Methods for Assessing Core Muscle Co-Activation in the Lumbar Region: A1 Narrative Review

Methods for Assessing Core Muscle Co-Activation in the Lumbar Region: A Narrative Review

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Abstract

Purpose:

Core muscle co-activation is a key neuromuscular mechanism for lumbar spine stability, and its quantitative assessment is important for understanding spinal control, identifying dysfunction, guiding rehabilitation, and informing injury prevention. This narrative review critically appraises current methods for assessing lumbar core muscle co-activation, focusing on their theoretical basis, technical characteristics, interpretive value, limitations, and practical applicability.

Methods:

Current assessment approaches were narratively synthesized and categorized into surface electromyography, co-contraction index calculations, musculoskeletal modeling, and multimodal approaches integrating electromyographic data with biomechanical simulations. The review examined how these methods capture, quantify, and interpret lumbar core muscle co-activation, and how methodological variability affects validity, reproducibility, comparability, and translation.

Results:

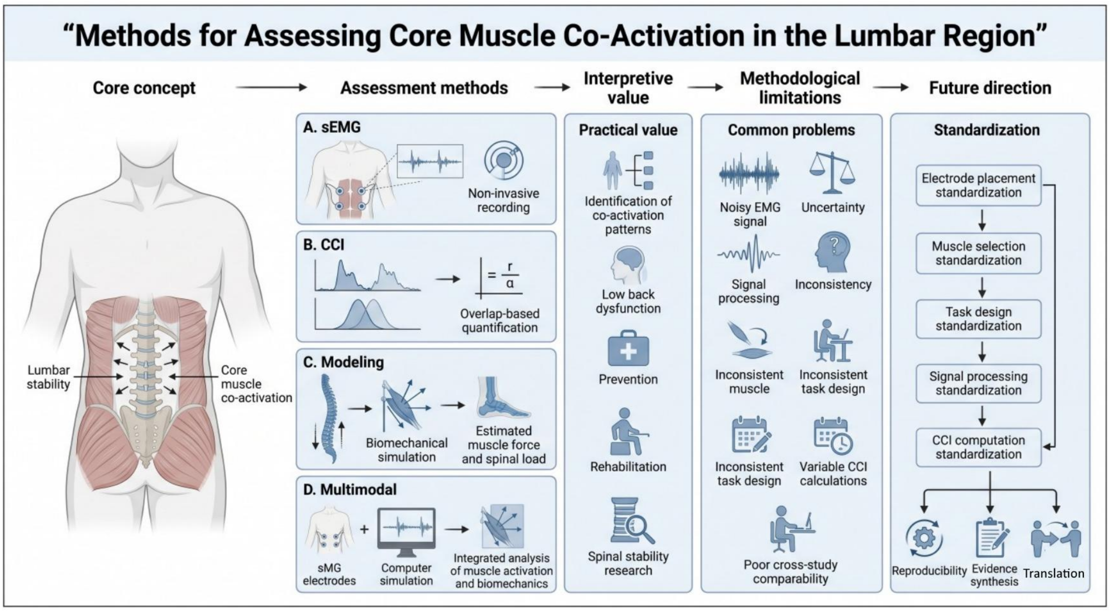
Surface electromyography is widely used to assess muscle activation but is affected by signal variability, electrode placement, normalization, crosstalk, and task dependency. Co-contraction index calculations quantify simultaneous muscle activation, yet their validity depends on muscle-pair selection, signal processing, time-window definition, and assumptions regarding agonist and antagonist roles. Musculoskeletal modeling estimates muscle force, spinal loading, and biomechanical consequences of co-activation, but outputs depend on anatomical assumptions, optimization criteria, and validation quality. Multimodal approaches may improve biomechanical interpretation but require technical expertise and standardized integration procedures.

Conclusion:

Existing methods provide valuable but heterogeneous insights into lumbar neuromuscular control and spinal stability. Future research should prioritize standardized protocols for electromyography processing, muscle selection, task design, co-contraction index computation, and multimodal model validation to enhance reproducibility, comparability, and clinical translation.

Keywords: core muscle co-activation; surface electromyography; co-contraction index; musculoskeletal modeling; spinal stability

Visual Abstract



Introduction

Core muscle coactivation is a fundamental neuromuscular control strategy for maintaining spinal stability, particularly in the lumbar region, where dynamic load transfer and postural regulation are essential for function (Panjabi, 1992; Cholewicki & McGill, 1996). It involves the simultaneous activation of agonist and antagonist muscles to enhance trunk stiffness, attenuate perturbations, and reduce mechanical stress on passive structures (Granata & Marras, 2000; Reeves et al., 2008). Through these mechanisms, coactivation contributes substantially to coordinated neuromuscular control and protection of the lumbar spine during both static and dynamic tasks (Cholewicki et al., 1999; Hodges & Richardson, 1997).

Given its physiological importance, accurate assessment of core muscle coactivation is essential for understanding spinal biomechanics, evaluating neuromuscular function, and guiding interventions in clinical and performance settings (Hodges & Moseley, 2003; Kibler et al., 2006). Surface electromyography (sEMG) is the most widely used tool for quantifying the amplitude and temporal characteristics of muscle excitation during static and dynamic tasks (Granata & Marras, 2000; Arjmand & Shirazi-Adl, 2006). However, study protocols vary substantially with respect to agonist-antagonist muscle pair selection, signal processing, task design, and normalization procedures, which limits cross-study comparability (Marshall & Murphy, 2003). In addition, because sEMG relies on surface recordings, its ability to capture deep muscle activity is inherently restricted, further constraining interpretation of lumbar muscle coordination (Hughes et al., 1995; Delp et al., 2007).

To address these limitations, more advanced approaches, including musculoskeletal modeling and simulation, have been introduced to improve the biomechanical relevance of coactivation assessment by estimating muscle forces, joint torques, and internal loading parameters (Arjmand & Shirazi-Adl, 2006; Palma et al., 2021). Nevertheless, these methods require complex model construction, accurate input data, and multiple assumptions that may limit generalizability across populations and task demands (Suo et al., 2024; Knapik et al., 2022).

Although coactivation has long been a topic of research interest, current assessment methods remain methodologically heterogeneous and lack a unified framework for classification and interpretation. Therefore, the aim of this narrative review is to synthesize and critically appraise current quantitative methods used to assess core muscle coactivation in the lumbar region, including sEMG, co-contraction index-based approaches, musculoskeletal modeling and simulation, and multimodal strategies. We hypothesise that these methods differ substantially in their theoretical assumptions, technical implementation, and interpretive value, and that the lack of standardization in signal processing, muscle selection, task design, and computational procedures constrains construct validity, reliability, and cross-study comparability. By clarifying the strengths, limitations, and practical implications of each approach, this review seeks to provide methodological guidance for researchers and clinicians involved in lumbar neuromuscular assessment.

Literature Search and Study Selection

Relevant literature was identified through searches of PubMed, Web of Science, Scopus, CINAHL, and SPORTDiscus from database inception to 27 December 2025. Because this narrative review covered several methodological domains, combinations of free-text terms and database-specific subject headings were adapted to each topic and database. The principal search concepts included terms related to the anatomical region and phenomenon of interest ("core muscle," "trunk muscle," "lumbar muscle," "abdominal muscle," "paraspinal muscle," "co-activation," "coactivation," "co-contraction," and "cocontraction"), combined, as appropriate, with method-specific terms such as "surface electromyography," "sEMG," "co-contraction index," "CCI," "musculoskeletal modeling," "biomechanical modeling," "simulation," "EMG-informed," and "EMG-driven." Additional terms related to "spinal stability," "lumbar stability," "muscle force," and "spinal loading" were used to identify studies addressing the biomechanical interpretation of co-activation.

English-language original studies were considered eligible when they developed, applied, evaluated, or compared quantitative methods for assessing lumbar or trunk muscle co-activation in human participants or human lumbar biomechanical models.

Studies involving healthy or clinical populations and static, dynamic, lifting, fatigue, or perturbation-based tasks were considered. Studies were excluded if they did not address lumbar or trunk musculature, examined only isolated muscle activation without an assessment of co-activation or intermuscular coordination, did not report a relevant quantitative assessment method, or were not published in English. Titles were initially screened for relevance, followed by examination of the available abstracts and full texts. The reference lists of eligible studies and relevant review articles were also examined to identify additional publications.

Classification and Technical Overview of Assessment Methods

Methods Based on Surface Electromyography

General sEMG-Based Metrics

Surface electromyography (sEMG) is the most commonly used method for assessing lumbar core muscle coactivation in experimental and applied settings (Reeves et al., 2008; Brown et al., 2006; Correia et al., 2016; Granata et al., 2001; Lavender et al., 1992; Potvin & O'brien, 1998; Chiou et al., 1999; Rossi et al., 2014; Lavender et al., 1993) (Table 1). As a non-invasive technique, it records surface myoelectric activity during a range of tasks, including quiet standing, postural control, trunk motion, lifting, stabilization, and externally perturbed conditions. In lumbar research, sEMG is primarily used to characterize activation of superficial trunk muscles, particularly the rectus abdominis, internal oblique, external oblique, and erector spinae.

Electrode placement is generally selected to maximize signal consistency from target trunk muscles, following standardized recommendations where available. The Surface EMG for Non-Invasive Assessment of Muscles (SENIAM) project provides guidance on skin preparation, electrode configuration, anatomical placement, signal acquisition, and reporting to improve signal quality, reproducibility, and comparability across studies (Hermens et al., 2000). However, SENIAM provides lumbar-region placement guidance for only a limited number of muscles, including longissimus, iliocostalis, and multifidus (Hermens et al., 2000). For muscles not explicitly covered, electrode placement is usually determined according to anatomical landmarks, fiber orientation, previous trunk EMG literature, and efforts to minimize cross-talk and motion artifact (Hermens et al., 2000; Merletti & Farina, 2016).

The sEMG assessment workflow generally includes signal acquisition, preprocessing, normalization, and extraction of descriptive activation variables. Sampling frequencies of approximately 1,000 Hz are commonly used to capture the physiological bandwidth of sEMG signals (Reeves et al., 2008). Preprocessing typically includes band-pass filtering, rectification or root mean square (RMS) processing, and low-pass filtering when a linear envelope is required. Signal amplitudes are usually normalized to maximum voluntary isometric contraction (%MVIC) or to a task-specific reference interval to support comparisons across individuals and conditions (Correia et al., 2016; Granata & Orishimo, 2001).

These procedures yield general sEMG-based metrics describing activation timing, relative amplitude, temporal activation profiles, and pre-activation characteristics (Vigotsky et al., 2018). In perturbation paradigms, pre-activation windows such as the 50 to 100 ms period before an external disturbance are often analyzed to characterize anticipatory neuromuscular responses (Brown et al., 2006; Granata & Orishimo, 2001). Metrics such as activation slope and median frequency may also be extracted to describe sustained activation or fatigue-related changes (Correia et al., 2016). Overall, sEMG provides a practical observational method for characterizing when lumbar trunk muscles are active, the relative magnitude of their activity, and how activation patterns vary across task demands (Figure 1).

*****Insert Figure 1 *****

*****Insert Table 1*****

sEMG with Calculation of Co-Contraction Index

Several studies have extended the use of sEMG by integrating it with co-contraction index (CCI) analysis to quantify the degree of simultaneous activation between paired core muscles (Palma et al., 2021; Johnston et al., 2021; P. Le et al., 2017; Schinkel-Ivy et al., 2013; Varrecchia et al., 2022; Nelson-Wong & Callaghan, 2010; Du et al., 2018; Peter Le et al., 2017; Le et al., 2018) (Table 2). This approach enables structured evaluation of neuromuscular coordination by mathematically characterizing agonist-antagonist interactions across tasks.

A commonly used CCI formula compares normalized sEMG amplitudes of paired muscles at each time point:

$$CCI=\Sigma(EMG\_low(i)/EMG\_high(i))\times[EMG\_low(i)+ EMG\_high(i)]$$

In this equation, EMG_low(i) and EMG_high(i) represent the lower and higher normalized EMG amplitudes of the muscle pair at each time point, typically expressed as %MVIC (Johnston et al., 2021). In relatively static or low-speed tasks, CCI is commonly derived from normalized amplitude ratios or summed amplitudes of selected muscle pairs.

To address the limitation of predefined muscle roles in traditional CCI calculations, Le et al. (Peter Le et al., 2017) proposed a torque-based method that dynamically classifies muscles as agonists or antagonists according to torque direction, using a dot product model to estimate each muscle's moment contribution. Le et al. (2018) (Le et al., 2018) subsequently extended this approach by incorporating weighting factors derived from biomechanical characteristics such as muscle cross-sectional area, estimated moment arms, and generic force-length and force-velocity relationships. Although this method did not implement a full musculoskeletal modeling framework, it allowed more context-sensitive estimation of coactivation while retaining the relative computational simplicity of CCI. Despite these developments, variability remains substantial in how CCI is applied across studies (Hodges & Richardson, 1996). Differences in muscle pair selection, normalization procedures, task design, and interpretation criteria may contribute to inconsistent findings and limit cross-study comparability. Nevertheless, sEMG-based CCI remains a useful intermediate approach between descriptive activation analysis and more mechanically informed modeling methods.

Insert Table 2

Musculoskeletal Modeling and Simulation

Musculoskeletal modeling and simulation has been used to evaluate the mechanical consequences of lumbar muscle co-activation by estimating internal variables that cannot be measured directly, including individual muscle forces, joint moments, spinal compression, shear loading, and stability-related parameters (Hughes et al., 1995; Granata & Wilson, 2001; Caimi et al., 2024; Gardner-Morse & Stokes, 1998; Stokes et al., 2011) (Table 3). In this review, this category refers primarily to modeling approaches that do not use experimentally recorded sEMG signals as direct constraints or excitation inputs. Instead, muscle recruitment and force-sharing patterns are prescribed or estimated according to mechanical equilibrium, stability requirements, optimization criteria, or predefined levels of muscle activation or co-activation.

Model construction typically integrates anatomical and mechanical inputs, including segment geometry, muscle attachment sites and lines of action, muscle moment arms, joint constraints, external forces, kinematic data, and muscle–tendon properties. These inputs may be obtained from anthropometric scaling, medical imaging, motion-capture systems, force platforms, or parameters reported in previous studies (Delp et al., 2007; Seth et al., 2018). Depending on the modeling framework, inverse dynamics, optimization procedures, multibody simulation, or other computational approaches may be used to resolve muscle redundancy and estimate the internal mechanical demands associated with a given posture or movement. Although sEMG may occasionally be used for external comparison or model validation, it does not constitute a direct model input within this category.

These approaches are particularly useful for testing how prescribed or model-predicted co-activation influences lumbar stability, muscle-force distribution, spinal compression, and shear loading under controlled conditions. They can also represent the potential contributions of deep muscles that are difficult to assess using surface recordings. However, their outputs depend strongly on model architecture, anatomical assumptions, parameter scaling, optimization criteria, and the representation of muscle recruitment. Because activation strategies are predicted or prescribed rather than derived directly from participant-specific muscle recordings, these models may have limited ability to capture individual and time-varying neuromuscular behavior. This limitation provides the rationale for integrating experimentally recorded sEMG with musculoskeletal modeling.

Insert Table 3

Integration of sEMG with Musculoskeletal Modeling and Simulation

Integrated sEMG–musculoskeletal modeling approaches incorporate experimentally recorded muscle activation into a biomechanical model to inform, constrain, or drive the estimation of muscle forces and spinal loading (Granata & Marras, 2000; Brown & McGill, 2008; Cholewicki et al., 2002; Granata et al., 2005; Lee et al., 2006) (Table 4). The defining feature of this category is that sEMG contributes directly to the model solution, rather than being used only for comparison or external validation. This integration links the temporal characteristics of recorded neuromuscular activation with the mechanical representation of the lumbar spine.

Two principal implementation strategies can be distinguished. In sEMG-informed approaches, processed sEMG signals are used to constrain inverse-dynamics or optimization procedures, thereby reducing the range of physiologically plausible solutions to the muscle-redundancy problem. In sEMG-driven approaches, processed sEMG signals are used as muscle-excitation inputs to forward simulations. These excitation signals are combined with activation dynamics, muscle–tendon properties, force–length and force–velocity relationships, and subject-specific or scaled anatomical parameters to estimate muscle forces and their mechanical consequences (Sartori et al., 2014; Higginson et al., 2006; Shi et al., 2023).

In addition to sEMG, integrated approaches commonly require anatomical or anthropometric information, trunk kinematics, external forces, muscle geometry, and muscle–tendon parameters. By combining these inputs, they can estimate individual muscle forces, force sharing, joint moments, spinal compression, shear loading, trunk stiffness, and stability-related outcomes that cannot be obtained from sEMG alone (Brown & McGill, 2008; Cholewicki et al., 2002; Granata et al., 2005). This approach therefore provides a more physiologically informed interpretation of lumbar co-activation than conventional modeling or sEMG alone. Nevertheless, it retains limitations associated with both components, including sensitivity to electrode placement, signal normalization and crosstalk, incomplete recording of deep muscles, uncertainty in model parameters, and dependence on the selected optimization or simulation framework.

*****Insert Table 4*****

Methodological Considerations and Comparative Analysis

Interpretive Capacity of Assessment Methods

The available methods differ substantially in the type of information they provide and in the level of inference they support. General sEMG-based metrics are most useful for describing activation timing, relative amplitude, and temporal activation patterns in superficial trunk muscles, and have been widely used to identify group differences and task-specific activation responses in lumbar research (Granata & Marras, 1995; Dankaerts et al., 2006). CCI-based approaches extend this descriptive role by quantifying the degree of simultaneous activation between selected muscle groups, thereby offering a more structured representation of neuromuscular coordination (Johnston et al., 2021; Peter Le et al., 2017; Granata & Marras, 1995). Musculoskeletal modeling and simulation move beyond surface activation patterns by estimating internal mechanical variables such as joint moments, muscle forces, and spinal loading (Hughes et al., 1995; Gardner-Morse & Stokes, 1998; Stokes et al., 2011). Integrated sEMG-modeling approaches provide the broadest interpretive scope by linking experimentally recorded activation patterns with biomechanical estimates of force sharing, compression, shear loading, and stability-related behavior (Brown & McGill, 2008; Granata et al., 2005; Cholewicki & Vanvliet Iv, 2002). Taken together, these approaches are not interchangeable tools, but methods with distinct interpretive ranges that should be matched to the specific research question and desired level of biomechanical inference.

Task Complexity and Variability in Muscle Function

Task complexity strongly affects the interpretability of lumbar coactivation assessment (Figure 2). In relatively simple postural or low-speed tasks, sEMG and conventional CCI methods can provide meaningful information on coordination patterns because muscle roles are comparatively stable and movement demands are easier to define (Vigotsky et al., 2018; Johnston et al., 2021). Their interpretive value decreases, however, during tasks involving trunk rotation, coupled motion, asymmetric loading, or rapidly changing external demands, where muscles may shift dynamically between stabilizing and movement-producing roles (Vigotsky et al., 2018; Peter Le et al., 2017). Under such conditions, amplitude-based or pairwise indices may oversimplify coordination behavior and may be less effective in capturing the biomechanical significance of coactivation. Modeling approaches are better suited to these contexts because they can estimate internal loading and force sharing, but their performance also depends on whether model assumptions adequately reflect task-specific coordination demands (Remus et al., 2023; Conconi et al., 2021; Harrington et al., 2024; Sylvester et al., 2021; Refai et al., 2024). Integrated sEMG-modeling approaches are particularly valuable in this respect, as they combine measured activation with biomechanical simulation, yet their interpretive strength still decreases when task complexity exceeds the representational capacity of the model or the available EMG coverage (Lerchl et al., 2023; Toumanidou & Noailly, 2015).

Insert Figure 2

Representation of Deep Muscles and Physiological Realism

A major methodological challenge across approaches is the limited representation of deep stabilizing muscles and the broader issue of physiological realism (Figure 3). Because sEMG records activity from the body surface, it primarily reflects superficial trunk muscles and may not adequately capture deeper structures such as transversus abdominis and lumbar multifidus (Lavender et al., 1992; Granata et al., 2005). This constrains both descriptive sEMG measures and CCI-based analyses, particularly when deep-muscle contributions are central to lumbar stability.

Intramuscular EMG, typically recorded using fine-wire electrodes, provides a more direct means of recording myoelectric activity from targeted deep muscles, including the transversus abdominis and deep fibers of the lumbar multifidus (Moseley et al., 2002; Okubo et al., 2010; Hofste et al., 2020). By positioning the electrode within the target muscle, sometimes with imaging guidance, this technique can obtain selective recordings that are not accessible using sEMG. However, intramuscular EMG is invasive and samples activity from a localized region surrounding the electrode rather than representing the behavior of the entire muscle (Merletti & Farina, 2016; Lothe et al., 2019). Although fine-wire recordings have been applied during limb movements, stabilization exercises, and perturbation tasks, specialized electrode placement and participant burden may limit their scalability for large cohorts and repeated assessments. Moreover, intramuscular EMG measures local myoelectric activity rather than muscle force or spinal loading. It therefore complements, but does not replace, sEMG and musculoskeletal modeling in the assessment of lumbar muscle co-activation.

Musculoskeletal modeling can partly address this limitation by estimating the contribution of muscles that are not directly recorded, but these estimates remain dependent on anatomical assumptions, scaling procedures, and force-generating properties that may not fully reflect subject-specific physiology (Luis et al., 2022; Hicks et al., 2015). The same concern applies to integrated sEMG-modeling approaches: although they provide more physiologically grounded estimates than either component method alone, deep-muscle behavior is still typically inferred rather than directly measured (Vigotsky et al., 2018; Granata et al., 2005). In addition, even anatomically detailed models do not fully reproduce the complexity of neural control, rapid neuromuscular adjustments, or perturbation-driven changes in activation strategy (Stokes et al., 2006; Abboud et al., 2023). Accordingly, no current method fully captures the entire stabilizing system of the lumbar spine.

****Insert Figure 3****

Methodological Heterogeneity and Standardization

Methodological heterogeneity remains a major barrier to cross-study synthesis and practical translation (Figure 4). In sEMG-based studies, differences in electrode placement, signal-processing pipelines, normalization procedures, task design, and target muscle selection can substantially influence the resulting activation profiles and reduce reproducibility (Granata & Wilson, 2001; Mirka & Marras, 1993). Similar issues affect CCI-based studies, where variability in muscle pair selection, computation formulas, and interpretation criteria further limits comparability (Johnston et al., 2021; Hodges & Bui, 1996). In model-based research, heterogeneity arises from differences in architecture, parameter assumptions, optimization strategies, and validation procedures, meaning that similar conclusions regarding spinal loading or stability may be derived from markedly different analytical frameworks (Knapik et al., 2022; Sciortino et al., 2023). Integrated approaches inherit variability from both sEMG methodology and biomechanical modeling, which may compound uncertainty across the workflow (Knapik et al., 2022; Brown & McGill, 2008; Nispel et al., 2023). Standardization should therefore be considered a central priority. More consistent reporting of acquisition procedures, normalization methods, muscle selection, task paradigms, model assumptions, and validation strategies would improve reproducibility, facilitate evidence synthesis, and strengthen translational application.

****Insert Figure 4****

Implications for Method Selection and Future Research

This review highlights the main methodological options currently available for assessing lumbar core muscle coactivation and the key priorities for improving their rigor and practical value. sEMG remains the most accessible approach for quantifying trunk muscle activity, but its limited ability to capture deep stabilizing muscles constrains interpretation. CCI provides a structured measure of coordination, although inconsistent calculation and normalization procedures reduce comparability across studies. Musculoskeletal modeling and simulation offer greater insight into internal loading and spinal mechanics, but their broader application is limited by reliance on subject-specific inputs and substantial computational demands. In practice, method selection should be guided by the research question, task characteristics, and target population, and findings should be interpreted in relation to the assumptions underlying each method. Future work should prioritize standardized CCI procedures, more generalizable sEMG-integrated modeling frameworks, and validation in larger and more diverse cohorts to strengthen clinical and performance applications (Table 5).

Conclusion

This narrative review identified four broad methodological approaches for assessing lumbar core muscle coactivation, including sEMG-based assessment, CCI-based quantification, musculoskeletal modeling and simulation, and integrated sEMG-modeling strategies. Although each approach offers distinct advantages, cross-study comparability remains limited by heterogeneity in task design, muscle selection, signal processing, and interpretive assumptions. sEMG provides the most practical means of characterizing activation behavior, whereas modeling-based approaches offer greater insight into internal loading and spinal stability. However, no single method fully captures the complexity of lumbar coactivation, particularly with regard to deep-muscle representation, task-specific demands, and methodological standardization. Overall, these findings highlight the need for a contextual framework to guide method selection and to improve the translational value of lumbar coactivation assessment in clinical and performance settings.

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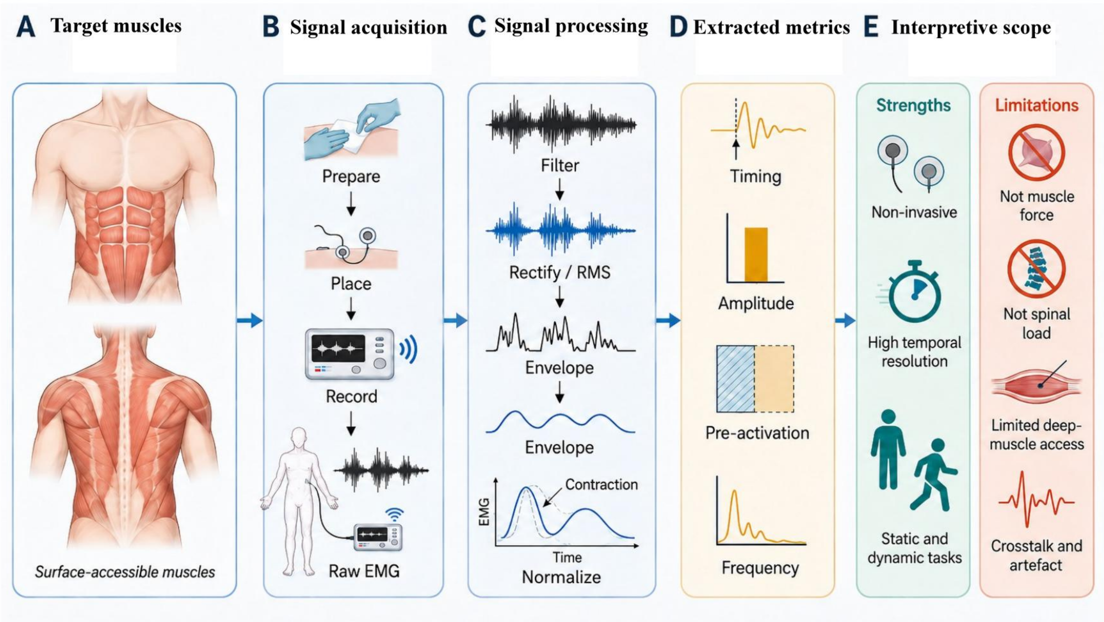

Figure 1. Surface electromyography workflow and interpretive scope for assessing lumbar core muscle co-activation. Surface electromyography (sEMG) assessment progresses from the selection of surface-accessible trunk muscles and signal acquisition to signal processing, normalization, and extraction of timing-, amplitude-, pre-activation-, and frequency-based metrics. sEMG provides non-invasive recording with high temporal resolution across static and dynamic tasks, but it does not directly quantify muscle force or spinal loading and has limited access

to deep muscles. RMS, root mean square.

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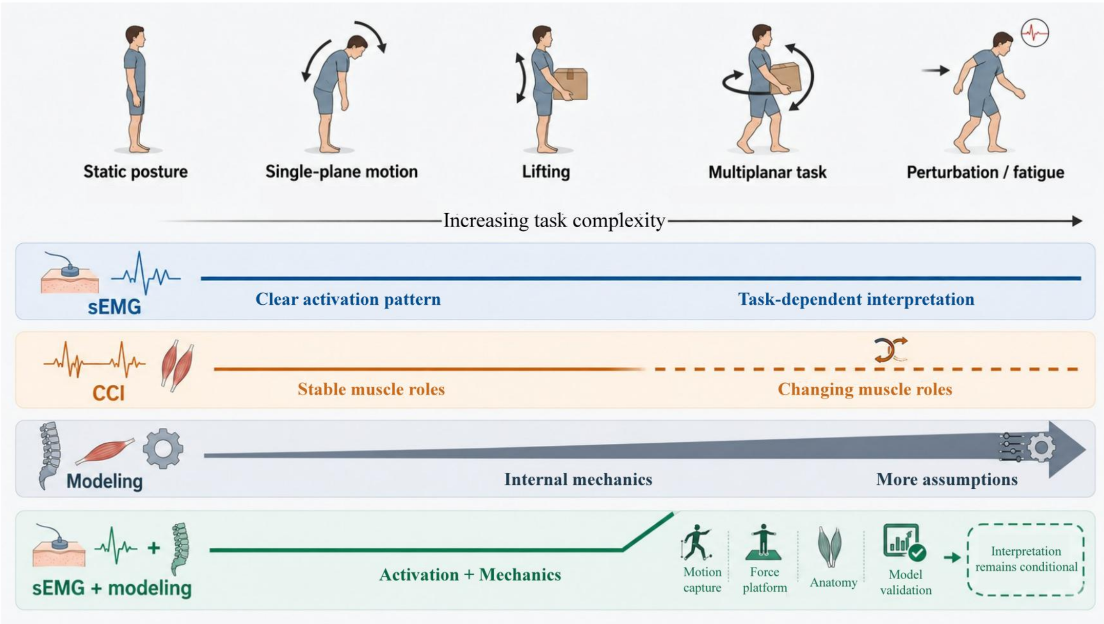

Figure 2. Influence of task complexity on methods for assessing lumbar core muscle co-activation. Task demands progress from static posture and single-plane movement to lifting, multiplanar motion, and perturbation or fatigue. sEMG interpretation becomes increasingly task-dependent, whereas conventional co-contraction indices are most interpretable when muscle roles remain relatively stable. Musculoskeletal modeling extends inference to internal mechanics but requires additional assumptions, while integrated sEMG-modeling combines activation and mechanical information but remains conditional in complex tasks. CCI, co-contraction index; sEMG, surface electromyography.

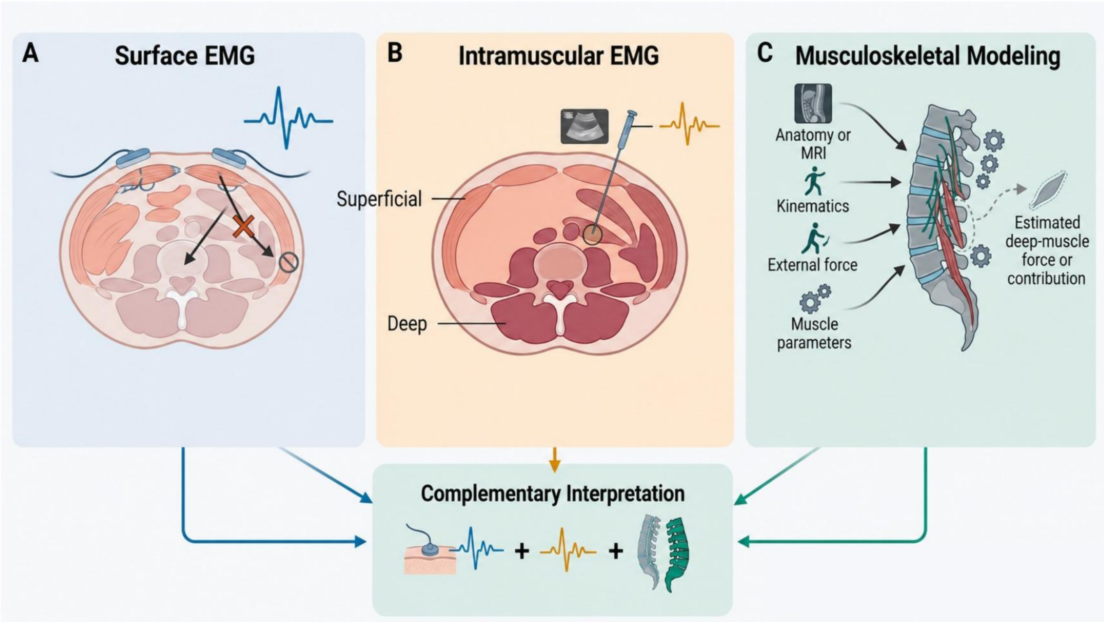

Figure 3. Complementary approaches to assessing deep lumbar muscle activity. Surface electromyography primarily records superficial muscle activity, whereas intramuscular electromyography enables targeted recording from deep muscles but is invasive and spatially localized. Musculoskeletal modeling can estimate deep-muscle forces or contributions from anatomical and mechanical inputs, although these estimates remain model-dependent. These approaches provide complementary evidence, and method selection should be guided by the research question. EMG, electromyography; MRI, magnetic resonance imaging.

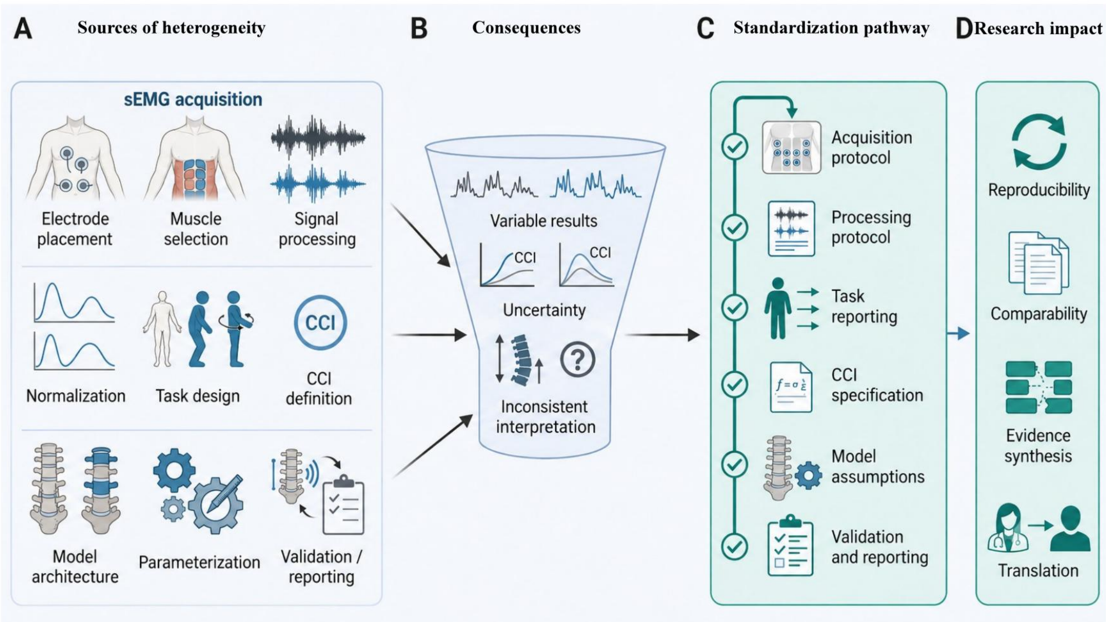

Figure 4. Methodological heterogeneity and standardization in lumbar core muscle co-activation assessment. Variation in electrode placement, muscle selection, signal processing, normalization, task design, CCI definition, model architecture,

parameterization, and validation can produce inconsistent results and interpretation. Standardized acquisition and processing protocols, explicit reporting of tasks and analytical definitions, transparent model assumptions, and appropriate validation can improve reproducibility, cross-study comparability, evidence synthesis, and translation. CCI, co-contraction index; sEMG, surface electromyography.

Table 1. Electromyography-based Approaches to Evaluating Core Muscle Co-activation

References (Year)	Experimental Aim	Muscle Selection
Brown (2006)	To quantify trunk muscle pre-activation and examine its relation to spinal stability, trunk stiffness, external force, and trunk kinematics under sagittal and 30° off-sagittal loading	Rectus Abdominis, External Oblique, Internal Oblique, Latissimus Dorsi, Lumbar Erector Spinae, Thoracic Erector Spinae, Multifidus
Correia (2016)	To quantify differences in EMG amplitude and frequency spectrum during fatiguing isometric tasks in tennis players with and without a recent history of LBP	Rectus Abdominis, External Oblique, and Both (Lumbar and Thoracic) Portions of the Erector Spinae
Granata (2001)	To quantify preparatory trunk muscle activity prior to unexpected trunk flexion loading and during static trunk extension without anticipated sudden load	Rectus Abdominis, External Oblique, Internal Oblique, and Erector Spinae
Lavender (1992a)	To quantify trunk muscle activity and relative co-activation during resistance to asymmetric external loading	Erector Spinae, Latissimus Dorsi, External Oblique, and Rectus Abdominis
Lavender (1992b)	To quantify trunk muscle EMG responses to variations in external torque magnitude and direction	Latissimus Dorsi, Erector Spinae, External Oblique, and Rectus Abdominis
Lavender (1993)	To quantify activation and co-contraction patterns of trunk muscles during resistance to externally applied torques in axial trunk rotation postures	Erector Spinae, Latissimus Dorsi, External Oblique, and Rectus Abdominis
Potvin (1998)	To assess fatigue responses of agonist and antagonist trunk muscles during a standardized isometric lateral bending task	Erector Spinae, Latissimus Dorsi, Rectus Abdominis, External Oblique, and Internal Oblique
Reeves (2008)	To determine whether trunk antagonist muscle activation is associated with neuromuscular dysfunction	Rectus Abdominis, External Oblique, Internal Oblique, and Erector Spinae
Chiou (1999)	To measure trunk muscle activity using eight-channel integrated EMG	Rectus Abdominis, External Oblique, Erector Spinae, and Latissimus Dorsi
Rossi (2014)	To compare antagonist co-activation patterns between local and global trunk muscles during Pilates exercises	Not reported

***. EMG: Surface Electromyography; LBP: Low Back Pain.**

Table 2. Methods Based on Electromyography and the Co-contraction Index for Evaluating Core Muscle Co-activation

References (Year)	Co-activation Calculation Method	Study Characteristics
Johnston (2021)	CCI = Σ (EMG_low(i) / EMG_high(i)) × [EMG_low(i) + EMG_high(i)]	Bilateral EMG signals were collected from eight trunk muscles
Le (2017)	Torque-based CCI using dynamic torque vectors to classify muscles as agonists or antagonists in real time; explicit formula not provided	Using a 16-channel MA400-28 EMG system, data were sampled at 1000 Hz. Signals underwent 30 Hz high-pass, 450 Hz low-pass, and 60 Hz notch filtering as well as anti-aliasing filtering, then were rectified and processed with zero-phase moving average filtering
Le (2018)	nEMG-based co-activation method combining normalized EMG amplitudes with estimated muscle moment contributions derived from anthropometric and biomechanical parameters; explicit formula not provided	Using a 16-channel MA400-28 EMG system, data were sampled at 1000 Hz, with electrodes bilaterally placed over the latissimus dorsi, erector spinae, rectus abdominis, external oblique, and internal oblique muscles
Schinkel (2013)	Muscle-pair-specific CCI used to quantify the extent of co-contraction; formula not provided	EMG data were obtained bilaterally from eight trunk muscles: rectus abdominis, external oblique, internal oblique, upper thoracic erector spinae, lower thoracic erector spinae, latissimus dorsi, lumbar erector spinae, and superficial lumbar multifidus
Varrecchia (2022)	Time-varying multi-muscle co-activation function (TMCf) combining EMG-derived co-activation across multiple muscles; formula not provided	Muscle co-activation parameters were used to distinguish movement strategies between individuals with and without low back pain during lifting tasks characterized by fatigue and frequency dependence
Nelson-Wong (2009)	CCI = $[\Sigma_i^N (EMG\_low_i / EMG\_high_i)] \times (EMG\_low_i + EMG\_high_i)$, where N denotes the number of data points; EMG_low and EMG_high represent the	Electrodes were placed over eight bilateral muscle groups, and MVICs were elicited in specific postures using manual

	lower and higher linear-enveloped EMG amplitudes of the selected muscle pair at each time point	resistance to standardize the EMG signals
Du (2018)	CCR = AEMGA / (AEMGB + AEMGA), where AEMGA is the normalized integrated EMG activity of the antagonist muscle and AEMGB is that of the agonist muscle	LDH group: 26 patients with low back pain symptoms within 3–12 months before data acquisition and diagnosed with LDH by CT or MRI. Healthy control group: 28 participants matched for sex, age, weight, height, and BM
Palma (2021)	Muscle co-activation index = 2 × sEMG_Ant / sEMG_Total × 100%	Twelve physically active young male participants were recruited

***. CCI: Co-contraction Index; EMG: Electromyography; TMCF: time-varying multi-muscle co-activation function; MVICs: maximal voluntary isometric contractions; CCR: Co-contraction Ratio: LDH: Lumbar Disc Herniation; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; BM: Body Mass.**

Table 3. Methods Based on Biomechanical Models for Evaluating Core Muscle Co-activation

References (Year)	Type of Model	Simulated Task	Analysis of Results
Caimi (2024)	Simple Synthetic Model and Lumbar Musculoskeletal Model	Conducted dynamic simulations of multiple bending movements to investigate muscle symmetry and how single- versus multi-joint muscles and two- versus three-dimensional models influence co-activation predictions	Antagonist muscle activity could be predicted when the model incorporated multi-joint muscles or was three-dimensional, but not when only single-joint muscles were included in a two-dimensional model
Gardner-Morse (1998)	Lumbar Spine Biomechanical Model	Measured the effects of different levels of rectus abdominis, internal oblique, and external oblique co-activation on the lumbar spine during extensor efforts (40%, 60%, and 80% of MVC and lateral flexion efforts (40%, 60%, and 80% of MVC)	The findings indicated that greater abdominal muscle co-activation markedly improved lumbar spinal stability, as evidenced by a reduction in the critical threshold
Hughes (1995)	The lumbar trunk model was reconstructed and referred to	Analyzed four tasks: trunk flexion, extension, left lateral bending, and clockwise rotation	Co-activation can markedly increase spinal compression forces. However, under certain specific

	as the MSC model		conditions, co-activation may slightly reduce the predicted spinal compression forces
Stokes (2011)	A detailed biomechanical model of the spine and associated musculature	Analyzed flexion, extension, lateral bending, and axial rotation torques applied in 20 Nm increments up to a maximum of 60 Nm	Model predictions indicated that spinal stability, quantified by the minimum eigenvalue, increased progressively with higher (IAP
Granata&Orishimo (2001)	2D Biomechanical Model	Predicted variations in trunk muscle co-contraction in response to changes in lifting height and external load	Model-predicted trends were compared with EMG data recorded during static trunk extension tasks, revealing that EMG activity of the trunk flexor muscles increased with the height of the external load, in agreement with the model predictions

***. MVC: maximal voluntary contraction; MSC: Minimal Stress Compression; IAP: intra-abdominal pressure; EMG: Electromyography.**

Table 4. Methods Based on Electromyography and Biomechanical Models for Evaluating Core Muscle Co-activation

References (Year)	Combined Approach	Multimodal Assessment Results	Model Optimization
Brown (2008)	EMG and Spinal Biomechanical Model	Variation in the EMG–torque relationship: When antagonist muscle activity was disregarded, the EMG–torque relationship appeared nonlinear, characterized by reduced torque output at higher activation levels. Incorporating the additional torque generated by antagonist muscles rendered the EMG–torque relationship more linear	The approach integrated electromyographic (EMG) signals with an anatomically detailed spinal biomechanical model and, crucially, incorporated antagonist muscle co-activation into the computations
Cholewicki (2002)	Employed an 18-degree-of-freedom, EMG-driven complex biomechanical model to quantify trunk muscle co-activation and assess it through	Spinal stability and compressive forces increased proportionally with IAP, regardless of whether participants intentionally generated or	An EMG-assisted optimization approach was employed in the model to balance the torque equations, demonstrating that EMG data were

	calculations of spinal compressive forces and stability	consciously avoided it. This increase was mediated by substantial co-activation of the 12 major trunk muscles	incorporated to resolve uncertainties in muscle mechanical calculations and achieve more accurate estimations of muscle forces
Granata (2005)	Employed a combined approach of EMG and biomechanical modeling to evaluate core muscle co-activation levels	Average co-activation during flexion exertions was roughly double that observed during extension, with the co-activation ratio being significantly greater in flexion than in extension	Used a three-dimensional, two-segment biomechanical model to estimate muscle forces and spinal loads, assessing balance and spinal stability while preserving model simplicity
Granata et al (1995)	EMG data recorded from five pairs of trunk muscles during dynamic lifting tasks and employed a complex biomechanical model to compute relative muscle forces, lifting torques, and spinal loading	Ignoring muscle co-activation can result in substantial underestimation of spinal loads during dynamic lifting — up to 45% for compressive loads and 70% for shear forces. In lifting tasks, trunk extensor torques were 47% greater than the applied lifting torque to offset antagonist flexor activity. The magnitude of spinal loading attributable to co-activation was affected by load weight, trunk extension velocity, and the number of active muscles incorporated in the model	Employed an iterative approach to model optimization, beginning with EMG data from the right and left erector spinae alone and progressively incorporating all five muscle groups into the model analysis
Granata et al (2000)	Developed an EMG-assisted biomechanical model for calculating spinal loading and stability	Trunk muscle co-activation resulted in a 12–18% increase in spinal compression loads. In dynamic lifting tasks, spinal loading rose markedly when antagonist muscle co-activation was incorporated into the model	Iincorporated analyses of dynamic balance and overall stability
Granata et al (2001)	Developed a two-dimensional inverted pendulum model to predict variations in antagonist muscle co-contraction with changes in lifting height and	According to the biomechanical model, contraction forces of the abdominal and paraspinal muscles were required to increase with	Model was developed under balance and stability constraints and incorporated specific anthropometric parameters, including trunk weight, center-of-mass

	external load	greater external load height	height, and the moment arm lengths of the flexor and extensor muscles
Lee (2006)	Combined EMG and biomechanical modeling approach to evaluate the influence of core muscle co-activation on trunk stiffness	During maximal co-contraction, EMG activity of the rectus abdominis exceeded that under minimal co-contraction by 12.5%. The EO increased by 19.4% and the IO by 7.5%, whereas the lumbar paraspinal muscles exhibited an upward trend that did not reach statistical significance	Force and displacement signals were low-pass filtered at 75 Hz and mean-centered before analysis to ensure accurate estimation of the correlation function. To mitigate system noise, white noise corresponding to 30% of one standard deviation of the input trunk force was added, and decorrelation procedures were applied to eliminate external noise and sampling artifacts
Mirka (2000)	Integration of EMG with Statistical and Simulation Modeling Approaches	Study yielded a descriptive model of trunk muscle co-activation, offering best-fit normalized integrated EMG distributions for each trunk muscle across all experimental conditions	To enhance model accuracy, EMG data were normalized before analysis to account for variability between subjects
Mirka (1993)	Combined EMG data acquisition with stochastic modeling techniques to characterize the randomness and variability of trunk muscle co-activation	The stochastic model developed in this study enabled the generation and analysis of probability distributions of trunk muscle activity levels instead of relying on single deterministic values	By applying advanced mathematical transformations and multivariate modeling methods, this study integrated fitted univariate distributions with inter-muscle correlations to produce multivariate distributions capable of capturing realistic co-activation patterns
Oomen (2015)	Employed a combined EMG and biomechanical modeling approach to evaluate core muscle co-activation	Both agonist and antagonist muscle activities increased significantly, reflecting enhanced muscle co-activation. A positive linear relationship was observed between trunk muscle activity and seat velocity, indicating that the	Parameters of the dynamic seated balance model, including fixed physical subject characteristics, were estimated from experimental data collected from a single participant performing a comparable seated balance task

		central nervous system scales muscle activation upward with increasing seat movement speed	
Song (2004)	Anatomical data from prior research were incorporated into the model. Beyond using the summed localized antagonist NEMG as a co-activation index, the study also computed the aggregate antagonist forces and their resultant torque about the L5/S1 joint to improve the mechanical interpretability of co-activation evaluation	Clear single-muscle activations were observed across all six external directions, with antagonist co-activation reaching its highest levels under short-duration loading conditions across all measured parameters	An EMG-assisted model was adopted in this study, with gain parameters optimized by minimizing the sum of squared errors between predicted and required torques. Conventional optimization models typically neglect individual antagonist co-activation and may underestimate joint compression forces by 23–43% compared with EMG-assisted models. These findings underscore the advantages of the EMG-assisted approach in addressing co-activation and predicting spinal loading
Song et al (2004)	Employed a combined EMG and biomechanical modeling approach to evaluate core co-activation	Antagonist activation levels were lower than those of agonists; however, with increasing load, training elicited differentiated co-activation patterns of specific antagonist muscles across various loading directions	Employed an EMG-assisted model to optimize joint gains by minimizing the sum of squared errors between predicted and required internal torques, thus achieving model optimization
Song et al (2007)	Employed a combined EMG and biomechanical modeling approach to evaluate core muscle co-activation	Co-activation levels were found to be significantly influenced by the direction and magnitude of the external torque	Such co-activation patterns and quantitative metrics provide critical value for assessing and developing approaches that integrate trunk muscle co-activation into optimization-based models for predicting trunk muscle forces
Thelen (1995)	Integration of EMG Signals with a Biomechanical Model of the Lumbar Trunk	The degree of co-contraction is largely determined by the direction of force application	System identification methods were employed to calibrate a dynamic model linking EMG signals to force for each participant. Model parameters were

			tuned to minimize the sum of squared torque prediction errors during calibration tasks. Parameter estimation issues arising from multicollinearity of muscle activity were resolved by assuming equivalence of parameters among muscles with highly correlated activation patterns
Vera-Garcia (2006)	Combined EMG with biomechanical modeling to examine how different levels of trunk co-activation influence the trunk's ability to respond to sudden loads	Abdominal co-activation markedly enhanced spinal stability and reduced lumbar motion following perturbation. Results demonstrated an asymptotic relationship between co-activation, stiffness, and stability, indicating that beyond roughly 20–30% MVC, additional co-activation yields minimal improvements in stiffness or stability while progressively increasing spinal compression	Optimized by an anatomically detailed model of the spine

***. EMG: Electromyography; IAP: intra-abdominal pressure; EO: external oblique; IO: internal oblique; MVC: maximal voluntary contraction.**

Table 5: Comparative overview of current methods for assessing core muscle co-activation in the lumbar region

Method / Approach	Core principle	Typical data inputs	Typical applications in lumbar co-activation research	Strengths	Limitations
Surface electromyography (sEMG)	Directly records surface myoelectric activity to describe the timing, relative amplitude, and	Surface EMG signals; electrode placement protocol; preprocessing procedures; normalization	Describing activation timing and amplitude; identifying anticipatory activation, compensatory	Non-invasive; high temporal resolution; widely accessible; suitable for both static and	Cannot directly estimate muscle force, joint torque, or spinal loading; primarily reflects

	temporal profile of activation in superficial trunk muscles	reference such as %MVIC or task-specific reference intervals	responses, and group differences during static postures, trunk motion, lifting, and perturbation tasks	dynamic tasks; useful for task-specific pattern identification and clinical screening	superficial muscles and provides limited access to deep stabilizers; susceptible to cross-talk, motion artifact, and normalization-related variability; interpretive strength decreases as task complexity increases; substantial methodological heterogeneity across studies
sEMG with calculation of co-contraction index (CCI)	Quantifies the degree of simultaneous activation between paired or grouped muscles using mathematical indices derived from processed sEMG signals	Processed and normalized sEMG signals from selected muscle pairs or groups; in some approaches, additional anthropometric or simplified biomechanical parameters such as estimated moment arms and cross-sectional area	Quantifying trunk muscle coordination; comparing co-activation between tasks or populations; evaluating lumbar stability strategies in static tasks and low-speed dynamic tasks; extending analysis to more complex tasks through torque-based or weighted CCI variants	Provides a structured and relatively simple quantitative index of coordination; supports statistical comparison across conditions or groups; more interpretable than descriptive amplitude measures alone; some advanced variants improve task specificity	Results depend strongly on muscle pair selection, normalization, and calculation method; conventional approaches require predefined agonist-antagonist classification, which may be inappropriate during dynamic or multi-planar tasks; advanced variants still rely on simplified

					biomechanical assumptions; limited standardization reduces comparability across studies
Musculoskeletal modeling and simulation	Uses biomechanical models to estimate internal mechanical variables associated with coordinated muscle activation, including muscle forces, joint moments, and spinal loading	Anatomical model parameters; anthropometric scaling and/or imaging data; motion capture or kinematic data; external loads or ground reaction forces; muscle-tendon properties; optimization or simulation algorithms	Estimating internal loading, force sharing, spinal compression, shear forces, and stability-related mechanics during isometric, controlled postural, and simple dynamic tasks; evaluating the biomechanical consequences of co-activation when direct measurement is not possible	Capable of estimating variables that cannot be obtained from sEMG alone; provides biomechanical interpretation of co-activation; can incorporate deep muscles through model-based estimation; useful for testing task-specific loading scenarios	Output validity depends heavily on model assumptions, parameterization, and optimization strategy; deep-muscle geometry and subject-specific properties are difficult to define accurately; limited physiological realism for rapid neuromuscular adjustments; less robust in highly dynamic, asymmetrical, perturbation-driven, or fatigue-related tasks; substantial methodological heterogeneity
Integration of sEMG with	Incorporates recorded	sEMG data combined	Linking activation	Combines the temporal	Retains limitations of both

musculoskeletal modeling and simulation	sEMG signals into biomechanical models to inform, constrain, or drive estimation of muscle forces and spinal loading	with anatomical model parameters, anthropometric or imaging data, motion capture, external force data, and muscle-tendon properties	patterns to mechanical outcomes; estimating force sharing, joint moments, spinal compression, shear loading, and stability-related behavior during static postures, controlled trunk movement, lifting, and other task-specific conditions	specificity of sEMG with the mechanical interpretability of modeling; provides more physiologically grounded estimates than either method alone; especially useful when antagonist activity substantially influences spinal stability or net torque	sEMG and modeling; deep stabilizer activity remains partly indirect because standard sEMG does not capture these muscles well; sensitive to errors in both EMG acquisition and model parameterization; computationally demanding; current applications remain more robust in controlled than highly complex dynamic tasks; lack of standardized integrated workflows limits reproducibility