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**Sensor-derived trunk motion analysis in people
with chronic low back pain: integration of clinical
and biomechanical assessment**

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CONTENTS

ABSTRACT	V
SOMMARIO	VII
CHAPTER 1 – INTRODUCTION	1
1.1 Background	1
1.2 State of the art	6
1.3 Aim and Research Questions	13
CHAPTER 2 – METHODS	15
2.1 Study design	15
2.2 Participants	16
2.3 Clinical assessment	17
2.4 Instrumentation	18
2.5 Experimental protocol	20
2.6 Signal processing and feature extraction	23
2.7 Statistical analysis	25
CHAPTER 3 – RESULTS	28
3.1 Preliminary validation results of the IMU system.....	28
3.2 Participants characteristics.....	33
3.3 Trunk range of motion: CLBP vs healthy people	34
3.4 Instrumented TUG outcomes	35
3.5 Multivariate models for trunk ROM	38
3.5 Exploratory cluster analysis	39
CHAPTER 4 – DISCUSSION	43
4.1 Preliminary validation of the IMU system	43
4.2 Trunk kinematics in CLBP vs healthy people	44
4.3 Movement quality and functional performance (TUG)	46

4.4 Clinical-biomechanical integration	48
4.5 CLBP phenotypes: a clinical-biomechanical perspective	48
4.6 Wearable technologies and IMU-based systems in rehabilitation.....	51
4.7 Limitations	53
4.8 Future perspectives	54
CHAPTER 5 – CONCLUSIONS	56
REFERENCES	57

ABSTRACT

Chronic low back pain (CLBP) is a highly prevalent and heterogeneous musculoskeletal condition associated with substantial disability, reduced quality of life, and considerable societal burden. Traditional clinical assessment, largely based on self-reported outcomes and standard functional tests, often fails to capture the complexity of movement behavior in this population. In this context, wearable technologies may provide objective biomechanical measures capable of complementing conventional evaluation. The aim of this doctoral work was to investigate the integration of sensor-based trunk motion analysis with clinical assessment in individuals with CLBP.

A cross-sectional observational study was conducted including 29 individuals with CLBP and 30 healthy controls. Before the experimental phase, a preliminary validation study was performed on 27 healthy adults to assess the accuracy of an inertial measurement unit (IMU)-based wearable sensor against a marker-based optoelectronic motion capture system for trunk range of motion (ROM) assessment. The validation analysis included accuracy indices, root mean square error (RMSE), Pearson's correlation coefficient, concordance correlation coefficient, and Bland–Altman analysis. In the main study, trunk ROM during flexion, extension, lateral bending, and axial rotation was quantified using the IMU sensor. In the CLBP group, clinical variables included pain intensity, disability, and fear of movement. In addition, movement quality during the Timed Up and Go test was assessed through IMU-derived metrics, including normalized root mean square acceleration (nRMS), improved harmonic ratio (iHR), and log dimensionless jerk (LDLJ). Correlation analyses, multivariate regression models, and exploratory cluster analysis were performed.

The validation study showed acceptable agreement between the IMU and the optoelectronic system, with the highest accuracy observed for trunk rotation (accuracy: 92.4%; $r = 0.944$; CCC = 0.927; RMSE = 1.09°). In the main study, individuals with CLBP exhibited significantly reduced lateral bending ($21.1^\circ \pm 11.7^\circ$ vs $33.5^\circ \pm 9.5^\circ$; $p = 0.0028$) and axial rotation ROM ($84.8^\circ \pm 29.2^\circ$ vs $107.7^\circ \pm 27.0^\circ$; $p < 0.001$) compared with healthy controls, while trunk flexion was significantly higher ($69.5^\circ \pm 16.4^\circ$ vs $57.4^\circ \pm 14.4^\circ$; $p = 0.0017$). Associations between clinical and biomechanical variables were limited, with only five significant correlations out of 297 tested associations, suggesting only partial overlap between subjective symptoms and objective movement behavior. Multivariate models identified gender as a significant predictor of trunk flexion ($\beta = 13.92$; $p = 0.032$; $R^2 = 0.37$) and age as a significant predictor of trunk rotation ($\beta = -1.14$; $p = 0.007$; $R^2 = 0.40$). Exploratory cluster analysis revealed three distinct clinical–biomechanical profiles within the CLBP group, while the first two principal components explained 72.1% of the total variance, supporting the presence of different combinations of pain, disability, fear-avoidance behavior, trunk mobility, and movement quality.

Overall, these findings support the use of wearable IMU technology as a feasible tool for trunk motion analysis in CLBP and reinforce the multidimensional nature of the condition. While direct associations between clinical and biomechanical domains were limited, the identification of distinct clinical–biomechanical profiles suggests that integrated approaches may help capture underlying heterogeneity. These preliminary findings provide a basis for future research aimed at refining phenotype-based classifications and developing more personalized assessment and rehabilitation strategies.

SOMMARIO

Il dolore lombare cronico (CLBP) rappresenta una condizione muscoloscheletrica altamente prevalente ed eterogenea, associata a significativa disabilità, riduzione della qualità della vita e rilevante impatto socio-economico. La valutazione clinica tradizionale, basata prevalentemente su misure auto-riferite e test funzionali standardizzati, risulta spesso insufficiente nel cogliere la complessità del comportamento motorio in questa popolazione. In questo contesto, le tecnologie indossabili possono fornire misure biomeccaniche oggettive in grado di integrare la valutazione convenzionale. L'obiettivo di questo lavoro di dottorato è stato quello di indagare l'integrazione tra analisi del movimento del tronco basata su sensori e valutazione clinica in soggetti con CLBP.

È stato condotto uno studio osservazionale trasversale che ha coinvolto 29 soggetti con CLBP e 30 controlli sani. Prima della fase sperimentale, è stato realizzato uno studio preliminare di validazione su 27 adulti sani per valutare l'accuratezza di un sensore inerziale indossabile (IMU) rispetto a un sistema optoelettronico marker-based per la misurazione del range of motion (ROM) del tronco. L'analisi di validazione ha incluso indice di accuratezza, root mean square error (RMSE), coefficiente di correlazione di Pearson, concordance correlation coefficient e analisi di Bland–Altman. Nello studio principale, il ROM del tronco in flessione, estensione, inclinazione laterale e rotazione assiale è stato quantificato tramite sensore IMU. Nel gruppo CLBP sono state raccolte variabili cliniche relative a intensità del dolore, disabilità e paura del movimento. Inoltre, la qualità del movimento durante il Timed Up and Go test è stata valutata mediante metriche derivate da IMU, tra cui normalized root mean square (nRMS), improved harmonic ratio (iHR) e log dimensionless jerk (LDLJ). Sono state eseguite analisi di correlazione, modelli di regressione multivariata e un'analisi esplorativa di cluster.

Lo studio di validazione ha mostrato un livello di accordo accettabile tra IMU e sistema optoelettronico, con la maggiore accuratezza osservata nei movimenti di rotazione del tronco (accuratezza: 92,4%; $r = 0,944$; CCC = 0,927; RMSE = 1,09°). Nello studio principale, i soggetti con CLBP hanno mostrato una riduzione significativa del ROM in inclinazione laterale ($21,1^\circ \pm 11,7^\circ$ vs $33,5^\circ \pm 9,5^\circ$; $p = 0,0028$) e rotazione assiale ($84,8^\circ \pm 29,2^\circ$ vs $107,7^\circ \pm 27,0^\circ$; $p < 0,001$) rispetto ai controlli sani, mentre la flessione del tronco risultava significativamente aumentata ($69,5^\circ \pm 16,4^\circ$ vs $57,4^\circ \pm 14,4^\circ$; $p = 0,0017$). Le associazioni tra variabili cliniche e biomeccaniche sono risultate limitate, con solo cinque correlazioni significative su 297 associazioni testate, suggerendo una sovrapposizione solo parziale tra sintomi soggettivi e comportamento motorio oggettivo. I modelli multivariati hanno identificato il genere come predittore significativo della flessione del tronco ($\beta = 13,92$; $p = 0,032$; $R^2 = 0,37$) e l'età come predittore significativo della rotazione ($\beta = -1,14$; $p = 0,007$; $R^2 = 0,40$). L'analisi esplorativa di cluster ha evidenziato tre distinti profili clinico-biomeccanici all'interno del gruppo CLBP, mentre le prime due componenti principali spiegavano il 72,1% della

varianza totale, supportando la presenza di differenti combinazioni di dolore, disabilità, paura del movimento, mobilità del tronco e qualità del movimento.

Nel complesso, questi risultati supportano l'utilizzo della tecnologia IMU come strumento fattibile per l'analisi del movimento del tronco nel CLBP e rafforzano la natura multidimensionale della condizione. Sebbene le associazioni dirette tra domini clinici e biomeccanici siano risultate limitate, l'identificazione di distinti profili clinico-biomeccanici suggerisce che approcci integrati possano contribuire a cogliere l'eterogeneità sottostante. Questi risultati preliminari forniscono una base per studi futuri finalizzati a raffinare classificazioni fenotipiche e a sviluppare strategie di valutazione e riabilitazione più personalizzate

CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 Chronic Low Back Pain: definition, epidemiology and clinical relevance

Chronic low back pain (CLBP) is commonly defined as low back pain persisting for longer than three months, a temporal criterion widely adopted in both clinical practice and research. However, this duration-based definition represents only a partial approximation of a condition that is intrinsically heterogeneous and multifaceted. Chronicity in low back pain cannot be fully captured by symptom persistence alone and encompasses qualitative dimensions related to recurrence patterns, functional impact, and underlying pathophysiological uncertainty (1).

Several definitional approaches have been proposed in the literature. The most prevalent relies on symptom duration, typically identifying CLBP as pain lasting at least three months. Nonetheless, many individuals conceptualize chronicity in terms of pain frequency and recurrence rather than uninterrupted duration, with intermittent but repeatedly recurring episodes often perceived as chronic (2). Other frameworks emphasize clinical impact, incorporating pain intensity, interference with daily activities, work limitations, and reduced physical function, thereby shifting the focus from pain duration to functional relevance (3).

Early conceptual models further described CLBP as pain extending beyond the expected tissue healing period, frequently in the absence of clearly identifiable structural pathology, and affecting individuals intermittently over prolonged periods. Collectively, this variability in definitional criteria contributes to the marked heterogeneity observed across epidemiological studies and limits cross-study comparability. Such definitional ambiguity highlights the need for assessment frameworks capable of capturing not only the temporal dimension of pain, but also its functional and movement-related manifestations (4).

Furthermore, CLBP represents one of the most prevalent and burdensome musculoskeletal conditions worldwide, constituting a major challenge for healthcare systems and rehabilitation sciences. Epidemiological evidence consistently indicates that CLBP affects a substantial proportion of the adult population, although prevalence estimates vary widely depending on age, case definition, observation window, and population context. Point prevalence in the general adult population is commonly reported between approximately 4% and 10%, whereas substantially higher estimates emerge when longer observation periods or age-enriched samples are considered, with 12-month prevalence rates exceeding 30% in older adults. Such variability does not reflect contradictory

findings, but rather highlights the heterogeneous nature of CLBP epidemiology and the methodological complexity inherent to its measurement (5).

A clear and consistent epidemiological pattern is the strong association between CLBP prevalence and advancing age, with rates increasing progressively from early adulthood and peaking in late middle age or older populations. Women are disproportionately affected across most geographic regions and age strata, suggesting the contribution of biological, psychosocial, and occupational determinants. In addition, CLBP prevalence is markedly elevated in occupational groups exposed to prolonged biomechanical loading, repetitive trunk movements, or sustained postural demands, underscoring the relevance of mechanical factors in the transition from acute or recurrent low back pain to chronicity (6,7).

Beyond its high prevalence, the clinical relevance of CLBP lies in its profound impact on functional capacity, quality of life, and participation. Individuals with CLBP frequently report moderate to severe disability, with functional limitations that interfere with daily activities, work performance, and social roles. Standardized disability measures, such as the Roland–Morris Disability Questionnaire, consistently demonstrate clinically meaningful impairment in this population (8). Importantly, CLBP rarely occurs in isolation: comorbid conditions, particularly depression, anxiety, sleep disturbances, and other chronic musculoskeletal disorders, are highly prevalent and contribute to a multidimensional burden that extends beyond pain intensity alone (8).

From a societal perspective, CLBP is associated with substantial healthcare utilization and economic costs. Patients with chronic symptoms are more likely to seek repeated medical care, undergo pharmacological treatments—including long-term use of analgesics and opioids—and access multiple healthcare providers (5). Direct medical costs per patient are markedly higher compared to individuals without chronic pain, while indirect costs related to work absenteeism, reduced productivity, and disability benefits account for an even greater proportion of the overall economic burden. Globally, CLBP is estimated to contribute to millions of lost workdays each year, reinforcing its role as a leading cause of years lived with disability (4).

Despite the magnitude of this burden, the natural history of low back pain (LBP) is characterized by a relapsing–remitting pattern rather than continuous symptom persistence. Although many individuals experience remission within the first months following an acute episode, a substantial proportion develop recurrent or chronic symptoms over time. This dynamic clinical course suggests that CLBP cannot be adequately understood as a static condition, but rather as a fluctuating process influenced by biological, psychological, and mechanical factors (9). Within this transition, central sensitization may represent a relevant neurophysiological mechanism contributing to the persistence and amplification of pain in a subgroup of individuals with CLBP (10,11). Central sensitization is generally described as an increased responsiveness of nociceptive neurons within the central nervous system to normal or subthreshold afferent input, and it may clinically manifest through pain

hypersensitivity, disproportionate pain responses, and altered pain modulation. Although it should not be interpreted as a universal mechanism underlying all cases of CLBP, its potential involvement supports the view of chronicity as a multidimensional process in which nociceptive, neurophysiological, psychological, and behavioral factors may interact. In this perspective, pain-related fear, avoidance behaviors, and kinesiophobia may not only contribute to disability and movement restriction, but also help characterize specific clinical phenotypes within the broader CLBP population (12).

Consequently, epidemiological indicators based solely on pain duration or prevalence fail to fully capture the functional and biomechanical dimensions of chronicity that are most relevant from a rehabilitation perspective (9).

1.1.2 The trunk as a biomechanical and functional hub

The trunk represents a fundamental biomechanical and functional foundation for human movement, providing proximal stability that is essential for efficient force transmission, movement control, and functional performance. Rather than acting as a passive link between the upper and lower limbs, the trunk actively contributes to the regulation of mechanical loads and the coordination of intersegmental motion across multiple physiological domains.

From a motor control perspective, core stability has been defined as the ability to control trunk position and motion in order to optimize force production and transfer during functional tasks (9). This definition highlights the trunk as a dynamic regulator of movement efficiency rather than a purely structural entity. Experimental evidence supports this view, showing that coordinated coactivation of trunk flexor and extensor muscles contributes to mechanical spinal stability, with muscle activation increasing in response to external loading conditions (13).

Beyond local spinal control, the trunk exhibits a broader compensatory and force-modulating role within the musculoskeletal system. Alterations in trunk biomechanics have been observed in individuals with distal joint disorders, such as knee pathologies, suggesting that trunk adaptations may emerge as a strategy to redistribute loads and preserve overall functional performance (14). These findings reinforce the concept that trunk behavior reflects global motor adaptations rather than isolated local impairments.

In parallel, trunk muscle strength has been consistently associated with balance performance, functional capacity, and fall prevention. Strengthening interventions targeting trunk musculature have been shown to elicit substantial gains in core strength, accompanied by clinically meaningful improvements in balance and functional outcomes (15). Collectively, these findings position the trunk as a central contributor to movement quality and functional performance across different populations.

In the context of CLBP, this biomechanical and functional centrality becomes particularly relevant. CLBP primarily affects the trunk region, yet its consequences extend beyond local pain, influencing movement strategies, load distribution, and motor control during everyday activities. Individuals with CLBP may adopt antalgic motor strategies, including protective guarding, characterized by cautious, stiffened, or movement-restrictive behaviors intended to minimize perceived threat, pain, or mechanical load (16). Although such strategies may be adaptive in the short term, their persistence may contribute to reduced movement variability, increased trunk rigidity, and less efficient functional performance. Accordingly, alterations in trunk function should not be interpreted solely as local deficits, but rather as manifestations of system-level motor adaptations to persistent pain, in which protective motor behaviors, psychological factors, and biomechanical constraints may interact (17).

Taken together, evidence from biomechanics, motor control, and functional performance research underscores the trunk's multifaceted physiological significance and its pivotal role in the functional expression of CLBP. This conceptual framework provides a strong rationale for focusing on trunk motion as a key target of assessment and supports the integration of quantitative trunk movement analysis with clinical evaluation in people with chronic low back pain.

1.1.3 Limits of traditional clinical assessment in CLBP

Clinical assessment represents the cornerstone of chronic low back pain (CLBP) management and remains indispensable for diagnosis, clinical decision-making, and treatment planning. A comprehensive evaluation typically integrates patient history, physical examination, pain intensity scales, and patient-reported outcome measures, providing essential information on symptom severity, perceived disability, and psychosocial context. These tools are well validated and widely adopted in both clinical practice and research settings (4).

However, despite their clinical relevance, traditional assessment methods present inherent limitations when applied to the multidimensional nature of CLBP. A substantial proportion of commonly used outcome measures relies on self-reported data, such as pain intensity scales and disability questionnaires. While these instruments are sensitive to changes over time and capture the patient's subjective experience, they are intrinsically influenced by contextual, emotional, and cognitive factors. As a result, self-reported pain and disability do not always reflect actual movement capacity or motor performance, particularly in conditions characterized by fluctuating symptoms and adaptive movement strategies (18-20).

Functional assessment in clinical practice often involves the use of standardized tests, such as timed mobility tasks or observational movement analysis. Although these approaches provide valuable insights into gross functional capacity, they are frequently limited by coarse scoring systems, ceiling effects, and reduced sensitivity to subtle yet clinically meaningful changes. Moreover, qualitative

observation of movement is inherently examiner-dependent and may lack the resolution required to identify nuanced alterations in motor control, coordination, and segmental contribution (21,22).

These limitations are particularly evident when considering trunk function. As previously outlined, the trunk plays a central role in movement control, load transmission, and functional performance; however, its assessment in routine clinical settings is typically restricted to static range-of-motion measures or qualitative judgments of movement quality. Such approaches offer limited information on how the trunk behaves during dynamic tasks, how movement strategies are adapted in the presence of pain, or how compensatory patterns emerge across different functional contexts (23).

Consequently, traditional clinical assessment struggles to capture the “how” of movement execution, focusing primarily on task completion rather than movement quality. In individuals with CLBP, this distinction is critical, as protective or rigid movement strategies may allow task performance while masking underlying alterations in motor control that contribute to functional inefficiency and symptom persistence (24).

Taken together, these considerations highlight the existence of an assessment gap between subjective symptom evaluation and the objective characterization of movement behavior. Addressing this gap requires complementary approaches capable of quantifying trunk motion and movement quality in a functional context, thereby enriching clinical assessment without replacing its essential components. This perspective provides the conceptual foundation for integrating sensor-based trunk motion analysis with traditional clinical evaluation in people with CLBP.

1.1.4 Wearable technologies in movement analysis

Wearable technologies (WT) have been increasingly recognized as valuable tools for the quantitative analysis of human movement across clinical, sports, and health-related domains. Their rapid development has enabled the objective assessment of movement patterns outside highly controlled laboratory environments, allowing for continuous and ambulatory monitoring in real-world conditions. This shift represents a relevant methodological advancement, particularly in the context of musculoskeletal disorders, where functional limitations often emerge during everyday activities rather than under experimental constraints (25).

Over the last years, studies have highlighted the growing maturity and versatility of WT. Evidence suggests that wearable sensors have reached a level of technological readiness that supports their use in routine clinical contexts, particularly for movement assessment and functional monitoring. In parallel, their applicability has been widely demonstrated in sports science, where wearable systems have been employed to analyze performance, workload, and movement efficiency in ecological settings (26). Importantly, WT allow biomechanical data acquisition beyond the spatial and logistical

limitations of motion analysis laboratories, thereby expanding the scope of movement evaluation to more representative functional scenarios (25).

From a technological perspective, wearable systems commonly rely on inertial measurement units (IMUs) integrating accelerometers, gyroscopes, and, in some configurations, magnetometers. These sensors enable the measurement of acceleration and angular velocity and the estimation of segment orientation, providing multidimensional information on movement execution. Wearable technologies are commonly described according to the type of information they acquire and the monitoring purpose they serve, including movement and location tracking, physiological or biometric monitoring, and activity- or performance-related assessment (27,28). Specifically, location-based systems track spatial position and movement trajectories, biometric sensors monitor physiological parameters such as heart rate or muscle activity, and performance-tracking devices quantify kinematic and kinetic aspects of movement, including speed, acceleration, and smoothness. (29).

Despite their increasing adoption, WT are not without limitations. technical challenges such as signal drift, sensitivity to sensor placement, and susceptibility to environmental interference may affect measurement accuracy and data interpretation (30). Additionally, methodological heterogeneity in sensor configuration, data processing pipelines, and outcome selection complicates cross-study comparability. Nevertheless, these limitations are progressively being addressed through advances in sensor fusion algorithms, calibration procedures, and standardized protocols (31).

Overall, WT offer a unique opportunity to complement traditional clinical assessment by providing objective, continuous, and context-sensitive measures of movement behavior. Their capacity to capture dynamic motor patterns in naturalistic environments makes them particularly well suited for investigating functional impairments and movement adaptations in CLBP. Within this framework, wearable sensor-based analysis emerges as a promising approach to bridge the gap between clinical evaluation and biomechanical characterization of movement (25,26,31,32).

1.2 State of the art

1.2.1 Trunk kinematics in chronic low back pain

Alterations in trunk kinematics have been consistently investigated as a key feature of CLBP, reflecting changes in movement strategies, motor control, and load management associated with persistent symptoms. A growing body of literature indicates that individuals with CLBP exhibit distinct trunk movement patterns compared to pain-free controls, particularly during gait and functional tasks requiring intersegmental coordination (33).

Across studies, reduced trunk and lumbar range of motion emerges as a recurrent finding in people with CLBP. Specifically, smaller lumbar spine excursions have been reported in the frontal plane

during dynamic activities, suggesting constrained movement strategies possibly aimed at limiting spinal loading (34). In parallel, alterations are not confined to the lumbar region alone, as more asymmetrical thoracic spine motion has been observed, indicating a redistribution of movement across trunk segments rather than a uniform reduction in mobility (35).

Beyond changes in movement amplitude, several investigations have emphasized qualitative alterations in trunk kinematics. Increased movement variability, particularly in the transverse plane, has been documented during walking and functional movements in individuals with CLBP. While heightened variability has traditionally been interpreted as a marker of impaired motor control, emerging perspectives suggest that such variability may reflect adaptive strategies to cope with pain and uncertainty by redistributing mechanical demands across segments (36,37).

Altered coordination between the trunk and pelvis represents another salient feature of CLBP-related motor behavior. Evidence indicates a reduced capacity to adapt trunk–pelvis coordination in response to changes in walking velocity, suggesting a diminished flexibility of motor control strategies under varying task demands. This reduced adaptability may contribute to inefficient movement patterns and increased energetic cost during everyday activities (38).

Collectively, these kinematic alterations are commonly interpreted as compensatory motor control strategies aimed at enhancing spinal stability and mitigating pain-related threat. However, the underlying mechanisms driving these adaptations remain incompletely understood, particularly with respect to whether they represent protective, maladaptive, or context-dependent responses to chronic pain. Importantly, trunk kinematic changes have been observed even during low-demand tasks, supporting the notion that CLBP is associated with persistent reorganization of movement rather than transient pain-related inhibition (39,40,41)

Despite the consistency of certain findings, the literature remains characterized by substantial methodological heterogeneity (33). Differences in task selection, measurement systems, outcome variables, and analytical approaches limit direct comparison across studies and complicate the synthesis of evidence (42). Moreover, many investigations rely predominantly on discrete kinematic parameters, such as peak angles or total range of motion, which may not fully capture movement quality, coordination, or adaptability. The limited integration of trunk kinematic measures with clinical outcomes further constrains the clinical interpretability of these findings (43).

In summary, current evidence supports the presence of altered trunk kinematics in individuals with CLBP, encompassing reduced mobility, modified intersegmental coordination, and changes in movement variability. Nevertheless, the variability of reported results and the incomplete linkage between kinematic behavior and clinical presentation highlight a critical gap in the literature. Addressing this gap requires approaches capable of capturing trunk motion in functional contexts

while facilitating meaningful integration with clinical assessment—an issue that underpins the rationale for the present research. Further details are reported in Table 1.

Table 1. Summary of the main evidence on CLBP kinematics.

Evidence domain	Supporting references	Summary of evidence	Relevance to the present thesis
Reduced trunk/lumbar mobility	Gombatto et al., 2015; Laird et al., 2014	Individuals with LBP/CLBP commonly show reduced lumbar or trunk range of motion during gait and functional movement tasks.	Supports the use of trunk ROM as a relevant biomechanical outcome in CLBP assessment.
Segmental redistribution of movement	Rum et al., 2021	Alterations may involve not only the lumbar region but also thoracic and whole-trunk movement patterns.	Suggests that CLBP-related movement adaptations should be interpreted as system-level rather than purely local impairments.
Altered movement variability	Steele et al., 2014; Alsubaie et al., 2023	Movement variability is altered in CLBP, although the direction and meaning of these changes vary across studies, tasks, and analytical methods.	Supports the need to go beyond discrete ROM measures and consider qualitative features of movement.
Altered trunk–pelvis coordination	Lamoth et al., 2002; Lamoth et al., 2006	CLBP is associated with altered pelvis–thorax and trunk–pelvis coordination during walking, including reduced adaptability to speed changes.	Highlights impaired or modified intersegmental coordination as a key feature of CLBP motor behavior.
Pain-related protective adaptations	Pakzad et al., 2016; Hodges & Tucker, 2011	Motor adaptations may reflect protective responses to pain or threat, but may also become maladaptive depending on persistence and context.	Provides a theoretical framework for interpreting rigid or constrained movement patterns observed through IMU-based assessment.
Alterations during functional tasks	Hemming et al., 2018; Lamoth et al., 2006	Trunk kinematic changes are detectable during walking and everyday functional tasks, not only during maximal or high-demand movements.	Supports the ecological relevance of assessing trunk motion in functional contexts.
Methodological heterogeneity and limited clinical integration	Laird et al., 2014; Papi et al., 2018; Dal Farra et al., 2025	Differences in task selection, measurement systems, outcome variables, and clinical integration limit comparability and synthesis of evidence.	Justifies the need for studies integrating quantitative trunk kinematics with clinical assessment in CLBP.

1.2.2 Instrumented assessment of gait and trunk motion

The quantitative assessment of trunk and spinal kinematics has traditionally relied on laboratory marker-based optoelectronic motion capture systems (MoCap), which are widely considered the reference standard for 3D movement analysis. These systems provide high spatial resolution and detailed segmental tracking; however, their use is constrained by high costs, dedicated laboratory settings, time-consuming setup procedures, and limited ecological validity. As a result, their routine integration into clinical assessment remains impractical in most rehabilitation contexts. In recent years, wearable IMU sensors have emerged as a viable alternative for instrumented spinal motion analysis. IMUs typically integrate accelerometers, gyroscopes, and, in some configurations, magnetometers, enabling the estimation of segment orientation, angular velocity, and acceleration in real-world environments. Their portability, reduced setup time, and relatively low cost make them particularly attractive for clinical applications involving individuals with CLBP (44).

Evidence comparing IMU-based systems with MoCap suggests that wearable sensors can achieve levels of accuracy and reliability that are clinically acceptable. A recent systematic review synthesizing data from 15 studies involving 305 participants, including 109 individuals with low back pain, reported that IMUs provide valid and reliable measurements of lumbar spine motion comparable to MoCap, with weighted root mean squared differences (RMSE) below 2.4° and intraclass correlation coefficients (ICC) exceeding 0.84. These findings support the potential of IMUs as robust tools for quantifying spinal kinematics in both research and clinical contexts (45).

However, measurement accuracy is not uniform across movement planes. Comparative analyses indicate that IMUs demonstrate good-to-excellent agreement with MoCap in primary planes of movement, with RMSE values ranging from approximately 3.03° to 10.30° after outlier removal. In contrast, agreement tends to decrease in non-primary planes, where RMSE values have been reported between 2.19° and 45.88° , reflecting greater susceptibility to drift, soft tissue artefact, and sensor misalignment. These findings underscore the importance of considering movement direction and task characteristics when interpreting IMU-derived kinematic data (46).

Further evidence supports the validity of IMUs for assessing sagittal lumbopelvic–hip motion in individuals with LBP. A recent study demonstrated strong correlations between IMU-derived measures and optical motion capture during sagittal plane range-of-motion tasks, with minimal measurement error and clinically acceptable levels of agreement (47).

Taken together, current evidence suggests that IMU-based wearable systems offer a clinically valid alternative to laboratory-based MoCap, especially for assessing primary plane trunk movements. While certain limitations remain—particularly in multi-planar accuracy and sensitivity to sensor placement—the balance between measurement validity, ecological applicability, and feasibility strongly favors wearable solutions in contexts where continuous, functional assessment is required.

From a translational perspective, the comparability between IMU and MoCap provides an important methodological foundation for integrating sensor-based trunk motion analysis into clinical assessment frameworks. If wearable sensors can capture trunk kinematics with acceptable accuracy under functional conditions, they may enable a shift from laboratory-restricted biomechanical evaluation toward accessible, real-world movement analysis in individuals with CLBP.

1.2.3 Sensor-derived metrics for movement quality

Beyond traditional kinematic descriptors such as range of motion and peak angular displacement, increasing attention has been directed toward sensor-derived metrics capable of capturing qualitative aspects of movement. In the context of trunk motion analysis, IMU and, in laboratory settings, MoCap enable the extraction of parameters that reflect rhythmicity, smoothness, variability, and dynamic stability of movement patterns. These higher-order metrics provide insight into motor control organization and functional adaptability, dimensions that are particularly relevant in individuals with CLBP (48).

Among the most widely investigated parameters is the harmonic ratio (iHR), a frequency-domain measure derived from trunk acceleration signals during gait. The iHR quantifies the symmetry and rhythmicity of trunk oscillations by comparing the relative contribution of even and odd harmonics within the acceleration signal. Higher iHR values are generally interpreted as reflecting more regular and symmetrical gait patterns, whereas lower values suggest reduced rhythmic stability and potential alterations in trunk control. In individuals with CLBP, reduced harmonic structure has been associated with disrupted trunk coordination and altered load distribution during walking, potentially reflecting protective or compensatory strategies aimed at minimizing spinal stress (49).

Another parameter frequently employed in IMU-based analyses is the normalized root mean square (nRMS) of trunk acceleration signals. The nRMS represents the magnitude of trunk oscillations normalized to account for individual or task-related variability, thereby enabling comparison across participants and conditions. Increased nRMS values may indicate greater trunk movement amplitude or instability, whereas reduced values may reflect constrained or rigid movement strategies. In CLBP populations, both increased and decreased trunk acceleration magnitudes have been reported, suggesting heterogeneous motor adaptations that may depend on pain severity, task demand, or behavioral coping strategies (50).

Smoothness-related metrics further enrich the characterization of trunk movement quality. The log dimensionless jerk (LDLJ), derived from the third derivative of displacement with respect to time, provides a scale-invariant measure of movement smoothness. Lower jerk values indicate smoother, more coordinated motion, whereas higher values reflect fragmented or less efficient motor execution. The LDLJ is particularly useful for evaluating functional tasks such as sit-to-stand transitions or trunk

flexion–extension movements, where motor planning and segmental coordination are critical. In CLBP, altered smoothness profiles may reveal subtle impairments in motor control that are not detectable through simple amplitude-based measures (51).

Collectively, metrics such as iHR, nRMS, and LDLJ extend the analytical framework of trunk motion assessment beyond static or discrete kinematic parameters. They allow the investigation of movement organization, dynamic stability, and adaptability under functional conditions. Importantly, these parameters can be derived from both IMU and MoCap systems, although wearable IMU solutions offer greater feasibility for ambulatory and ecologically valid assessments. Nevertheless, the integration of movement quality metrics into trunk kinematic analysis represents a critical advancement in the study of CLBP. By capturing dimensions of rhythmicity, magnitude, and smoothness, IMU-derived parameters offer the possibility of linking biomechanical behavior with clinical presentation in a more physiologically grounded manner. This perspective strengthens the rationale for combining sensor-based trunk motion analysis with clinical assessment to better understand functional performance in individuals with CLBP (52).

1.2.4 Clinical–biomechanical integration: current gaps

Despite the growing body of evidence documenting altered trunk kinematics in individuals with LBP and CLBP, and the increasing availability of wearable IMU-based motion analysis, a substantial gap persists between biomechanical quantification and clinical interpretation. Most studies investigating trunk kinematics focus on identifying between-group differences in discrete parameters without systematically relating these measures to pain intensity, disability, or functional performance outcomes (42). As a result, biomechanical findings often remain descriptively informative but clinically under-contextualized. Conversely, traditional clinical assessment primarily relies on self-reported pain scales and disability questionnaires, which, although indispensable, provide limited insight into the underlying movement organization. Functional tests are typically evaluated using coarse temporal or ordinal scores, with minimal integration of objective trunk motion data. This parallel evolution of clinical and biomechanical assessment has led to two partially overlapping yet insufficiently connected domains of knowledge (53).

Furthermore, the interpretation of altered trunk kinematics in CLBP remains conceptually ambiguous. Reduced mobility, increased variability, or altered coordination may represent maladaptive motor impairment, protective stabilization strategies, or context-dependent adaptations to pain. Without integrated models that combine clinical variables with quantitative and reliable sensor-derived metrics, it remains difficult to determine whether specific kinematic patterns are associated with functional limitation, compensatory efficiency, or risk of persistence (54).

In this context, cluster analysis represents a potentially useful exploratory approach to address this interpretative ambiguity, as it allows individuals to be grouped according to multivariate patterns rather than single isolated variables. By integrating clinical indicators and IMU-derived biomechanical measures, such an approach may help identify distinct clinical–biomechanical profiles in which similar kinematic alterations can be interpreted in relation to pain, disability, fear-related variables, and functional performance.

Therefore, the current literature highlights a critical need for approaches capable of linking IMU-derived trunk motion parameters with clinically meaningful outcomes. Bridging this gap requires frameworks that integrate biomechanical data and clinical assessment within the same analytical model, enabling a more comprehensive understanding of functional performance in individuals with CLBP. This integrative perspective forms the conceptual foundation of the present research.

1.3 Aim and Research Questions

1.3.1 General aim

The general aim of this doctoral research is to investigate the integration of sensor-based trunk motion analysis with traditional clinical assessment in individuals with CLBP. Specifically, this study seeks to explore whether objective trunk kinematic parameters derived from wearable IMU systems can provide complementary and clinically meaningful information beyond conventional self-reported and performance-based measures. By combining biomechanical quantification and clinical variables within a unified analytical framework, the project aims to advance the understanding of functional performance in CLBP from both mechanistic and clinical perspectives.

The study aims to be grounded on a preliminary validation of the IMU-based system against a gold-standard optoelectronic motion capture system, thus ensuring the methodological reliability of the biomechanical measurements employed.

1.3.2 Specific aims

The specific aims of this study are:

1. to preliminarily validate the accuracy and agreement of the IMU-based wearable sensor for trunk range of motion assessment against a marker-based optoelectronic system;
2. to quantify trunk kinematics during functional tasks in individuals with CLBP and healthy controls using wearable IMU technology;
3. to identify differences in trunk range of motion, movement variability, and movement quality metrics—including iHR, nRMS, and LDLJ—between groups;

4. to examine the association between IMU-derived trunk motion parameters and clinical outcomes such as pain intensity, disability, and functional performance;
5. to develop multivariate models exploring the combined contribution of clinical and biomechanical variables in explaining functional capacity in CLBP.

1.3.3 Research questions and hypotheses

Based on the current literature and the identified clinical–biomechanical gap, the study addresses the following research questions:

1. Do individuals with CLBP exhibit altered trunk kinematics and movement quality compared to asymptomatic controls during functional tasks?
2. Are IMU-derived trunk motion parameters (e.g., iHR, nRMS, LDLJ) associated with clinical measures of pain and disability?
3. Does the integration of biomechanical and clinical variables improve the characterization of functional performance compared to clinical assessment alone?

It is hypothesized that individuals with CLBP will demonstrate altered trunk kinematics characterized by reduced mobility, modified coordination, and changes in movement variability and smoothness. Furthermore, it is expected that specific IMU-derived metrics will show meaningful associations with clinical outcomes and that integrated models combining biomechanical and clinical parameters will provide a more comprehensive explanation of functional performance than either domain considered in isolation.

CHAPTER 2

METHODS

2.1 Study design

The present investigation was designed as a cross-sectional observational study aimed at integrating clinical assessment with wearable-based biomechanical analysis in individuals with CLBP and healthy controls. Data were collected at “Istituto Auxologico Italiano of Piancavallo” in the period ranging from November 2024 to March 2026.

The methodological framework of the study was based on the assumption that CLBP represents a multidimensional condition in which subjective clinical variables—such as pain intensity, functional disability, and fear of movement—interact with objective alterations in motor behaviour. In order to address this complexity, the study protocol combined standardized clinical questionnaires with instrumented movement assessment using wearable inertial sensors.

All experimental procedures were conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. The study protocol was approved by the Ethics Committee of Politecnico di Milano (protocol no. 22/2021) for the validation study in healthy individuals, and by the Ethics Committee of Istituto Auxologico Italiano (approval code: 2021_05_18_14) for the comparative assessment involving both individuals with CLBP and healthy controls. Written informed consent was obtained from all participants before their inclusion in the study.

2.1.1 Preliminary validation of the IMU system

Prior to the present investigation, a preliminary validation study was conducted to assess the accuracy and agreement of the IMU-based wearable sensor (Baiobit, Rivelo Srl—BTS Bioengineering, Milan, Italy) in measuring trunk range of motion (ROM), using a marker-based optoelectronic motion capture system as the reference standard. The validation study was designed as a cross-sectional investigation involving 27 healthy adults (11 males and 16 females; mean age: 31.1 ± 11.0 years), who performed standardized trunk movements while being simultaneously recorded with the IMU-based system and the marker-based MoCap system.

The reference system consisted of a SMART DX 400 optoelectronic motion capture system (BTS Bioengineering, Milan, Italy), equipped with eight cameras operating at a sampling frequency of 100 Hz. Passive reflective markers were positioned according to a customized upper-body marker set derived from the Davis protocol. Specifically, markers were placed bilaterally on the acromia and anterior superior iliac spines, and additionally on C7, the sacrum, and the sternum. Anatomical

landmarks were identified manually through palpation by two operators, with particular attention to regions characterized by limited soft tissue interposition.

The IMU-based system consisted of a single Baiobit sensor, a compact medical wearable device integrating a tri-axial accelerometer, gyroscope, and magnetometer, with a sampling frequency of 100 Hz. According to the manufacturer's instructions, the sensor was positioned approximately at the L5/S1 vertebral level using a customized elastic belt. The belt was manually adjusted for each participant to ensure comfort and minimize unwanted sensor displacement during movement. Before data acquisition, the IMU was calibrated in quiet upright standing, allowing the device to establish a baseline orientation under static zero-motion conditions.

Starting from a neutral standing position, participants performed four standardized trunk movement tasks: flexion, extension, lateral bending, and axial rotation. During trunk flexion, participants bent forward at the waist while maintaining knee extension; during extension, they extended the trunk backward while maintaining hip stability. For lateral bending, participants bent the trunk to the right and left while maintaining pelvic stability, and for axial rotation they rotated the upper body to the right and left while keeping the hips oriented forward. Each task was performed in two sets of six repetitions, with side-specific repetitions for bilateral movements. Participants were instructed to perform all movements at their natural, self-selected pace.

Data analysis included the calculation of accuracy indices, Root Mean Square Error (RMSE), Pearson's correlation coefficient, concordance correlation coefficient (CCC), and Bland–Altman limits of agreement. This preliminary validation provided methodological support for the use of the IMU sensor in trunk motion analysis and constituted the basis for its application in the present study involving both healthy individuals and people with CLBP.

2.2 Participants

Participants were recruited through convenience sampling from the general population. They recruited through convenience sampling by word of mouth and through the investigators' personal, clinical, and academic networks. Although this sampling strategy was chosen for feasibility reasons, potential selection bias was mitigated by applying predefined eligibility criteria to both groups and by avoiding recruitment based on specific clinical, occupational, or lifestyle characteristics. In particular, individuals with CLBP were not selected according to pain severity, disability level, physical activity habits, sedentary behavior, treatment-seeking status, or motivation toward rehabilitation. Therefore, the CLBP group should be interpreted as a pragmatic sample of adults with non-specific chronic low back pain rather than as a narrowly defined clinical subgroup.

The study included two groups: individuals with CLBP and asymptomatic healthy controls. Participants in the CLBP group were recruited on the basis of a previous medical diagnosis of non-specific low back pain. The research team did not formulate a new medical diagnosis, but verified participants' eligibility for the study by confirming the chronicity criterion and by checking the absence of exclusion criteria. The CLBP group consisted of adults presenting non-specific low back pain lasting longer than three months, in accordance with commonly accepted definitions of chronicity in musculoskeletal pain research (2). Eligibility criteria were defined in order to ensure the ability of participants to safely complete the experimental protocol and to reduce the influence of major neurological, systemic, or traumatic conditions on movement performance. Individuals aged between 18 and 65 years who were able to independently perform the required motor tasks were considered eligible for participation. Exclusion criteria included neurological disorders affecting movement control, systemic musculoskeletal diseases, recent spinal surgery, metabolic and vestibular conditions, acute traumatic injuries, or cognitive conditions that could interfere with the execution of the experimental tasks.

Following the screening process, the final sample consisted of 29 individuals with chronic low back pain and 30 healthy control participants. These 30 subjects were distinct from the 27 participants recruited for the validation study. Nevertheless, because the sample was not randomly selected and may have included individuals more willing or able to participate in a movement-analysis protocol, the possibility of residual selection bias cannot be excluded. Accordingly, the observed kinematic patterns should be interpreted as exploratory and may not be fully generalizable to all individuals with CLBP, particularly those with severe disability, high pain irritability, marked psychosocial burden, or limited capacity to perform functional tasks.

2.3 Clinical assessment

Participants in the CLBP group underwent a standardized clinical evaluation aimed at capturing key dimensions of the condition, including pain intensity, disability, and fear of movement.

Pain intensity

Pain intensity was assessed using the Visual Analog Scale (VAS), a widely used tool for the quantification of subjective pain perception. Participants were asked to indicate their perceived level of pain on a 10-centimeter horizontal line anchored by the descriptors “no pain” and “worst imaginable pain”; the measured distance was then expressed as a score ranging from 0 to 10. This procedure was used both to assess pain intensity at the time of evaluation and to estimate the average pain intensity experienced during the previous 30 days (55).

Disability

Functional disability associated with low back pain was evaluated using the Oswestry Disability Index (ODI), one of the most commonly used questionnaires for assessing the impact of low back pain on daily activities. The ODI evaluates multiple functional domains, including personal care, lifting, walking, sitting, standing, and social life, providing an overall estimate of disability related to spinal conditions (56).

Pain-related fear

Fear of movement was assessed using the Tampa Scale for Kinesiophobia (TSK), a validated questionnaire designed to measure fear-avoidance beliefs associated with physical activity and movement. Kinesiophobia has been widely recognized as an important psychological factor contributing to pain persistence and functional limitation in individuals with chronic musculoskeletal disorders (57).

These clinical measures were subsequently used in the statistical analysis to explore the relationship between subjective patient-reported outcomes and objective biomechanical parameters extracted from wearable sensor data.

2.4 Instrumentation

Movement analysis was conducted using an IMU (BaioBit, Rivelto Srl – BTS Bioengineering, Milan, Italy), a medical device specifically designed for clinical motor assessment (Figure 1).



Figure 1. Wearable IMU sensor implemented in the study for trunk motion analysis

Inertial measurement units are increasingly used in human movement analysis due to their portability, relatively low cost, and ability to provide reliable kinematic measurements outside laboratory-based environments (33). These systems integrate multiple inertial sensors—including accelerometers, gyroscopes, and magnetometers—which allow the estimation of body segment orientation and movement characteristics through sensor fusion algorithms.

The device used in this study integrates a triaxial accelerometer, a triaxial gyroscope, and a triaxial magnetometer, allowing the estimation of three-dimensional orientation within the sensor coordinate system. The IMU has dimensions of 70 × 40 × 18 mm, weighs approximately 37 grams, and acquires data at a sampling frequency of 100 Hz. All the IMU device main characteristics are resumed in Table 2.

Table 2. Technical specifications of the IMU device used in the study

Parameter	Specification
Sensor type	Inertial Measurement Unit (IMU)
Accelerometer	Triaxial
Gyroscope	Triaxial
Magnetometer	Triaxial
Orientation estimation	3D orientation in sensor coordinate system
Dimensions	70 × 40 × 18 mm
Weight	~37 g
Sampling frequency	100 Hz

For the purposes of this study, the sensor was positioned at the lumbo-sacral region (approximately at the L4–L5 level) using an adjustable elastic belt. This placement allowed the device to capture trunk movements while maintaining adequate sensor stability during task execution. The positioning

of both the IMU sensor and the markers (MoCap) is illustrated in the Figure 2. Note that markers were only adopted during the preliminary validation study, whereas the IMU sensor was implemented both in the validation and in the experimental phase of the study.

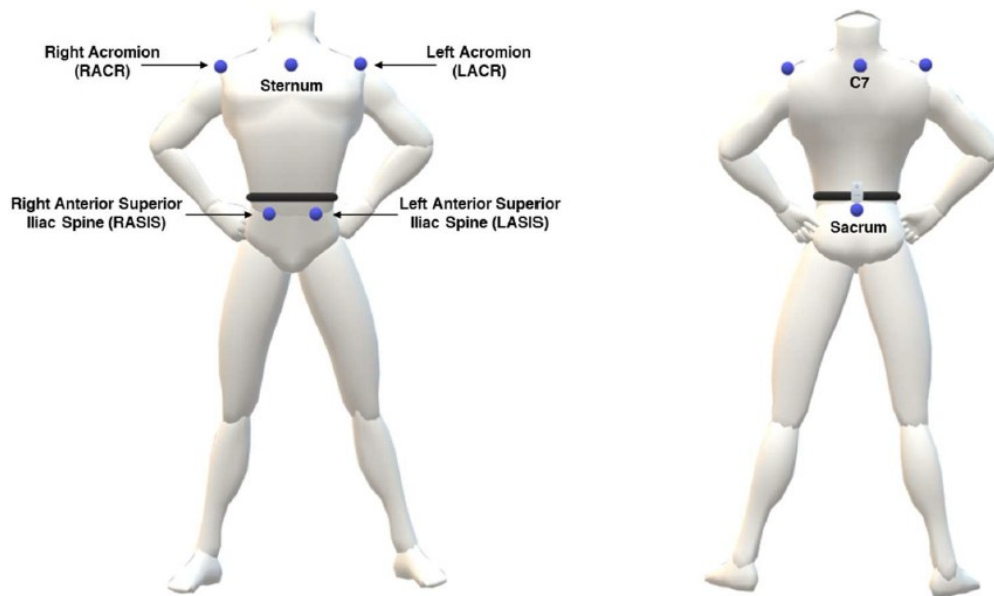


Figure 2. Visual representation of markers and IMU sensor placement on the body used for data collection.

Before the beginning of each acquisition session, the IMU underwent a static calibration procedure. During this phase, participants stood upright in a neutral posture while the system established a reference orientation and corrected potential sensor bias.

2.5 Experimental protocol

Each participant completed a standardized experimental session composed of two main components: trunk mobility assessment and functional mobility evaluation through the Timed Up and Go (TUG) test (58). The TUG test was selected not primarily as a frailty or fall-risk screening tool, but as a standardized and clinically feasible functional task that includes short-distance walking and turning, both relevant to everyday mobility. In the context of CLBP, this structure allows gait-related trunk motor behavior to be assessed under controlled yet ecological conditions, while avoiding the higher mechanical demands and potential symptom provocation associated with more strenuous tasks such as repetitive lifting. Given that the present study focused on IMU-derived indicators of

postural stability, gait symmetry, and movement smoothness, the TUG was considered appropriate for extracting quantitative parameters from walking-related sub-phases, providing information beyond the traditional total completion time (59). A schematic representation of the test is provided in Figure 3.

Trunk mobility was evaluated through a series of controlled movements performed from an upright standing posture. Participants were instructed to perform trunk flexion, trunk extension, lateral bending to both sides, and axial rotation to both sides. These movements were chosen in order to capture the main planes of trunk motion commonly investigated in clinical and biomechanical studies of spinal function.

For each movement, participants performed two sets of six repetitions. All tasks were executed at a self-selected comfortable speed in order to approximate natural motor behaviour while ensuring adequate control of the movement execution. Each trunk mobility task was performed in two sets of six repetitions. This choice was adopted to maintain consistency with the preliminary validation protocol of the IMU-based system, in which the same repetition structure was used for trunk flexion, extension, lateral bending, and axial rotation. The protocol was intended to provide a sufficient number of movement cycles for reliable extraction of ROM values while limiting fatigue, learning effects, and potential symptom provocation in participants with CLBP.

In addition to trunk mobility assessment, participants with CLBP performed the TUG test, a functional mobility test widely used to assess dynamic balance and locomotor performance. The instrumented TUG was performed only by the CLBP group because this component of the protocol was specifically aimed at exploring gait-related movement quality within the clinical sample, rather than at conducting a between-group comparison. In particular, the objective was to characterize IMU-derived indicators of postural stability, gait symmetry, and movement smoothness during walking-related sub-phases in individuals with CLBP. This choice was also influenced by feasibility constraints and by the broader scope of the study, which prioritized the integration of clinical and biomechanical variables within the CLBP group. However, the absence of TUG data in the healthy control group represents a methodological limitation, as it precluded between-group comparisons of gait-related movement quality metrics. Therefore, TUG-derived parameters should be interpreted as exploratory descriptors of functional movement within the CLBP group rather than as markers of impairment relative to healthy individuals. During the TUG test, participants were asked to stand up from a chair, walk forward for three meters, perform a turn, return to the chair, and sit down again. Each participant completed two trials of the test, with short rest intervals between repetitions. Throughout the execution of all tasks, trunk motion signals were continuously recorded by the IMU sensor. The workflow of the study has been illustrated in Figure 4.

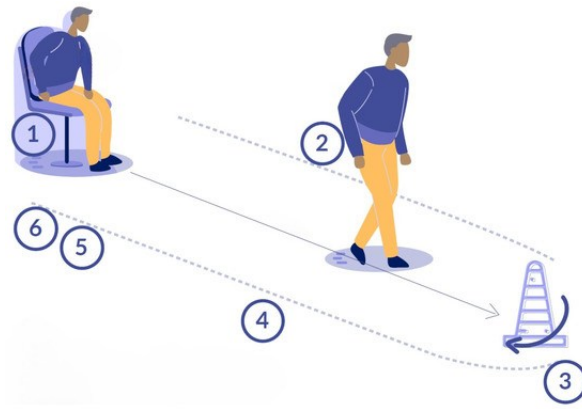


Figure 3. Schematic representation of the Timed Up and Go (TUG) test. The participant starts from a seated position, stands up, walks forward, turns around a marker, walks back, and returns to the seated position. In the present study, the walking task was segmented into forward, turning, and backward phases for the analysis of IMU-derived movement metrics.

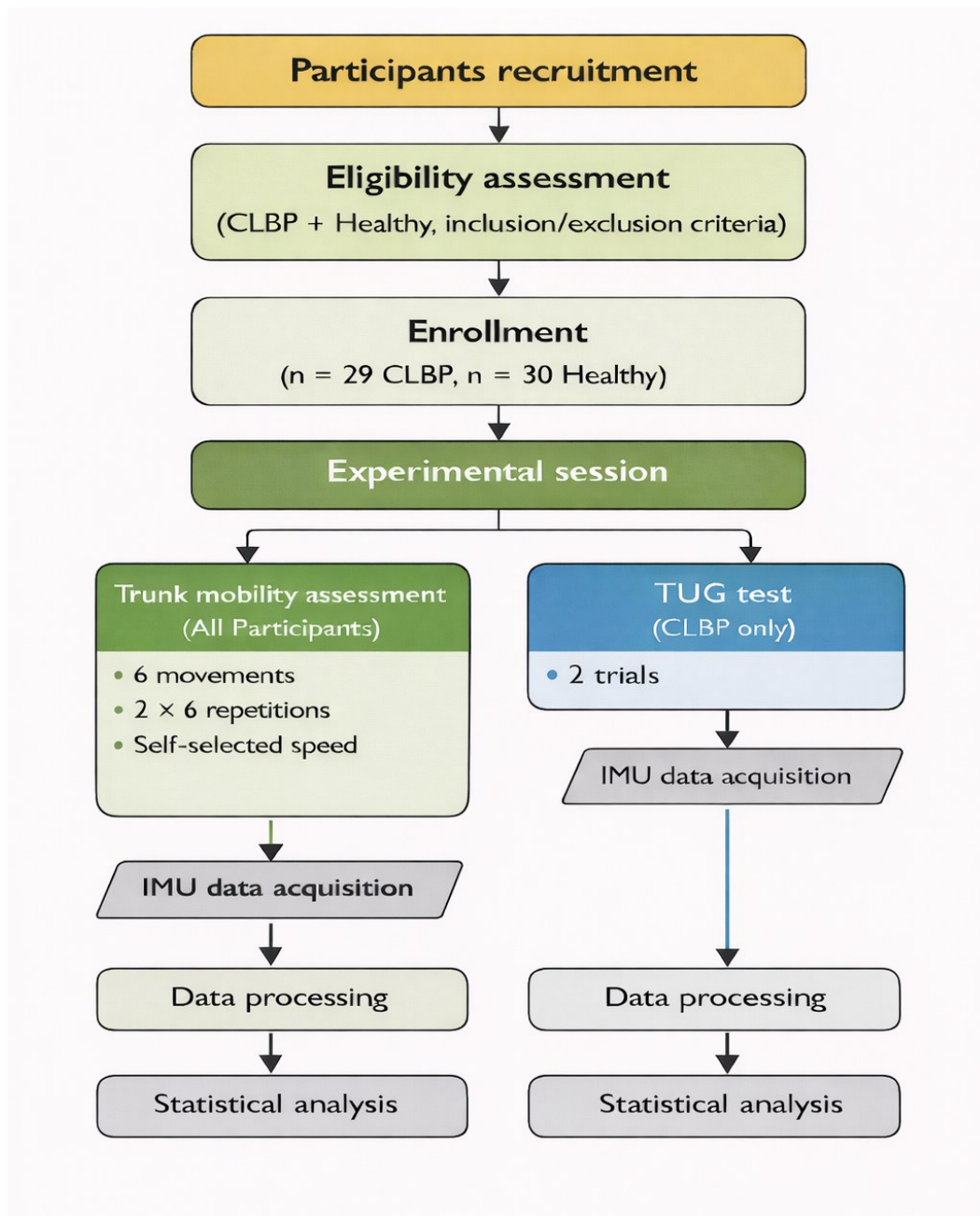


Figure 4. Study workflow of the experimental procedure and data analysis.

2.6 Signal processing and feature extraction

Raw IMU signals were exported and processed using custom routines developed in MATLAB (MathWorks Inc., Natick, MA, USA).

The IMU provided orientation data derived from the fusion of accelerometer and gyroscope signals. From these signals, trunk orientation was expressed through Cardan angles calculated using a YZX rotation sequence, corresponding respectively to flexion–extension around the Y axis, lateral bending around the Z axis, and axial rotation around the X axis.

Acceleration data were collected at a sampling frequency of 100 Hz. Prior to metric calculation, the raw acceleration signals were detrended and filtered to remove noise and baseline drift. Specifically, a zero-phase 4th-order Butterworth bandpass filter was applied with cut-off frequencies set at 0.5 Hz and 20 Hz.

IMU-derived metrics

For trunk mobility tasks, range of motion (ROM) was calculated as the difference between the maximum and minimum angular values observed during each repetition.

In addition to trunk mobility parameters, the analysis of the Timed Up and Go test allowed the extraction of several acceleration-derived metrics describing different aspects of movement quality.

For the purpose of the present analysis, the TUG test was segmented into three walking-related phases: forward walking, turning, and backward walking. The sit-to-stand and stand-to-sit transitions were not included in the computation of IMU-derived movement-quality metrics, because the main focus of the present study was the characterization of gait-related trunk behavior, including postural stability, gait symmetry, and movement smoothness during locomotor phases. Moreover, sit-to-stand and stand-to-sit are biomechanically distinct transition tasks, characterized by different acceleration profiles and movement constraints compared with walking, and their inclusion would have required a dedicated phase-specific analytical approach beyond the scope of the present investigation.

Postural stability was quantified through the normalized root mean square (nRMS) of trunk acceleration signals (60). Movement smoothness was quantified using the Log Dimensionless Jerk (LDLJ) (61), while gait symmetry was evaluated using the improved harmonic ratio (iHR) (62). These metrics were computed along the three spatial axes of trunk acceleration: antero-posterior, medio-lateral, and vertical. The specific formulas for each of the IMU-derived metrics are reported below.

- 1) nRMS: normalized root mean square of trunk acceleration;

$$nRMS = \frac{\sqrt{\frac{\sum_{i=1}^N x_i^2}{N}}}{\sqrt{\frac{\sum_{i=1}^N y_i^2}{N}}}$$

where x_i and y_i represent acceleration samples along two orthogonal axes, and N is the total number of samples.

2) iHR_j: improved harmonic ratio computed for the *j*-th axis:

$$iHR_j = \frac{\sum_{i=1}^K P_L^i}{\sum_{i=1}^K (P_L^i + P_E^i)} \times 100$$

where P_L^i and P_E^i represent the power of harmonic components, and K is the number of harmonics considered.

3) LDLJ_s: log dimensionless jerk of the signal $s(t)$

$$LDLJ_s = -\ln \left(\frac{(t_2 - t_1)^3}{\max(\|s(t)\|_2^2)} \int_{t_1}^{t_2} \left\| \frac{d}{dt} s(t) \right\|_2^2 dt \right)$$

where $s(t)$ is the acceleration signal, $\frac{d}{dt} s(t)$ its derivative (jerk), and t_1, t_2 define the movement interval.

2.7 Statistical analysis

All statistical analyses were performed using Jamovi statistical software (version 2.6.13).

Descriptive statistics were calculated for all variables and are reported as mean and standard deviation. The normality of continuous variables was assessed using the Shapiro–Wilk test. Based on the distribution of the data and the study design, parametric or non-parametric statistical procedures were selected as appropriate.

To evaluate the agreement between the IMU-based system and the marker-based optoelectronic system, a comprehensive set of statistical analyses was performed. Specifically, the accuracy index was calculated to quantify the relative difference between the two measurement systems in estimating trunk range of motion (ROM). In addition, the Root Mean Square Error (RMSE) was computed to assess the magnitude of measurement error between the IMU and the reference system. The formulas used to calculate the accuracy index and RMSE are reported below.

$$Accuracy = 1 - \frac{|ROM_{IMU} - ROM_{MoCap}|}{ROM_{MoCap}} \times 100$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}} = \sqrt{\sum_{i=1}^n \frac{e_i^2}{n}}$$

The strength of the linear relationship between the two systems was investigated using Pearson's correlation coefficient (r), allowing the classification of the association according to its magnitude. To further evaluate the agreement by jointly considering precision and accuracy, the concordance correlation coefficient (CCC) was calculated.

Finally, Bland–Altman analysis was performed to visually and quantitatively assess the level of agreement between the two measurement methods. This approach enabled the estimation of systematic bias and the calculation of the limits of agreement, providing insight into the distribution and extent of discrepancies across the range of measured values.

Differences between individuals with chronic low back pain and healthy controls in trunk range of motion were assessed using Welch's t -tests. For between-group comparisons, effect sizes were also calculated using Cohen's d in order to quantify the magnitude of the observed differences and support their clinical interpretation beyond statistical significance.

The relationships between clinical variables and biomechanical parameters were investigated using Spearman correlation coefficients (ρ), given the ordinal nature and/or non-normal distribution of several clinical variables. To further explore predictors of trunk mobility, multiple linear regression models were constructed including demographic and clinical variables as potential explanatory factors.

Finally, an exploratory unsupervised clustering analysis was performed within the CLBP group using the k -means algorithm. Prior to clustering, all variables were standardized using z -scores to ensure comparability across different measurement scales. The optimal number of clusters was determined using silhouette analysis. The stability of the clustering solution was considered exploratory, given the limited sample size and the absence of validation in an independent cohort.

To facilitate visualization of the clustering structure, principal component analysis (PCA) was applied as a dimensionality reduction technique. Principal components were extracted from the covariance matrix of the standardized variables, and eigenvalues were computed to quantify the variance explained by each component. Components with eigenvalues greater than 1 were considered relevant according to the Kaiser criterion, and the cumulative explained variance was examined to assess the proportion of total variability captured. For visualization purposes, the first two principal

components, accounting for the largest share of variance, were retained to project the clustering solution in a reduced two-dimensional space.

The level of statistical significance was set at $p < 0.05$.

CHAPTER 3

RESULTS

3.1 Preliminary validation results of the IMU system: participants and results

The preliminary validation study was conducted on a sample of 27 healthy adults (11 males, 16 females; mean age: 31.1 ± 11.0 years), recruited to perform standardized trunk movements under simultaneous IMU and marker-based motion capture recording. All the demographic characteristics of the sample are reported in Table 3.

Table 3. Demographic characteristics of the sample involved in the validation study.

Variable	Value
Gender N (M/F)	27 (11/16)
Age (years)	31.1 ± 11.0
Body mass (kg)	64.9 ± 9.68
Height (cm)	171 ± 8.46
BMI (kg/m^2)	22.1 ± 2.16

Data are expressed in mean $\pm$ standard deviation

The results demonstrated that the IMU-based system showed an overall good level of agreement with the marker-based MoCap system in measuring trunk range of motion, although with variability depending on the movement plane. In particular, rotational movements exhibited the highest level of agreement, with excellent accuracy (92.4%), a very strong correlation ($r = 0.944$; $p < 0.001$), and high concordance ($\text{CCC} = 0.927$), indicating a strong consistency between the two measurement systems.

Conversely, flexion, extension, and lateral bending demonstrated moderate agreement, with lower accuracy values and correlation coefficients (r ranging from 0.430 to 0.703; $p < 0.05$), suggesting that these movement planes are more susceptible to measurement discrepancies. All the obtained results in the comparison between MoCap and IMU technologies are reported in Figure 5 and 6, and in Tables 4 and 5.

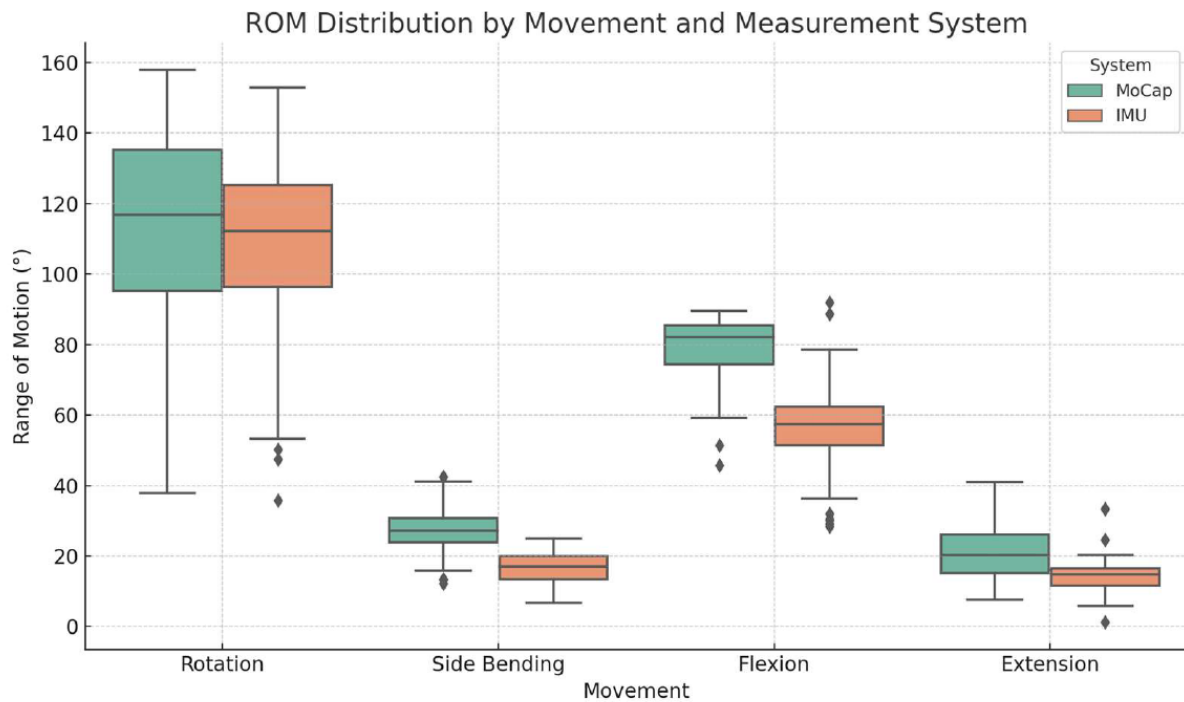


Figure 5. ROM distribution by movement and measurement system (MoCap and IMU).

The Root Mean Square Error ranged from 1.09° in rotation to 3.01° in flexion, indicating an overall acceptable level of measurement error for clinical and research applications. Notably, higher variability was observed in flexion tasks, reflecting increased dispersion of IMU-derived values compared to the reference system.

Table 4. Descriptive statistics, accuracy, and Root Mean Square Error (RMSE) for trunk movements assessed using IMU and marker-based MoCap technologies. Data are expressed as mean $\pm$ standard deviation.

Analyzed Movement	MoCap (°)	IMU (°)	Accuracy (%)	RMSE (°)
Flexion	78.5 $\pm$ 9.8	57.4 $\pm$ 14.4	72.1 $\pm$ 12.7	3.01 $\pm$ 1.32
Extension	21.2 $\pm$ 8.1	14.7 $\pm$ 5.9	64.1 $\pm$ 23.5	1.15 $\pm$ 0.83
Lateral bending	27.2 $\pm$ 6.9	16.7 $\pm$ 4.8	61.4 $\pm$ 16.8	1.59 $\pm$ 0.84
Rotation	113.0 $\pm$ 28.3	108.0 $\pm$ 27.0	92.4 $\pm$ 7.6	1.09 $\pm$ 1.01

Abbreviations. MoCap: ROM detected using marker-based motion capture system; IMU: ROM detected using inertial measurement unit sensor; Accuracy: accuracy index expressed as percentage; RMSE: Root Mean Square Error between the two measurement systems.

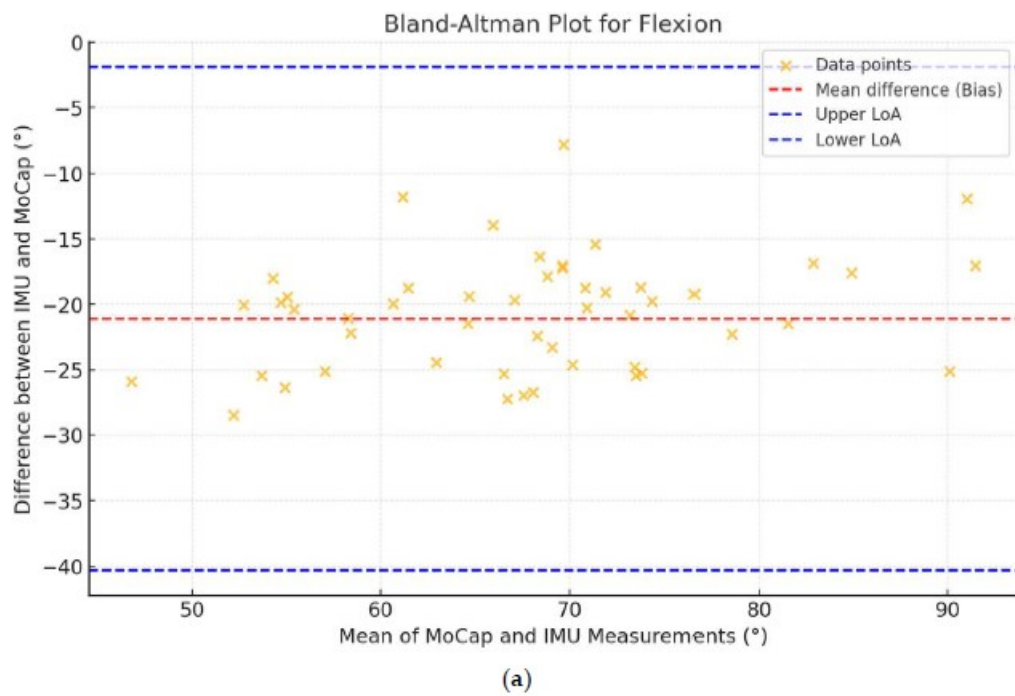
Table 5. Correlation and Bland–Altman statistics for trunk movements assessed using IMU and marker-based MoCap technologies.

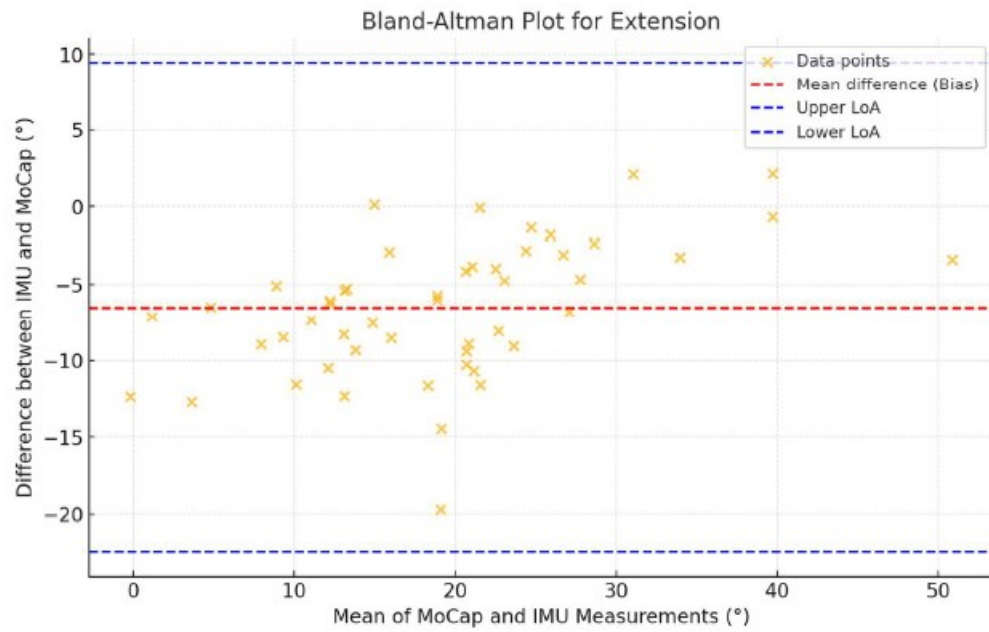
Motion	Pearson r	p-value	CCC (95% CI)	Bias (°)	LoA Lower (°)	LoA Upper (°)
Flexion	0.703	<0.001	0.262 (0.156–0.363)	–21.09	–41.18	–1.01
Extension	0.564	<0.001	0.375 (0.187–0.537)	–6.53	–19.96	6.91
Lateral bend.	0.430	0.003	0.155 (0.004–0.260)	–10.48	–23.23	2.26
Rotation	0.944	<0.001	0.927 (0.877–0.957)	–5.12	–23.56	13.31

Abbreviations. r: Pearson correlation coefficient (–1 to +1); CCC: concordance correlation coefficient (–1 to +1); CI: confidence interval; Bias: systematic error between the two measurement systems; LoA: limits of agreement.

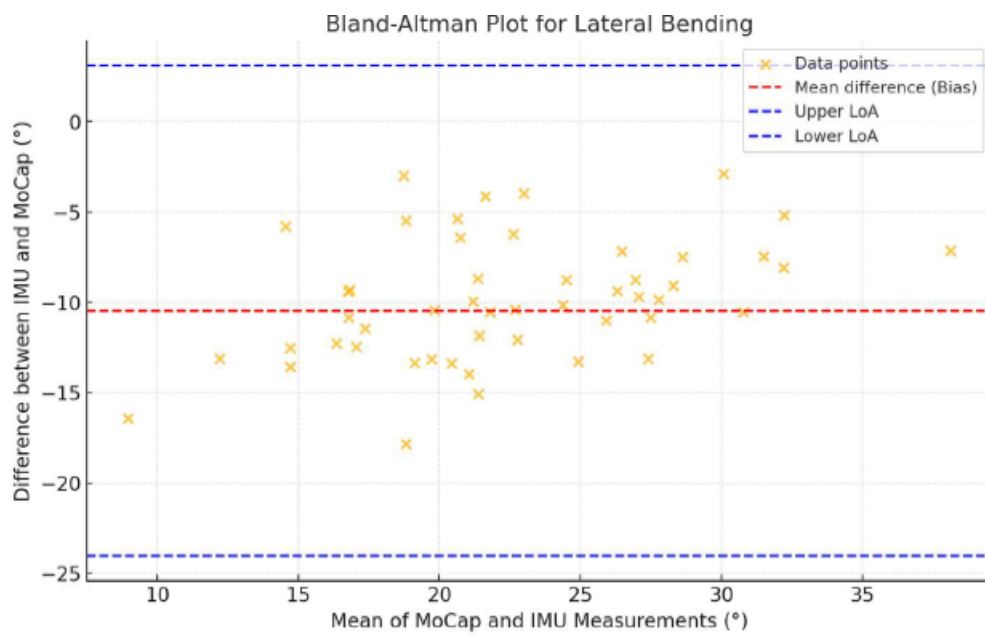
Bland–Altman analysis further revealed a systematic underestimation of ROM by the IMU system across all movements, with wider limits of agreement observed in flexion and lateral bending compared to rotation. Despite this systematic bias, the distribution of differences suggested the absence of substantial proportional error, supporting the stability of the measurement across different ROM amplitudes.

Overall, these findings supported the concurrent validity of the IMU sensor for trunk motion analysis, particularly for rotational movements, while highlighting some limitations in other planes of motion. This preliminary validation provided a robust methodological foundation for the use of the IMU system in the subsequent experimental protocol involving both healthy individuals and people with CLBP.





(b)



(c)

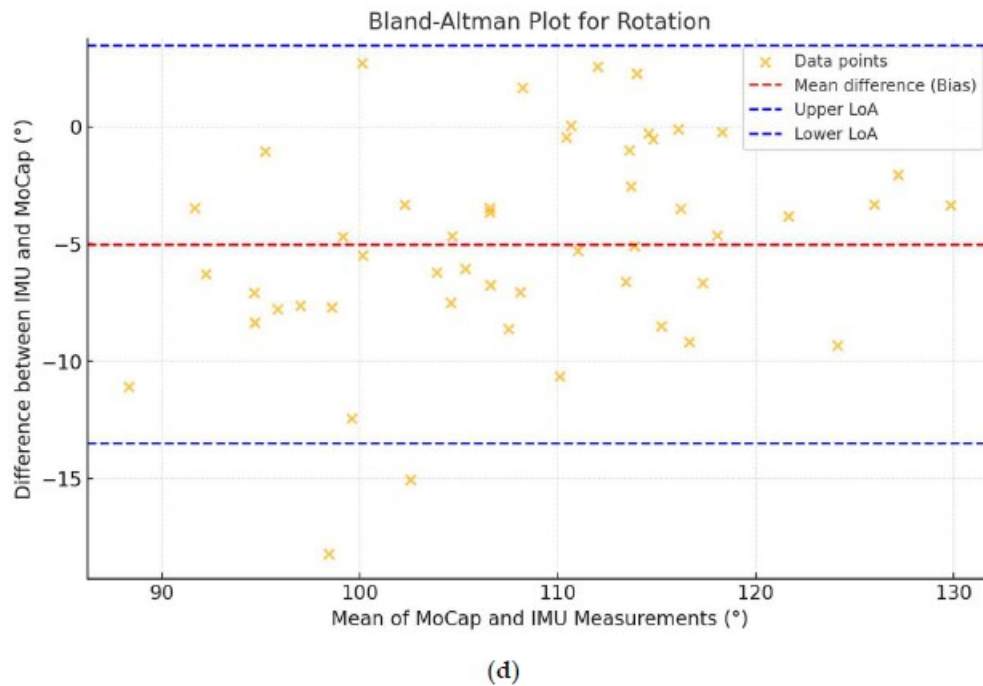


Figure 6. Bland–Altman plots comparing trunk range of motion measurements obtained with IMU and marker-based MoCap systems across different movement planes: (a) flexion; (b) extension; (c) lateral bending; (d) rotation. The solid line represents the mean difference (bias), while the dashed lines indicate the 95% limits of agreement (mean $\pm$ 1.96 SD), within which most differences between the two measurement methods are expected to lie.

3.2 Participants characteristics of the second part of study (clinical study)

A total of 59 participants were included in the second stage of the study, comprising 29 individuals with chronic low back pain (CLBP) and 30 healthy people. The two groups were comparable in demographic characteristics. Mean age was 39.4 ± 8.6 years in the CLBP group and 37.9 ± 7.9 years in healthy people ($p = 0.49$). Sex distribution was similar between groups (CLBP: 16 females, 13 males; healthy people: 17 females, 13 males; $p = 0.88$). Body mass index did not significantly differ between groups (CLBP: 23.16 ± 2.79 kg/m²; healthy people: 22.18 ± 2.36 kg/m²; $p = 0.15$).

In the CLBP group, mean pain intensity measured with the Visual Analog Scale (VAS) was 3.79 ± 1.78 , while average pain during the previous 30 days was 4.10 ± 2.04 . Disability assessed using the Oswestry Disability Index (ODI) was 32.84 ± 18.25 , and mean kinesiophobia measured with the Tampa Scale of Kinesiophobia (TSK) was 27.31 ± 7.13 . All the clinical and demographic characteristics of the sample are reported in Table 6.

Table 6. Demographic characteristics of the CLBP and healthy people groups.

Variable	CLBP (n=29)	Healthy people (n=30)	p-value
Age (years)	39.4 ± 8.6	37.9 ± 7.9	0.49
Sex (F/M)	16 / 13	17 / 13	0.88
BMI (kg/m ²)	23.16 ± 2.79	22.18 ± 2.36	0.15
VAS 0-10	3.79 ± 1.78		
VAS 0-10 (30-days average)	4.10 ± 2.04		
TSK total score	27.31 ± 7.13		

3.3 Trunk range of motion: CLBP vs Healthy people

Comparison of trunk mobility between groups revealed significant differences in selected movement planes. Individuals with CLBP showed significantly reduced lateral bending ($21.1^{\circ} \pm 11.7^{\circ}$, $p = 0.0028$) compared with healthy people. A similar reduction was observed for axial rotation ($84.8^{\circ} \pm 29.2^{\circ}$, $p < 0.001$).

Trunk extension was lower in the CLBP group ($11.7^{\circ} \pm 6.6^{\circ}$) compared with healthy people, although this difference did not reach statistical significance ($p = 0.052$). Conversely, trunk flexion was higher in the CLBP group ($69.5^{\circ} \pm 16.4^{\circ}$) than in healthy people ($p = 0.0017$). All the obtained results regarding the comparison between CLBP and healthy people are reported in Table 7 and Figure 7.

Table 7. Comparison of trunk range of motion between CLBP and healthy people.

Movement (°)	CLBP	Healthy people	p-value	Cohen's d
Flexion	69.5 ± 16.4	57.4 ± 14.4	0.0017	0.78
Extension	11.7 ± 6.6	14.7 ± 5.9	0.052	-0.48
Lateral bending	21.1 ± 11.7	33.5 ± 9.5	0.0028	-1.17
Rotation	84.8 ± 29.2	107.7 ± 27.0	<0.001	-0.81

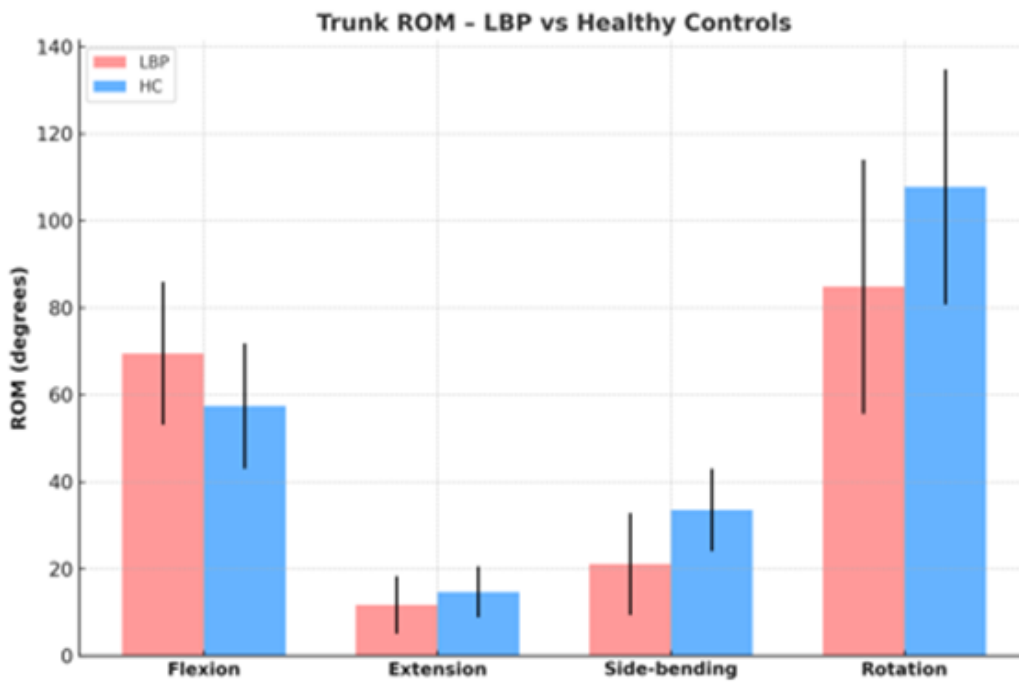
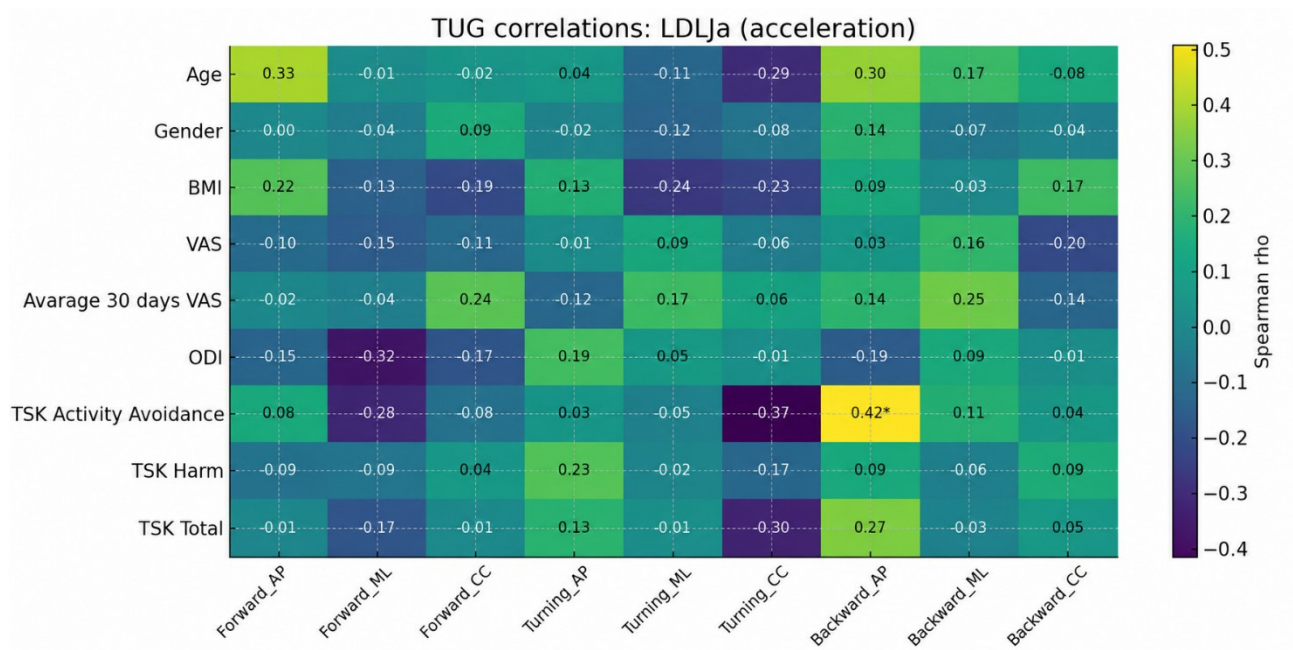


Figure 7. Comparison of trunk range of motion between CLBP and healthy people.

3.4 Instrumented TUG outcomes

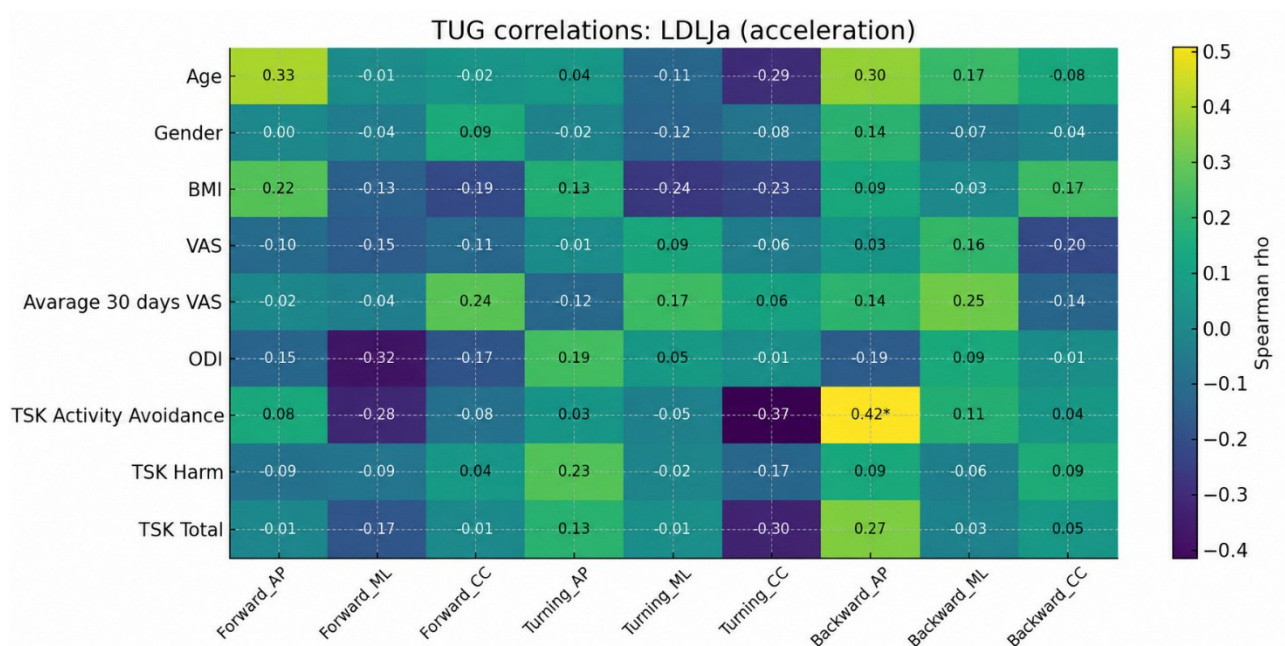
Instrumented Timed Up and Go (TUG) analysis was performed using trunk-mounted IMU sensors. The test was segmented into forward walking, turning, and backward walking phases. Metrics extracted from trunk accelerations included normalized root mean square acceleration (nRMS), improved harmonic ratio (iHR), and log dimensionless jerk (LDLJ).

Across 297 tested correlations between clinical variables and TUG-derived metrics, only five reached statistical significance ($p < 0.05$). The significant associations involved gender and fear-avoidance behaviour. In particular, TSK Activity Avoidance showed correlations with reduced movement symmetry and smoothness during specific TUG phases. All the correlation values are reported in Figures 8,9,10,11.



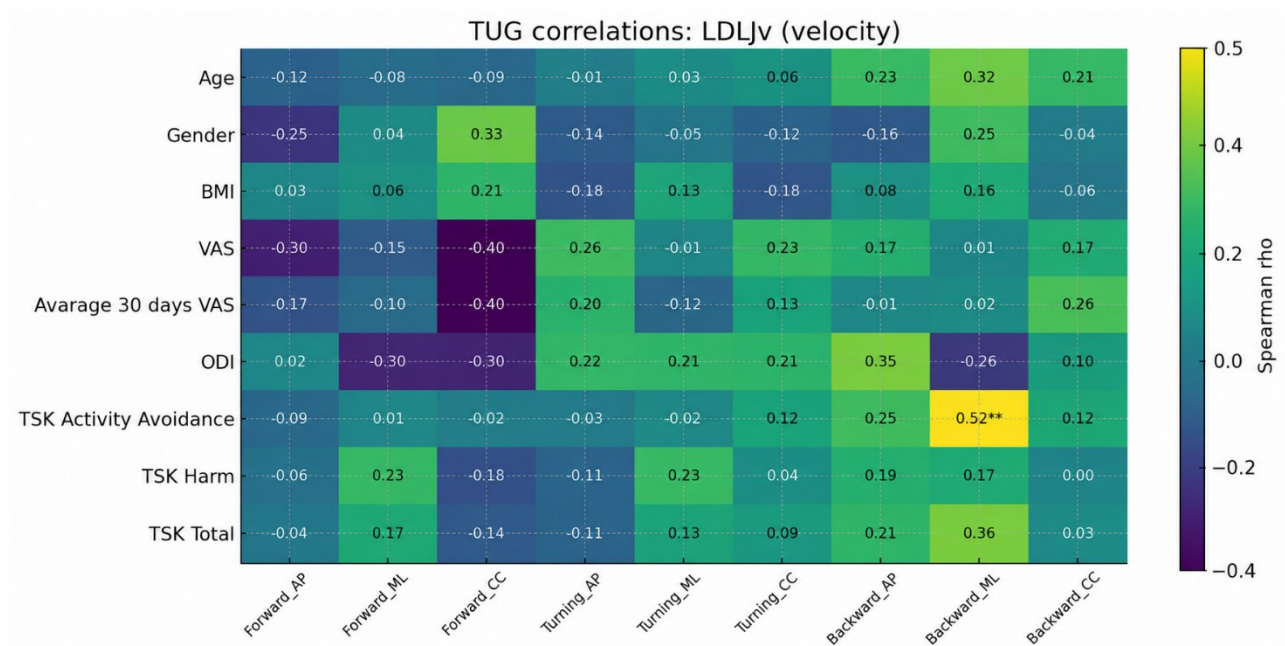
*= statistically significant ($p < 0.05$)

Figure 8. Heatmap of correlations between iHR-derived TUG metrics and clinical variables.



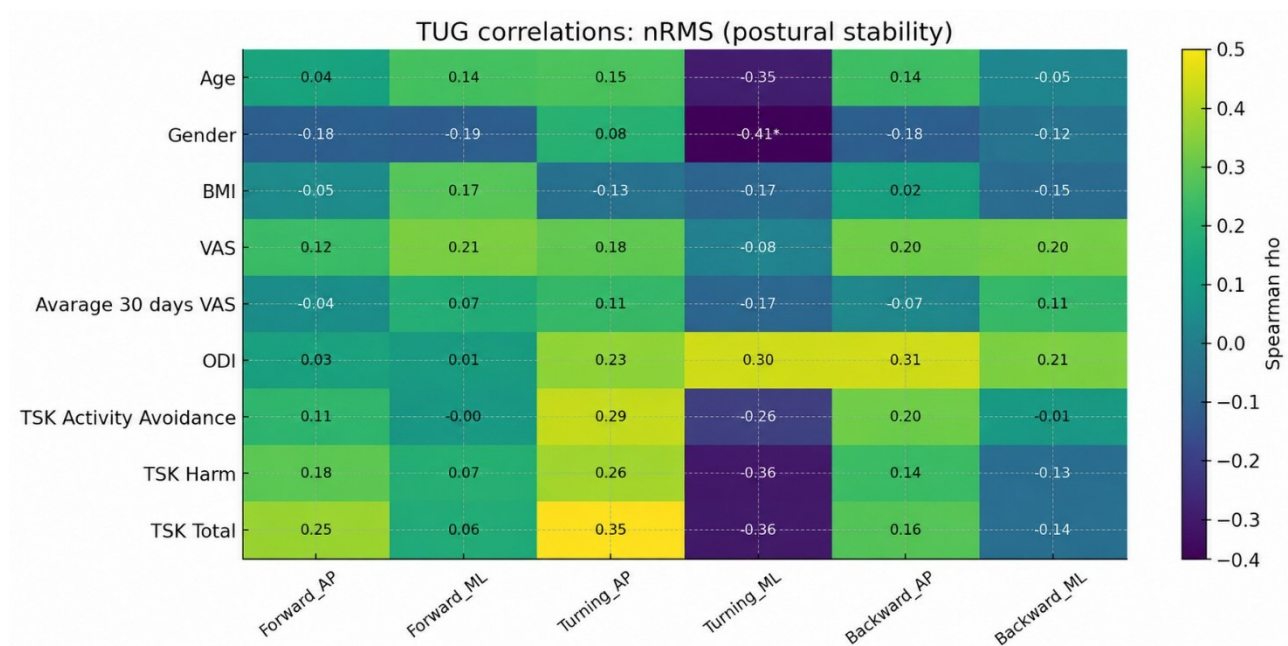
*= statistically significant ($p < 0.05$)

Figure 9. Heatmap of correlations between LDLJa-derived TUG metrics and clinical variables



*= statistically significant ($p < 0.05$)

Figure 10. Heatmap of correlations between LDLJv-derived TUG metrics and clinical variables.



*= statistically significant ($p < 0.05$)

Figure 11. Heatmap of correlations between nRMS-derived TUG metrics and clinical variables.

3.5 Multivariate models for trunk ROM

Multivariate regression models (Table 8) were performed to identify predictors of trunk range of motion. Gender emerged as a significant predictor of trunk flexion ($\beta = 13.92$, $p = 0.032$, $R^2 = 0.37$), while age significantly predicted trunk rotation ($\beta = -1.14$, $p = 0.007$, $R^2 = 0.40$). No significant predictors were found for extension or lateral bending.

Table 8. Multivariate regression models for trunk range of motion.

Dependent variable	Significant predictor	β	p-value	R ²
Flexion	Gender	13.92 (6.23;19.72)	0.032	0.37
Rotation	Age	-1.14 (-1.06; -1.21)	0.007	0.40
Extension	None	–	–	0.02
Lateral bending	None	–	–	0.17

3.6 Exploratory cluster analysis

K-means clustering was applied to explore the presence of distinct clinical-biomechanical phenotypes within the CLBP group. Prior to clustering, all variables were standardized (z-scores) to ensure comparability across different measurement scales. The clustering solution was evaluated using silhouette analysis, which indicated that a three-cluster solution provided the best balance between within-cluster cohesion and between-cluster separation.

The clustering model included both clinical (pain intensity, disability, fear-avoidance behaviour) and biomechanical variables (trunk range of motion and IMU-derived movement quality indexes), allowing for an integrated characterization of patient profiles.

The three identified clusters showed distinct patterns:

- Cluster 1 was characterized by higher levels of pain and disability, increased fear-avoidance behaviour, reduced trunk mobility (particularly in rotation and lateral bending), and poorer movement smoothness during functional tasks.
- Cluster 2 included individuals with relatively low pain and disability, preserved trunk mobility, and more optimal movement quality, suggesting a more adaptive or less impaired profile.
- Cluster 3 was mainly characterized by elevated fear-avoidance behaviour despite relatively preserved biomechanical performance, indicating a potential mismatch between clinical perception and motor function.

To facilitate the visualization and interpretation of the clustering structure, a principal component analysis (PCA) was performed on the standardized variables included in the model. Eigenvalues were computed to quantify the variance explained by each principal component. The first principal component (PC1) showed an eigenvalue of 2.05 and accounted for 41.1% of the total variance, while the second principal component (PC2) had an eigenvalue of 1.55 and explained 31.1%, resulting in a cumulative explained variance of 72.1%. The third component (PC3) had an eigenvalue of 0.68 and contributed an additional 13.5% of variance, increasing the cumulative variance to 85.7%.

According to the Kaiser criterion (eigenvalue > 1), only the first two components were retained. Although the inclusion of PC3 would have increased the total explained variance, the first two components were considered sufficient to capture the main structure of the data while allowing effective two-dimensional visualization. The third component provided limited additional interpretability and did not substantially improve cluster separation. It is important to note that clustering was performed in the original multidimensional feature space, whereas PCA was used exclusively as a visualization tool and therefore did not influence cluster identification.

Overall, these findings suggest that CLBP is a heterogeneous condition, in which patients may present with different combinations of clinical and biomechanical features. The identified clusters provide preliminary insights into potential phenotypic subgroups that could be relevant for personalized assessment and treatment strategies.

All the obtained results related to the cluster analysis and the PCA are reported in Table 9 and 10, and in Figure 12 and 13.

Table 9. Summary of the cluster-derived phenotypes.

Cluster	Pain / Disability	Fear-Avoidance	Rotation ROM	Smoothness (LDLJa AP)	Interpretation
0	High	Moderate-High	Low	Low	Severe pain + stiff-poor control
1	Low	Low	High	High	Resilient / well-functioning
2	Near average	Very High	High	High	Fear-driven phenotype

Table 10. Eigenvalues, explained variance, and cumulative variance of the principal components derived from standardized clinical and biomechanical variables.

Principal Component	Eigenvalue	Explained Variance (%)	Cumulative Variance (%)
PC1	2.05	41.1	41.1
PC2	1.55	31.1	72.1
PC3	0.68	13.5	85.7
PC4	0.42	8.5	94.2
PC5	0.29	5.8	100.0

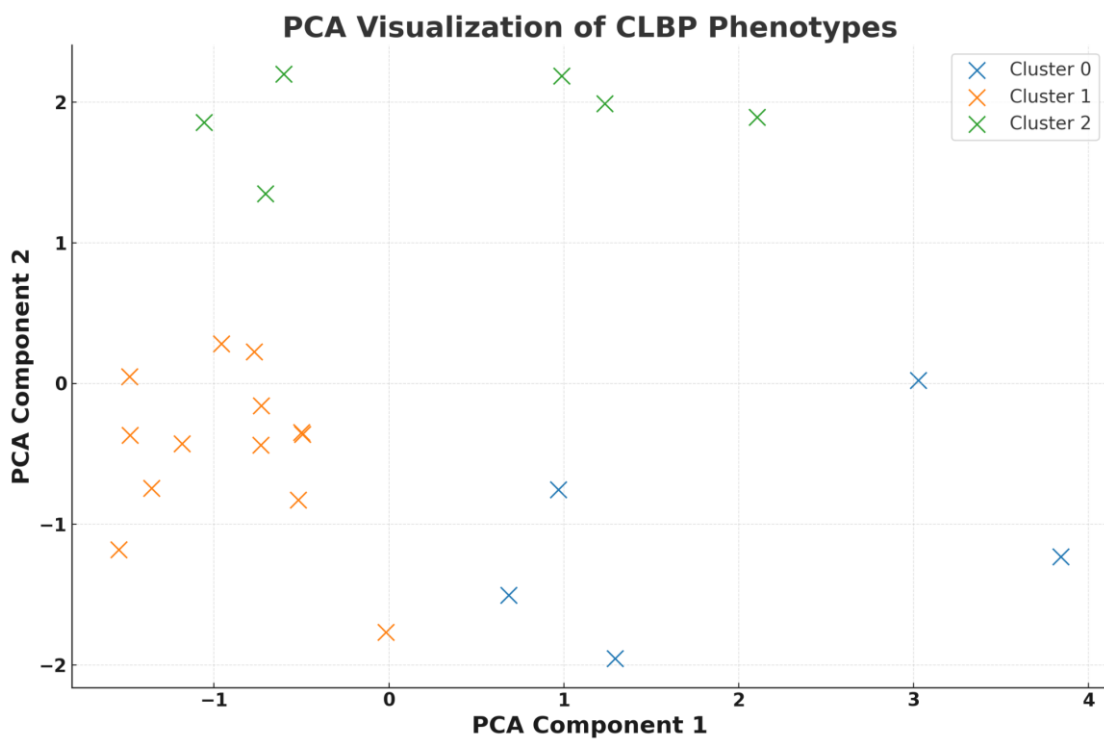


Figure 12. PCA visualization of the cluster-derived phenotypes

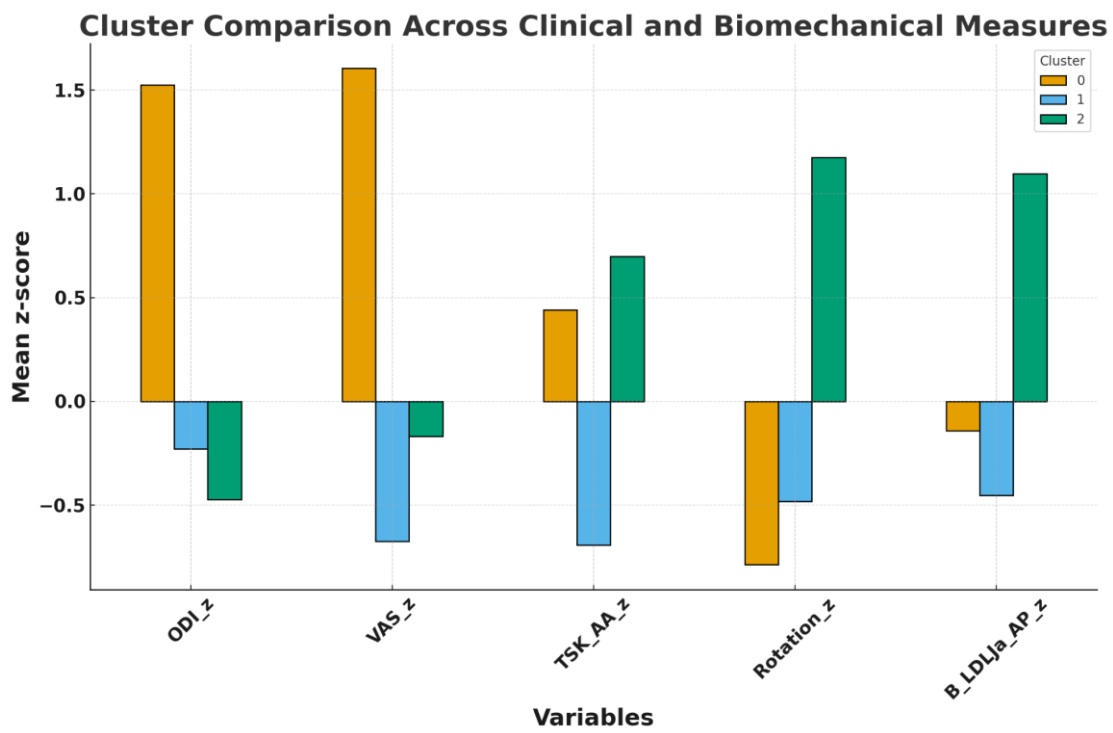


Figure 13. Comparison across clusters for selected clinical and biomechanical variables.

CHAPTER 4

DISCUSSION

4.1 Preliminary validation of the IMU system

A preliminary validation of the IMU-based wearable sensor was conducted prior to its application in the present clinical investigation, with the aim of establishing its accuracy and agreement in measuring trunk ROM against a gold-standard MoCap system. This step was essential to ensure the methodological robustness of the biomechanical measurements employed in the subsequent analyses and to support the interpretability of sensor-derived outcomes in a clinical context.

The findings of the validation study demonstrated that the IMU system provided an overall acceptable level of agreement with the reference MoCap system, although the degree of accuracy varied across movement planes. In particular, trunk rotation showed the highest level of agreement, with excellent accuracy (92.4%), very strong correlation ($r = 0.944$), and high concordance (CCC = 0.927), indicating that IMU-based measurements can reliably capture axial rotational movements of the trunk (43). Conversely, flexion, extension, and lateral bending exhibited only moderate levels of agreement, with lower correlation coefficients and accuracy values, suggesting that these movement planes are more susceptible to measurement discrepancies when assessed using a single-sensor configuration (43).

A consistent finding across all movement tasks was the systematic underestimation of ROM by the IMU compared to the MoCap system. This bias, particularly evident in flexion and lateral bending, may be attributed to several intrinsic and methodological factors, including soft tissue artefacts, sensor-to-segment misalignment, and slight relative displacement of the sensor during movement execution (63-65). These sources of error are well documented in the literature and represent a known limitation of wearable inertial systems, especially when a single sensor is used to estimate complex multi-planar trunk kinematics (66).

Despite these limitations, the magnitude of measurement error remained within clinically acceptable ranges, as reflected by RMSE values spanning from 1.09° in rotation to 3.01° in flexion. These results are consistent with previous validation studies reporting comparable levels of accuracy for IMU-based trunk motion assessment, supporting the use of wearable sensors as a feasible alternative to laboratory-based motion capture systems for selected applications (67,68).

An important aspect of the present validation is the use of a single IMU positioned at the lumbo-sacral region. While this configuration enhances feasibility, reduces setup time, and aligns with real-world clinical applicability, it may limit the ability to accurately capture complex intersegmental dynamics of the trunk. Previous research has shown that multi-sensor configurations generally

provide improved accuracy and segmental resolution, albeit at the cost of increased complexity and reduced clinical usability (66).

Overall, the results of this preliminary validation support the concurrent validity of the IMU-based system for trunk ROM assessment, particularly for rotational movements, while highlighting some limitations in other planes of motion. Importantly, this validation phase provides a solid methodological foundation for the subsequent application of the IMU sensor in individuals with CLBP, allowing the interpretation of observed biomechanical differences within a framework of known measurement properties. In this perspective, the validation step represents a critical bridge between technological reliability and clinical applicability, reinforcing the rationale for integrating wearable sensor-based motion analysis into the assessment of functional performance in musculoskeletal conditions.

4.2 Trunk kinematics in CLBP versus healthy people

The comparison between individuals with CLBP and healthy people revealed distinct alterations in trunk kinematics, which appear consistent with, yet also partially extend, the current body of literature. Overall, the present findings support the concept that CLBP is associated with modifications in movement strategies rather than a simple global reduction in mobility, reflecting a complex interaction between biomechanical, neuromuscular, and behavioral factors.

In the present study, individuals with CLBP exhibited significantly reduced ROM in lateral bending and axial rotation compared with healthy people, while trunk extension showed a non-significant tendency toward reduction. These findings are in line with a substantial portion of the literature, which consistently reports reduced movement amplitude in CLBP, particularly in the frontal plane and during functional tasks such as gait and trunk movements (68–70). Reduced ROM is commonly interpreted as a protective strategy aimed at minimizing pain-provoking movements, often associated with increased trunk stiffness and enhanced muscle co-contraction (69,71).

From a biomechanical perspective, this reduction in mobility appears to be part of a broader motor control adaptation characterized by increased in-phase coordination between trunk segments. CLBP individuals tend to adopt more rigid movement patterns, with reduced intersegmental dissociation between the trunk and pelvis, particularly during repetitive or cyclical tasks such as walking (68,70,72). This strategy likely serves to stabilize the spine and limit mechanical stress on painful structures but may come at the cost of reduced movement efficiency and adaptability.

However, the present results also highlighted a less intuitive finding: individuals with CLBP demonstrated greater trunk flexion compared with healthy people. This observation may initially appear contradictory to the concept of generalized movement restriction, yet it aligns with emerging

evidence suggesting that CLBP-related kinematic alterations are not uniformly characterized by reduced ROM. Rather, they reflect a redistribution of movement across segments and planes (70,73). In this context, increased flexion may represent a compensatory strategy, whereby mobility is preserved or even amplified in specific directions to offset restrictions in others. One possible explanation for the increased trunk flexion observed in the CLBP group may be related to compensatory movement redistribution. Individuals with CLBP often exhibit reduced mobility in the frontal and transverse planes, and it is conceivable that greater sagittal-plane excursion may emerge as an alternative movement strategy during trunk tasks. However, this interpretation should be considered speculative. Although the concept of relative flexibility has been proposed to explain preferential movement occurring in less constrained regions (73), it traditionally refers to the distribution of motion among anatomical segments rather than to compensatory increases in overall range of motion across different movement planes. Therefore, the mechanisms underlying the greater flexion ROM observed in the present study remain uncertain and warrant further investigation.

Further insight into this compensatory behavior is provided by studies showing increased transverse plane motion and altered spine–pelvis ratios in CLBP, suggesting a shift toward segmental redistribution of movement rather than uniform stiffness (73). Similarly, task-specific increases in sagittal plane motion have been observed in certain functional conditions, supporting the notion that CLBP is characterized by context-dependent motor adaptations rather than fixed biomechanical deficits (68).

Another key aspect emerging from the literature concerns movement variability. Although variability was not directly quantified in the ROM analysis, some of the observed findings of this research—particularly those related to functional tasks—may be interpreted within a broader body of evidence indicating altered variability patterns in CLBP. Specifically, CLBP individuals may exhibit reduced variability during simple, controlled movements, reflecting a rigid and protective motor strategy, while increased variability emerges during more complex or demanding tasks, revealing underlying deficits in motor control (68,74). This dual behavior suggests that reduced variability should not be interpreted as improved motor control, but rather as a potential marker of constrained movement strategies.

At the neuromuscular level, these kinematic alterations are strongly associated with increased muscle activation and reduced capacity for relaxation, particularly in the lumbar extensors. The loss of normal flexion–relaxation patterns and the presence of sustained co-contraction contribute to increased trunk stiffness and may explain both the reduced ROM observed in certain planes and the altered coordination patterns (69,75). Over time, these adaptations may become maladaptive, leading to increased mechanical loading on adjacent segments and reduced motor efficiency.

Importantly, the heterogeneity observed in the literature—and partially reflected in the present findings—suggests that trunk kinematic alterations in CLBP are highly task-dependent. Differences in movement direction, task complexity, and biomechanical demands can lead to apparently contrasting results across studies, including both reduced and increased ROM depending on the context (68,72). This variability underscores the importance of interpreting trunk kinematics within a functional framework, rather than as isolated biomechanical parameters.

Overall, the findings of the present study reinforce the view that CLBP is associated with a reorganization of movement rather than a simple impairment of mobility. Reduced lateral bending and rotation, combined with increased flexion, suggest the presence of compensatory strategies aimed at maintaining functional performance despite pain. These results highlight the importance of adopting a multidimensional perspective in the assessment of CLBP, integrating quantitative kinematic analysis with clinical evaluation to better capture the complexity of motor behavior in this population.

4.3 Movement quality and functional performance (TUG)

The analysis of movement quality and functional performance through the instrumented TUG revealed a limited number of significant associations between IMU-derived metrics (iHR, nRMS, LDLJ) and clinical variables, with only five significant correlations emerging out of a large set of tested relationships. At first glance, this finding might suggest a weak relationship between biomechanical parameters and clinical status. However, from a broader interpretative perspective, the limited number of associations observed in the present study should not be considered a limitation per se, but rather as an important indication of the complex and multidimensional nature of CLBP.

Indeed, current evidence increasingly supports the notion that clinical measures such as pain intensity, disability, and fear of movement only partially reflect underlying motor behavior. Several studies have highlighted that subjective clinical outcomes and objective kinematic parameters often show weak or inconsistent relationships, suggesting a partial dissociation between perceived symptoms and movement execution (76,77). In this context, the findings of the present study are consistent with the literature, reinforcing the idea that pain and disability cannot be directly inferred from biomechanical performance alone.

From a mechanistic perspective, this dissociation may be explained by the coexistence of multiple interacting factors in CLBP, including neurophysiological, psychological, and behavioral components. Pain-related fear, for instance, has been shown to influence movement strategies independently of actual physical impairment, leading to protective or avoidant behaviors that do not necessarily correspond to measurable kinematic alterations (78). This is partially reflected in the

present results, where some of the few significant associations involved fear-avoidance constructs rather than pain intensity or disability per se.

Another key element to consider is the task-dependent nature of motor behavior in CLBP. The TUG represents a complex, multi-phase functional task involving transitions between sitting, standing, walking, turning, and postural control. Such complexity requires the integration of multiple motor control processes, making it unlikely that global or linear relationships with clinical variables can be consistently detected. Previous studies have shown that kinematic alterations in CLBP tend to emerge more clearly under specific task conditions or phases, rather than across entire functional tasks (75,79). This may explain why only a limited number of associations were identified in the present analysis, despite the use of sensitive IMU-derived metrics.

Furthermore, the literature on movement variability and smoothness provides additional insight into these findings. Metrics such as iHR, nRMS, and LDLJ capture higher-order aspects of motor control, including rhythmicity, stability, and coordination. These parameters are known to be influenced not only by pain and disability, but also by motor adaptability and neuromuscular control strategies (74,80). In CLBP, variability can exhibit a dual behavior: reduced variability during simple or controlled tasks, reflecting a rigid and protective strategy, and increased variability during more complex or demanding conditions, indicating impaired motor control (68,74). As a result, the relationship between these metrics and clinical variables is inherently non-linear and context-dependent.

Importantly, the apparent lack of strong associations at the global level does not imply the absence of meaningful relationships, but rather suggests that such relationships may be better captured through more advanced or stratified analytical approaches. In this regard, the exploratory cluster analysis performed in the present study provides a complementary perspective, revealing the presence of distinct clinical-biomechanical phenotypes within the CLBP population. This finding supports the hypothesis that biomechanical and clinical variables may interact differently across subgroups, thereby masking associations when analyzed using traditional correlation-based methods.

Overall, the results of the TUG analysis highlight the need to move beyond simplistic one-to-one relationships between clinical and biomechanical variables. Instead, they support a multidimensional framework in which movement quality reflects the interaction of multiple factors, including motor control strategies, psychological influences, and task-specific demands. Within this perspective, IMU-derived metrics should not be interpreted as direct proxies of pain or disability, but rather as complementary indicators of functional motor behavior.

These findings further reinforce the rationale for integrating clinical assessment with sensor-based biomechanical analysis. While traditional clinical measures remain essential for capturing the

subjective experience of CLBP, wearable technologies provide access to objective dimensions of movement that may reveal alterations not detectable through conventional evaluation alone. The combination of these approaches may therefore offer a more comprehensive understanding of functional performance in individuals with CLBP, particularly when supported by analytical frameworks capable of capturing the inherent complexity of the condition.

4.4 Clinical–biomechanical integration

Taken together, the findings of the present study support the view that clinical and biomechanical variables capture partially overlapping but non-redundant dimensions of CLBP. Across both trunk kinematic analyses and instrumented functional assessment, objective movement parameters revealed measurable alterations in motor behavior, whereas their associations with pain intensity, disability, and fear-related variables remained limited. This cross-domain pattern suggests that subjective clinical status and sensor-derived biomechanical performance should not be interpreted as interchangeable constructs, but rather as complementary components of a multidimensional condition. Such dissociation is consistent with evidence showing that motor control changes in LBP are heterogeneous and may arise from different mechanisms, including protective adaptations, altered coordination strategies, and psychosocial influences (81–83). Moreover, the limited linear associations observed in the present study suggest that the relationship between clinical and biomechanical domains may be non-linear and subgroup-dependent, requiring analytical approaches capable of capturing latent patterns rather than isolated variable-to-variable relationships (84,85). Within this framework, wearable IMU technology provides a clinically feasible means of quantifying movement behavior, but its outputs require integration with clinical assessment to support meaningful interpretation (86,87). Therefore, the main contribution of the present findings lies not in any single biomechanical or clinical result, but in demonstrating the need for an integrated clinical–biomechanical framework to better characterize the heterogeneity of CLBP.

4.5 CLBP phenotypes: a clinical-biomechanical perspective

The exploratory cluster analysis performed in the present study identified three distinct clinical–biomechanical phenotypes within the CLBP population, characterized by different combinations of pain, disability, fear-avoidance behavior, trunk mobility, and movement quality. These findings provide further support to the concept that CLBP is not a homogeneous condition, but rather a multifaceted syndrome encompassing heterogeneous presentations that cannot be fully captured through single-domain analysis.

The first cluster was characterized by high levels of pain and disability, associated with reduced trunk rotation ROM and impaired movement smoothness. This phenotype may be interpreted as a “high pain–low mobility” profile, in which movement restriction and reduced motor efficiency coexist. From a biomechanical perspective, the reduced ROM observed in this group is consistent with protective movement strategies aimed at minimizing pain, often associated with increased trunk stiffness and altered neuromuscular activation patterns (69,75). The concomitant reduction in movement smoothness suggests impaired motor control, possibly reflecting both pain-related inhibition and decreased movement adaptability. Importantly, the reduced smoothness observed in this phenotype should not be interpreted exclusively as an immediate consequence of pain-related inhibition. Although current pain may acutely constrain movement execution, persistent exposure to pain may also promote the development of stable protective motor habits, characterized by cautious, fragmented, and less adaptable movement strategies. Therefore, in the “high pain–low mobility” profile, impaired smoothness may reflect both short-term pain-related guarding and longer-term maladaptive motor control adaptations that persist beyond moment-to-moment fluctuations in pain intensity. This phenotype aligns with previous literature describing subgroups of CLBP patients characterized by high disability and altered movement patterns, often associated with poorer functional outcomes (88,89).

The second cluster, in contrast, was characterized by low levels of pain and disability, preserved trunk mobility, and higher movement quality. This profile may be interpreted as a “resilient” or “well-functioning” phenotype, in which individuals maintain relatively normal movement behavior despite the presence of chronic symptoms. The preservation of both ROM and movement smoothness suggests a more efficient motor control strategy, potentially reflecting better adaptability and lower levels of protective behavior. Similar profiles have been described in the literature, where individuals with LBP exhibit minimal functional impairment and maintain near-normal kinematic patterns, highlighting the dissociation between pain and movement capacity (76,81). This finding further reinforces the notion that the presence of pain alone is not sufficient to determine functional limitation.

The third cluster presented a particularly interesting pattern, characterized by relatively preserved trunk mobility and movement quality, but markedly elevated fear-avoidance behavior. This “fear-dominant” phenotype reflects a dissociation between psychological and biomechanical domains, in which individuals report high levels of kinesiophobia despite exhibiting near-normal movement characteristics. Such a profile is consistent with the fear-avoidance model of chronic pain, which posits that cognitive and emotional factors can strongly influence behavior and perception independently of physical impairment (83,90). The identification of this phenotype underscores the importance of considering psychological factors in the assessment of CLBP, as these may not be directly reflected in objective movement analysis. One possible explanation for this apparent

mismatch is that the controlled and predictable nature of the experimental setting may have allowed these individuals to perform the required tasks with relatively preserved biomechanical efficiency. In a supervised assessment, movements are standardized, anticipated, and performed in a safe environment, potentially reducing the expression of avoidance behavior. Conversely, fear-avoidance may become more evident in less predictable real-world contexts, where movements involve unexpected perturbations, variable loads, time pressure, or perceived risk of symptom exacerbation. Thus, the “fear-dominant” phenotype may not necessarily indicate preserved function in all contexts, but rather a dissociation between laboratory-based motor performance and perceived vulnerability during daily-life movement.

Taken together, these three clusters highlight the heterogeneous and multidimensional nature of CLBP, demonstrating that similar levels of pain or disability may be associated with markedly different movement strategies, and vice versa. Importantly, the presence of distinct phenotypes provides a possible explanation for the limited associations observed between clinical and biomechanical variables in the present study. While global correlation analyses suggested weak relationships, the clustering approach revealed that meaningful patterns emerge when individuals are grouped according to shared clinical–biomechanical characteristics. This finding supports the hypothesis that the relationship between domains is not uniform across the population, but rather varies according to underlying phenotypic profiles.

From a methodological standpoint, these results emphasize the added value of data-driven approaches such as cluster analysis in the study of CLBP. Traditional analytical methods, based on linear associations, may fail to capture the complexity of interactions between variables, whereas unsupervised techniques allow the identification of latent structures within the data. Similar approaches have been increasingly adopted in recent years to identify subgroups of patients based on clinical, biomechanical, and psychosocial features, with the aim of improving patient stratification and treatment targeting (85,91).

From a clinical perspective, these preliminary findings tentatively suggest that the identification of distinct CLBP phenotypes may have potential implications for assessment and management. The “high pain–low mobility” phenotype may point to the relevance of evaluating both pain-related factors and movement quality, including mobility and smoothness. In contrast, the “resilient” phenotype may indicate that some individuals with CLBP maintain relatively preserved biomechanical performance despite chronic symptoms, highlighting the importance of avoiding assumptions based solely on pain presence. The “fear-dominant” phenotype, on the other hand, suggests that psychological factors such as fear of movement and maladaptive beliefs may require specific attention even when objective movement performance appears relatively preserved. However, given the exploratory nature of the cluster analysis and the limited sample size, these phenotype-based interpretations should not be considered as direct treatment recommendations. Prospective validation in larger and

independent cohorts is required before cluster-derived profiles can meaningfully inform clinical decision-making.

Overall, the cluster analysis performed in this study supports a preliminary shift from a “one-size-fits-all” interpretation toward a more stratified model of CLBP assessment. By integrating clinical, biomechanical, and psychological dimensions, this approach allows a more nuanced characterization of patient profiles and may provide a basis for future studies aimed at improving clinical decision-making and rehabilitation planning.

4.6 Wearable technologies and IMU-based systems in rehabilitation: integration with the present findings

The use of wearable technologies, and in particular IMU-based systems, represents a rapidly evolving field in rehabilitation and clinical movement analysis. In the present thesis, the adoption of a single-sensor IMU system allowed both the validation of trunk kinematic measurements against a gold-standard MoCap system and the subsequent application of this technology to the assessment of individuals with CLBP. This dual approach provides a valuable framework for discussing the current role of wearable sensors not only from a theoretical perspective, but also in light of their practical implementation and performance in a clinical research context.

The preliminary validation phase demonstrated that the IMU system provided acceptable agreement with the MoCap system, particularly for trunk rotation, while showing moderate accuracy in other planes of motion. These findings are consistent with the broader literature, which supports the validity of IMU-based measurements for trunk kinematics, although with some variability depending on movement complexity and sensor configuration (92,93). Importantly, the systematic underestimation of ROM observed in the present study reflects known limitations of wearable sensors, including soft tissue artefacts and sensor-to-segment misalignment, which have been widely reported in previous validation studies (93-97). Despite these limitations, the level of accuracy observed supports the use of IMUs as a feasible alternative to laboratory-based systems for specific clinical applications.

A key aspect emerging from the present work is the use of a single IMU positioned at the lumbo-sacral region. This configuration inevitably limited the ability to capture intersegmental trunk dynamics and prevented the distinction between lumbar, thoracic, and pelvic contributions to the observed movement patterns. For example, the increased trunk flexion observed in individuals with CLBP cannot be attributed specifically to greater lumbar motion, thoracic contribution, pelvic strategy, or a combination of these components. Similarly, the single-sensor setup does not allow a detailed analysis of segmental coordination or compensatory redistribution across trunk regions. Nevertheless, this methodological choice was justified by the specific aim of the study, which was to explore the clinical feasibility of a simple wearable-based assessment rather than to provide a full

segmental biomechanical reconstruction. In this sense, the single-IMU configuration represents a deliberate trade-off between anatomical resolution and clinical applicability, reducing setup time, technical complexity, and participant burden while preserving the possibility of extracting clinically relevant trunk motion and movement-quality parameters (92,94).

The application of the IMU system to individuals with CLBP further highlights the clinical relevance of wearable technologies. The present findings demonstrated that IMU-derived parameters were able to detect significant differences in trunk kinematics between CLBP and healthy individuals, as well as to capture aspects of movement quality during functional tasks such as the TUG. These results are in line with previous studies showing that wearable sensors can provide objective and sensitive measures of motor behavior, often revealing alterations that are not detectable through standard clinical assessment alone (94,95). In particular, the ability to quantify movement smoothness and variability represents a significant added value, as these parameters reflect higher-order aspects of motor control that are difficult to assess through traditional methods.

However, the present study also highlighted important limitations in the interpretation of IMU-derived data. The limited associations observed between biomechanical metrics and clinical variables suggest that wearable sensor data should not be interpreted as direct proxies of pain or disability. This finding is consistent with the current literature, which emphasizes that wearable technologies provide complementary, rather than substitutive, information with respect to clinical assessment (95,96). In this context, the integration of sensor-based measurements with clinical and psychological variables becomes essential for a comprehensive evaluation of CLBP.

From an evidence-based perspective, the current literature supports the clinical validity of wearable technologies, with studies reporting moderate to strong correlations between IMU-derived parameters and established clinical measures, as well as high sensitivity and specificity in detecting movement alterations. Nevertheless, the quality of evidence remains heterogeneous, with a limited number of randomized controlled trials and a predominance of observational and validation studies (95-98). This limitation is particularly relevant when considering the translation of wearable technologies into routine clinical practice.

Several practical and methodological challenges also emerge, both from the literature and from the experience of the present study. These include issues related to standardization of protocols, sensor placement, and data processing, as well as the need for clinician training and user-friendly data interpretation tools (93,97). Furthermore, factors such as data privacy, accessibility, and cost-effectiveness represent important considerations for large-scale implementation (95,98).

Looking forward, the integration of wearable technologies with advanced analytical approaches represents a promising direction. In particular, the combination of IMU-based data with machine learning techniques may enable the identification of complex patterns and the development of

predictive models for patient stratification, as suggested by the cluster analysis performed in the present study (96,99). Such approaches may help overcome the limitations of traditional linear analyses and support a more personalized approach to rehabilitation.

Overall, the findings of this thesis support the role of IMU-based wearable technologies as practical and clinically relevant tools for movement analysis in CLBP. While not without limitations, these systems offer a unique opportunity to bridge the gap between laboratory-based biomechanics and real-world clinical assessment. Their integration with clinical and psychological evaluation, as demonstrated in the present work, represents a key step toward a more comprehensive and multidimensional understanding of functional performance in individuals with CLBP.

4.7 Limitations

Several limitations of the present study should be acknowledged when interpreting the findings.

First, the cross-sectional design does not allow causal inferences regarding the relationship between clinical and biomechanical variables. The observed associations should therefore be interpreted as descriptive rather than explanatory, reflecting concurrent patterns rather than directional mechanisms.

Second, the sample size, although adequate for exploratory analyses, may limit the generalizability of the results and the stability of more complex analytical approaches, such as cluster analysis. In particular, the identification of clinical–biomechanical phenotypes should be considered preliminary and requires validation in larger and independent cohorts.

From an instrumental perspective, the use of a single IMU represents both a strength and a limitation. While this configuration enhances clinical feasibility and ecological validity, it does not allow the assessment of intersegmental dynamics and may reduce the accuracy of trunk kinematic reconstruction, particularly in complex multi-planar movements (93,97). In addition, known sources of measurement error, such as soft tissue artefacts and sensor misalignment, may have influenced the estimation of ROM.

From a methodological standpoint, the large number of variables explored in relation to a relatively limited sample size increases the risk of both type I and type II errors. Therefore, the significant associations and cluster-derived profiles should be interpreted as exploratory rather than confirmatory. However, this limitation does not reduce their conceptual relevance; rather, the present findings should be considered as a hypothesis-generating foundation for larger, adequately powered studies aimed at testing the stability, reproducibility, and clinical usefulness of the proposed clinical–biomechanical profiles. Moreover, the use of linear statistical approaches may not fully capture the

complex and potentially non-linear relationships between clinical and biomechanical domains, as suggested by the limited number of significant associations observed.

Another relevant aspect concerns the use of the TUG as a functional task. Although widely adopted in clinical practice, the TUG is a multi-component test that involves several motor and cognitive processes, and may not be sufficiently specific to isolate trunk-related biomechanical alterations.

Finally, the clinical assessment was based on commonly used self-reported measures, such as pain intensity, disability, and fear of movement. While these tools are well validated, they may not fully capture the multidimensional nature of CLBP, particularly with respect to central and cognitive aspects of pain.

Overall, these limitations highlight the need for cautious interpretation of the findings and support the importance of future studies adopting larger samples, longitudinal designs, and more integrated analytical approaches.

4.8 Future perspectives

The findings of the present study open several directions for future research, particularly in relation to the integration of clinical and biomechanical assessment in CLBP.

First, longitudinal study designs are needed to better understand the temporal evolution of the observed clinical–biomechanical relationships. While the present results highlight a partial dissociation between domains, future studies should investigate how these interactions change over time and in response to rehabilitation interventions, potentially identifying predictive markers of recovery or chronicity.

Second, the validation of the identified clinical–biomechanical phenotypes represents a key research priority. The cluster analysis performed in this study provides preliminary evidence of distinct CLBP profiles; however, replication in larger and independent cohorts is necessary to confirm their stability and clinical relevance. In this perspective, the integration of clustering techniques with supervised approaches may support the development of classification models for patient stratification (100).

Third, future research should explore more advanced analytical frameworks capable of capturing the complex and non-linear relationships between clinical and biomechanical variables. Traditional statistical approaches may be insufficient to fully describe the multidimensional nature of CLBP, whereas machine learning methods offer promising opportunities for modeling high-dimensional data and identifying latent patterns (100).

From a technological perspective, further developments in wearable sensor systems are expected to enhance their clinical applicability. Improvements in sensor accuracy, standardization of data

processing protocols, and the development of user-friendly interfaces for clinicians will be essential to facilitate their integration into routine practice. In addition, multi-sensor configurations may allow a more detailed assessment of intersegmental dynamics, complementing the single-sensor approach adopted in the present study.

Another relevant direction concerns the ecological assessment of movement. The ability of wearable technologies to monitor motor behavior in real-world environments should be further exploited, allowing the investigation of functional performance in daily life contexts, beyond controlled laboratory settings. This may provide more clinically meaningful information and improve the sensitivity of outcome measures.

Finally, future studies should aim to further integrate biomechanical, clinical, and psychological dimensions within unified assessment models. Such an approach may support the development of personalized rehabilitation strategies, tailored to specific patient profiles, and aligned with the growing emphasis on precision medicine in musculoskeletal care.

Overall, advancing the integration of wearable technologies, multidimensional assessment, and data-driven analytical approaches represents a key step toward improving the understanding and management of CLBP.

CHAPTER 5

CONCLUSIONS

The present study contributes to the understanding of CLBP by integrating clinical assessment with objective biomechanical analysis through IMU-based wearable technology. The preliminary validation demonstrated that the IMU system provides acceptable agreement with a gold-standard MoCap system, supporting its use for the assessment of trunk kinematics in a clinically feasible setting.

From a clinical-biomechanical perspective, the results confirmed that individuals with CLBP exhibit altered trunk kinematics compared with healthy people, particularly in terms of reduced rotation and lateral bending, alongside task-dependent adaptations in movement strategies. Importantly, IMU-derived metrics such as LDLJ and iHR provided objective information on movement quality, including smoothness and gait symmetry, which may be difficult to detect through visual observation and are not captured by traditional clinical scales. However, the limited associations observed between biomechanical metrics and clinical variables indicate that these domains capture only partially overlapping aspects of the condition, reinforcing the multidimensional nature of CLBP.

A key finding of this work is the identification of three distinct clinical–biomechanical phenotypes within the CLBP population, characterized by different combinations of pain, disability, fear-avoidance behavior, and movement patterns. These results highlight the heterogeneity of CLBP and support the need for stratified approaches to patient assessment and management. In particular, the identification of a “fear-dominant” phenotype suggests that clinicians should not rely exclusively on biomechanical performance when interpreting functional status, as psychological factors such as fear of movement may be clinically relevant even in the presence of relatively preserved movement quality.

Overall, the findings of this thesis support a multidimensional and integrative framework in which wearable sensor-based biomechanical analysis complements traditional clinical evaluation. This approach not only enhances the understanding of functional motor behavior in CLBP, but also provides a preliminary basis for the development of more personalized and targeted assessment strategies. Given the exploratory nature of the cluster analysis, these phenotype-based interpretations should be considered hypothesis-generating and require validation in larger and prospective studies before being used to guide clinical decision-making. This integrative approach may represent a step toward a more precise and functionally grounded characterization of CLBP.

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