-.557**	-.493**	-.449**	-.963**	-.903**
	EO	-.548**	-.480**	-.431**	-.966**	-.904**
	ML	-.056	.355*	.350*	.100	.580**
	IC	-.199	.239	.222	-.087	.417**
STS Movement group	RA	-.597**	-.516**	-.483**	-.942**	-.908**
	IO	-.552**	-.471**	-.434**	-.969**	-.877**
	EO	-.536**	-.472**	-.419**	-.971**	-.903**
	ML	.543**	.645**	.653**	.760**	.933**
	IC	.547**	.660**	.679**	.729**	.918**
STS Pain-free group	RA	-.917**	-.707**	-.710**		
	IO	-.905**	-.424**	-.440**		
	EO	-.870**	-0.279	-.334*		
	ML	.669**	.952**	.871**		
	IC	.656**	.945**	.902**		
FRR Stabilization group	ML	-.006	.268	.091	.784**	.932**
	IC	-.006	.268	.091	.784**	.932**
FRR	ML	-.008	.273	.093	.786**	.932**

Movement group	IC	-.008	0.273	.093	.786**	.932**
FRR Pain-free group	ML IC	.797** -.745**	.885** .157	.881** 0.037		

Correlation coefficient (pearson).RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb,external oblique before; EOa,external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; BMI, body mass index; ODI, oswestry disability index

TableS2: AUC_ROC of both software during double leg standing with eye open and closed, flexion relaxation ratio, forward flexion, and sit to stand before and after exercise in people with AENSLBP and pain-free controls

	Muscle	**AUC LR**	**AUC SPSS**		**AUC LR**	**AUC SPSS**
Eyes closed double leg				**Eyes open Double leg**		
Stabilization group	RAb	0.55	0.55		0.53	0.52
	RAa	0.55	0.55		0.53	0.52
	IOb	0.53	0.52		0.53	0.52
	IOa	0.53	0.52		0.59	0.58
	ERb	0.53	0.52	**Stabilization group**	0.53	0.52
	EOa	0.55	0.55		0.53	0.52
	MLb	0.51	0.49		0.52	0.5
	MLa	0.5	0.5		0.5	0.5
	ICb	0.5	0.5		0.51	0.5
	ICa	0.5	0.5		0.49	0.5
Movement group	RAb	0.47	0.47	**Movement group**	0.66	0.67
	RAa	0.45	0.45		0.66	0.66
	IOb	0.47	0.48		0.6	0.61
	IOa	0.47	0.48		0.6	0.6
	EOb	0.47	0.48		0.6	0.6
	EOa	0.45	0.45		0.64	0.64
	MLb	0.47	0.45		0.48	0.5
	MLa	0.48	0.47		0.61	0.58
	ICb	0.48	0.47		0.48	0.51
	Ica	0.47	0.45		0.55	0.55
Pain-free group	RA	0.57	0.56	**Pain-free group**	0.53	0.53
	IO	0.74	0.74		0.42	0.44
	EO	0.43	0.43		0.43	0.4
	ML	0.52	0.5		0.58	0.54
	IC	0.46	0.46			

Cont:

		AUC LR	**AUC SPSS**		**AUC LR**	**AUC SPSS**
Eyes closed one leg				**Eyes open One leg**		

Stabilization group	RAb	0.58	0.58	**Stabilization group**	0.53	0.52
	RAa	0.6	0.6		0.59	0.58
	IOb	0.62	0.63		0.61	0.61
	IOa	0.61	0.63		0.61	0.6
	EOb	0.66	0.68		0.58	0.57
	EOa	0.62	0.63		0.58	0.58
	MLb	0.51	0.52		0.56	0.58
	MLa	0.53	0.55		0.6	0.6
	ICb	0.5	0.5		0.55	0.58
	ICa	0.56	0.58		0.6	0.61
Movement group	RAb	0.6	0.6	**Movement group**	0.61	0.62
	RAa	0.6	0.6		0.61	0.62
	IOb	0.6	0.6		0.6	0.62
	IOa	0.56	0.57		0.61	0.62
	EOb	0.6	0.6		0.6	0.59
	EOa	0.6	0.6		0.61	0.62
	MLb	0.56	0.56		0.62	0.63
	MLa	0.56	0.56		0.66	0.67
	ICb	0.6	0.6		0.6	0.6
	ICa	0.6	0.6		0.7	0.7
Pain-free group	RA	0.48	0.47	**Pain-free group**	0.44	0.52
	IO	0.44	0.4		0.5	0.5
	EO	0.43	0.4		0.33	0.36
	ML	0.52	0.53		0.45	0.41
	IC	0.42	0.4		1	0.95

Cont:

	Muscle	**AUC LR**	**AUC SPSS**		**AUC LR**	**AUC SPSS**
STS				**FRR**		
Stabilization group	RAb	0.42	0.42	**Stabilization group**	0.73	0.3
	RAa	0.4	0.4		0.5	0.44
	IOb	0.42	0.42		0.7	0.65
	IOa	0.4	0.4		0.5	0.5
	EOb	0.42	0.42			
	EOa	0.42	0.42			
	MLb	0.43	0.47			
	MLa	0.92	0.75			
	ICb	0.5	0.53			
	ICa	0.74	0.66			

Movement group	RAb RAa IOb IOa EOb EOa MLb MLa ICb Ica	0.58 0.56 0.52 0.56 0.48 0.52 0.88 0.63 0.88 0.6	0.57 0.6 0.57 0.61 0.5 0.58 0.92 0.64 0.92 0.66	**Movement group**	0.66 1 0.62 0.62	0.67 0.97 0.64 0.64
Pain-free group	RA IO EO ML IC	0.71 0.6 0.84 0.8 0.9	0.7 0.73 0.9 0.8 0.8	**Pain-free group**	0.85 0.6	0.81 0.6
FF						
Stabilization group	MLb MLa ICb Ica	0.57 0.2 0.66 **0.84**	**0.76** 0.58 0.68 0.31			
Movement group	MLb MLa ICb ICa	0.58 0.71 0.5 0.71	0.64 0.65 0.48 0.65			
Pain-free group	ML IC	0.59 0.71	0.66 0.75			

AUC-LR, area under curve- logistic regression; RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb,external oblique before; EOa,external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; FF, forward flexion

Table S3: performance parameters of LRS-ML for predicting trunk muscles activity

	Muscle	**SENSITIVITY**	**SPECIFICITY**	**ACURACY%**	**F1-score**
Stabilization group one leg close	RAb	٠,٩٢	١	95	٠,٩٦
	RAa	٠,٩٣	١	95	٠,٩٦
	IOb	٠,٩٢	١	95	٠,٩٦
	IOa	٠,٩٢	١	95	0.96
	EOb	٠,٩٢	١	95	0.96
	EOa	٠,٩٢	١	95	0.96
	MLb	٠,٩٣	١	95	0.96
	MLa	٠,٩٦	١	98	0.98
	ICLb	٠,٩٣	١	95	0.96

	ICLa	۰,۹۳	۱	95	0.96
Movement group one leg close	RAb	0.93	1	95	0.96
	RAa	0.93	1	95	0.96
	IOb	0.92	1	95	0.96
	IOa	0.93	1	95	0.96
	EOb	0.92	1	95	0.96
	EOa	0.93	1	95	0.96
	MLb	0.92	1	95	0.96
	MLa	0.92	1	95	0.96
	ICLb	0.89	1	92	0.94
	ICLa	0.93	1	95	0.96
Pain-free group Double leg close	Ra	0.4	0.38	40	0.6
	Io	0.41	0.38	40	0.41
	Eo	0.44	0.4	42	0.88
	ML	0.42	0.4	0.55	0.75
	IC	0.46	0.43	0.45	0.5
Stabilization group double leg open	RAb	1	1	100	1
	RAa	1	1	100	1
	IOb	1	1	100	1
	IOa	1	1	100	1
	EOb	1	1	100	1
	EOa	1	1	100	1
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	0.94	1	98	0.97
	ICLa	1	1	100	1
movement group double leg open	RAb	0.96	0.92	95	0.96
	RAa	0.96	1	97	0.97
	IOb	0.93	0.92	92	0.96
	IOa	0.93	0.92	92	0.96
	EOb	0.93	0.92	92	0.96
	EOa	0.96	0.92	100	0.96
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
	ICLa	1	1	100	1
Pain-free group double leg open	Ra	0.48	0.46	47	0.5
	Io	0.45	0.41	64	0.45
	Eo	0.52	0.53	52	0.55
	ML	0.47	0.45	46	0.5
	IC	0.6	0.88	66	0.6

Stabilization group one leg open	RAb	1	1	100	1
	RAa	1	1	100	1
	IOb	1	1	100	1
	IOa	1	1	100	1
	EOb	1	1	100	1
	EOa	1	1	100	1
	MLb	0.84	1	9	0.91
	MLa	1	1	100	1
	ICLb	0.87	1	93	0.93
	ICLa	1	1	100	1
Movement group one leg open	RAb	0.93	1	95	0.96
	RAa	0.93	1	95	0.96
	IOb	0.92	1	95	0.96
	IOa	0.92	1	95	0.96
	EOb	0.92	1	95	0.96
	EOa	0.93	1	95	0.96
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
	ICLa	1	1	100	1
Pain-free group one leg open	Ra	0.4	0.38	55	0.4
	Io	0.45	0.42	56	0.46
	Eo	0.53	0.55	53	0.53
	ML	046	0.44	45	0.46
	IC	0.62	0.85	70	0.61
Stabilization group FRR	MLb	0.97	1	98	0.98
	MLa	1	0.88	98	0.98
	ICb	1	0.88	98	0.98
	ICa	0.97	1	98	0.98
Movement group FRR	MLb	1	0.88	98	0.98
	MLa	0.98	1	98	0.98
	ICb	1	0.88	98	0.99
	ICa	1	0.88	98	0.98
Pain-free group FRR	ML	0.37	0.35	36	0.4
	IC	0.45	0.42	44	0.45
Stabilization group FF	MLb	0.94	1	95	0.96
	MLa	1	1	100	1
	ICb	0.94	1	95	0.97
	ICa	1	1	100	1
Movement group FF	MLb	0.94	1	95	0.97
	MLa	1	1	100	1
	ICb	0.94	1	95	0.97
	ICa	1	1	100	1
Pain-free group FF	ML	0.49	0.49	50	0.5
	IC	0.72	0.79	75	0.71
Stabilization group STS	RAb	0.96	0.92	95	0.95
	RAa	0.97	1	97	0.95
	IOb	0.97	0.93	97	0.95
	IOa	0.96	1	97	0.97

Cont:

	EOb	0.93	0.92	92	0.93
	EOa	0.96	1	97	0.97
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
	ICLa	1	1	100	1
Movement group	RAb	0.96	0.92	95	۰,۹۵
	RAa	0.96	1	97	۰,۹۷
	IOb	0.93	0.92	92	۰,۹۳
STS	IOa	0.96	1	97	۰,۹۷
	EOb	0.93	0.92	۹۲	۰,۹۳
	EOa	0.96	1	۹۷	۰,۹۷
	MLb	1	1	۱00	۱
	MLa	1	1	۱00	۱
	ICLb	1	1	۱00	۱
	ICLa	1	1	۱00	۱
Pain-free group	RA	0.38	0.37	40	0.4
	IO	0.39	0.36	40	0.38
STS	EO	0.43	0.41	42	0.43
	ML	0.48	0.47	50	0.46
	IC	0.54	0.57	55	0.54

RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb, external oblique before; EOa, external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to stand; FF, forward flexion

Table S4: mean error of two software:

	Muscle	**Mean difference**	**P value**		**Muscle**	**Mean difference**	**P value**
Stabilization group One leg close	RAb	1.56	0.00	**Stabilization group One leg open**	RAb	1.54	0.00
	RAa	1	0.06		RAa	0.97	0.03
	IOb	1.19	0.04		IOb	1.51	0.00
	IOa	1.25	0.02		IOa	1.42	0.11
	EOb	1.5	0.41		EOb	1.56	0.00
	EOa	1.33	0.03		EOa	1.2	0.052
	MLb	4.08	0.00		MLb	-0.04	0.92
	MLa	3.94	0.002		MLa	1.64	0.07
	ICb	4.2	0.00		ICb	1.99	0.01
	ICa	2.19	0.00		ICa	1.95	0.01
Movement group One leg close	RAb	1.85	0.004	**Movement group One leg open**	RAb	0.32	0.32
	RAa	1.3	0.02		RAa	0.25	0.14
	IOb	1.7	0.006		IOb	0.55	0.47
	IOa	0.22	0.43		IOa	0.58	0.34
	EOb	1.41	0.01		EOb	-0.14	0.77
	EOa	2.2	0.01		EOa	0.27	0.49
	MLb	2	0.014		MLb	4.52	0.01
	MLa	1.42	0.03		MLa	2.06	0.004

	ICb ICa	1.44 2.03	0.016 0.023		ICb ICa	1.8 0.97	0.005 0.005
Pain-free group One leg close	RA IO EO ML IC	2.97 1.05 7.08 2.08 4.33	0.06 0.17 0.00 0.15 0.04	**Pain-free group One leg open**	RA IO EO ML IC	-1.14 -4.02 -1.6 -0.58 -0.35	0.04 0.09 0.25 0.64 0.53
Stabilization group FRR	MLb MLa ICb ICa	-0.09 -0.02 -0.07 -0.02	0.00 0.00 0.00 0.00	**Pain-free group FRR**	ML IC	0.01 0.00	0.08 0.59
Movement group FRR	MLb MLa ICb ICa	-0.02 -0.003 -0.02 -0.009	0.00 **0.82** 0.00 0.00	**Stabilization group FRR**	MLb MLa ICb ICa	-0.09 -0.02 -0.07 -0.02	0.00 0.00 0.00 0.00
Pain-free group FRR	ML IC	0.01 0.00	0.08 0.59	**Movement group FRR**	MLb MLa ICb ICa	-0.02 -0.003 -0.02 -0.009	0.00 **0.82** 0.00 0.00
Stabilization group FF	MLb MLa ICb ICa	-3.71 1.58 -1.86 1.4	0.008 **0.57** 0.005 **0.61**	**Stabilization group STS**	RAb RAa IOb IOa EOb EOa MLb MLa ICb ICa	0.95 0.41 0.59 0.21 0.47 0.37 2.5 1.41 2.7 3.5	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Movement group FF	MLb MLa ICb ICa	3.39 -0.04 1.07 0.07	0.00 **0.95** 0.02 **0.9**	**Movement group STS**	RAb RAa IOb IOa EOb EOa MLb MLa ICb ICa	-0.17 -0.04 -0.5 -0.7 -0.45 -0.23 0.3 1.42 0.4 0.36	0.54 0.67 0.00 0.14 0.00 0.26 0.43 0.1 0.38 0.36
Pain-free group FF	ML IC	2.01 0.09	0.14 0.09	**Pain-free group STS**	RA IO EO ML	-0.61 -0.26 -1 0.09	0.32 0.45 0.00 0.91

					IC	0.04	0.94

RAb, rectus abdominis before; RAa, rectus abdominis after; IOb, internal oblique before; IOa, internal oblique after; EOb, external oblique before; EOa, external oblique after; MLb, multifidus before; MLa, multifidus after; ICb, iliocostalis before; Ica, iliocostalis after; FRR, flexion relaxation ratio; STS, sit to