

PHD
PHYSIOTHERAPY

**POSTURAL SWAY IN OFFICE WORKERS: A
REAL-TIME INERTIAL SENSOR-BASED
ANALYSIS OF MOVEMENT VARIABILITY
IN CHRONIC SPINAL PAIN AND
PAIN-FREE ADULTS**

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Dedications

To my Family and Friends, even from a distance, have been a constant source of love and strength in realizing this work.

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*“For those whose lives have been shaped and strengthened by the challenges
of learning.” (Neumann, 2011)*

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List of abbreviations

Accelerometer **ACC**

Anterior-Posterior **AP**

Analysis of Variance **ANOVA**

Approximate Entropy **ApEn**

Artificial Intelligence **AI**

Autoridade Tributária e Aduaneira **AT**

Body Mass Index **BMI**

Center of Pressure **CoP**

Center of Mass **CoM**

Centre of Gravity **CoG**

Centimeters **CM**

Chronic Spinal Pain **CSP**

Coefficient of Variation **CV**

Control Group **CG**

Copenhagen Psychosocial Questionnaire II **CoPSOQ II**

Disability-Adjusted Life Years **DALYs**

Electromyography **EMG**

European Agency for Safety and Health at Work **EU-OSHA**

Global Burden of Diseases, Injuries, and Risk Factors Study **GBD**

Gyroscope **GYR**

Heart Rate **HR**

Hurst Exponent **H**

Inertial Measurement Units **IMUs**

Interquartile Range **IQR**

International Association for the Study of Pain **IASP**

International Classification of Diseases-11 **ICD-11**

International Labour Organisation **ILO**

International Physical Activity Questionnaire Short Form **IPAQ-SF**

Internet-of-Things **IoT**

Largest Lyapunov Exponent **LyE**

Low Back Pain **LBP**

Magnetometer **MAG**
Medial-Lateral **ML**
Metabolic Equivalent **MET**
Motion Capture **MoCap**
MultiFractal Detrended Fluctuation Analysis **MFDFA**
Multiscale Entropy **MSE**
Musculoskeletal **MSK**
Musculoskeletal Disorders **MSDs**
Neck Pain **NP**
Normalized Lumbar Flexion Angle **NLFA**
Numeric Pain Rating Scale **NPRS**
Odds Ratio **OR**
Ovako Working Posture Assessment System **OWAS**
Pain-Free Group **PG**
Partial Eta Squared ηp^2
Permuted Sample Entropy **PeSampEn**
Physical Activity **PA**
Prevention of Occupational Disorders in Public Administration Based on the Artificial Intelligence Project **PrevOccupAI**
Rapid Upper Limb Assessment **RULA**
Range of Motion **ROM**
Root Mean Square **RMS**
Rapid Office Strain Assessment **ROSA**
Rotation Vector **RV**
Sample Entropy **SampEn**
Spinal Postural Variability **SPV**
Thoracic Spine Pain **TSP**
Time Series Feature Extraction Library **TSFEL**
Work-Related Musculoskeletal Disorders **WMDs**
Years Lived with Disability **YLDs**

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Motivations behind publications

Building on an academic background in digital postural assessment during a BSc in Physiotherapy at Pontifícia Universidade Católica do Rio Grande do Sul (PUC-RS) and research on chronic spinal pain and its risk factors during an MSc in Musculoskeletal Physiotherapy at the University of Aveiro (UA), my focus naturally evolved toward musculoskeletal health and postural evaluation, particularly in addressing chronic spinal pain. Pursuing a PhD in Physiotherapy was a deliberate choice, as this discipline uniquely integrates clinical reasoning, movement science, and functional assessment, allowing research questions to be directly grounded in patient-centered care and evidence-based physiotherapy practice.

The introduction to the PrevOccupAI project by Professor Hugo provided an opportunity to align a PhD proposal with this initiative, which focuses on preventing occupational disorders in public administration workers through the integration of sensors, questionnaires, and tailored recommendations, among other objectives. PrevOccupAI is discussed throughout this thesis and has been instrumental in shaping the research trajectory and contributions.

Studies on sensor technologies for movement detection were conducted to provide a specific and innovative contribution. This research introduced a novel approach to characterizing the sitting postures of office workers, utilizing multiple features, validated questionnaires, and advanced data analysis methods.

Scientific contributions

Publications

Oliosí, M. E., Cepeda, C., Silva, L., Zagalo, D., Probst, P., Pinheiro, A. R., Vilas-Boas, J. P., & Gamboa, H. (2022). Human movement variability analysis in office workers: A review. In *Proceedings of the ICT + WBC + EH 2022* (pp. 147–154). IADIS Press. ISBN: 9789898704405

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Scientific Dissemination

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factors in public administration workers [Poster presentation]. 1st Forum on Innovation in Medicine and Biomedical Engineering: Synergies and Challenges.

Oliosi, E., Júlio, A. C., Silva, L., Probst, P., Vilas-Boas, J. P., Gamboa, H., & Pinheiro, A. R. (2025). Dynamics of neck pain intensity and postural control in office workers: A week-long study of movement variability [Conference abstract]. 11th National Congress of Biomechanics, Sesimbra, Portugal.

Abstract

Sitting is a dominant postural behavior in modern office work, with a substantial proportion of the working day spent seated. Although functionally necessary, prolonged sitting has been associated with an increased risk of chronic musculoskeletal disorders, particularly chronic spinal pain. Characterizing seated postural control may help physiotherapists better understand chronic spinal pain and support the development of preventive and therapeutic interventions. This thesis investigated trunk motor variability during seated work in office workers with and without chronic spinal pain. Postural sway was used as an indicator of postural control and trunk motor adaptation and was quantified using wearable inertial sensors in real-world occupational settings. Trunk movement time series were analyzed using both linear and nonlinear methods, while spinal pain characteristics were assessed using validated self-report questionnaires. The research comprised complementary studies, including a narrative review of movement variability analysis methods, a week-long multimodal data acquisition protocol integrating trunk kinematics and self-reported outcomes in Portuguese Tax Authority workers, and a cross-sectional field study examining real-world trunk postural sway. Comparisons between workers with and without chronic spinal pain and correlational analyses within the pain group were performed. Workers with chronic spinal pain often have alterations in postural sway behavior compared to pain-free workers, reflected in changes in movement variability and postural stability. Higher pain intensity tended to be associated with reduced trunk motor variability, suggesting a more constrained postural control strategy. Temporal analyses indicated that trunk sway patterns varied dynamically across the workday. These studies provide preliminary evidence that postural sway may be altered in office workers with chronic spinal pain.

Resumo

A posição sentada constitui um comportamento postural dominante no trabalho de escritório contemporâneo, ocupando uma parte substancial do dia laboral. Embora funcional, a manutenção prolongada da sedestação associa-se a um risco acrescido de distúrbios musculoesqueléticos crónicos, particularmente raquialgias. A caracterização do controlo postural em sedestação pode contribuir para uma melhor compreensão desta condição e apoiar o desenvolvimento de estratégias preventivas e terapêuticas em fisioterapia. Esta tese investigou a variabilidade motora do tronco durante o trabalho sentado em funcionários de escritório com e sem raquialgia crónica. A oscilação postural foi utilizada como indicador do controlo postural e da adaptação motora do tronco, sendo quantificada através de sensores inerciais vestíveis em contextos reais de trabalho. As séries temporais do movimento do tronco foram analisadas recorrendo a métodos lineares e não lineares, enquanto as características da raquialgia foram avaliadas por meio de questionários validados. A investigação integrou estudos complementares: uma revisão narrativa sobre metodologias de análise da variabilidade do movimento; o desenvolvimento de um protocolo multimodal de recolha de dados ao longo de uma semana, combinando cinemática do tronco e medidas autoavaliadas em funcionários da Autoridade Tributária Portuguesa; e um estudo de campo transversal que avaliou a oscilação postural em condições reais de trabalho. Os funcionários com raquialgia crónica apresentaram alterações específicas a determinadas métricas de oscilação postural, refletidas em modificações da variabilidade do movimento. Observou-se ainda uma tendência para associação entre maior intensidade da dor e menor variabilidade motora, sugerindo estratégias de controlo postural mais restritas. As análises temporais indicaram que os padrões de oscilação postural variaram dinamicamente ao longo do dia laboral. Estes resultados fornecem evidência preliminar de que a oscilação postural do tronco em sedestação pode encontrar-se alterada em trabalhadores de escritório com raquialgia crónica, reforçando a relevância da avaliação da variabilidade do movimento em contextos ocupacionais reais.

Chapter 1

Introduction

The evolution of movement is shaped by both adaptive and non-adaptive forces, optimizing traits for survival while introducing variability (Putnins & Androulakis, 2021). Over evolutionary time, physiological changes at the cellular and molecular levels, reflected in bone and organ systems, illustrate the integration of mechanical and biological adaptations (Torday, 2015). Mechanical forces, particularly gravity, have been central in shaping movement patterns and influencing the form, function, and motion of biological systems (Lu & Chang, 2012). Altered motor control contributes to discomfort and injury, underscoring the importance of understanding the interactions between the body and its environment (Lu & Chang, 2012; Merkle et al., 2020). Motor control has been defined as the scientific study of the natural laws governing these interactions, positioning it within the physical approach to biological movement (Latash, 2017a).

Understanding these processes requires both epidemiological data to identify risk factors and mechanistic insights into how environmental stressors disrupt cellular structures and functions (Chaffin, 2009). These principles are essential for addressing movement patterns in sedentary settings, particularly through injury prevention and ergonomic interventions (Ciccarelli et al., 2013). The central nervous system generates complex motor outputs by combining motor primitives optimized through cost functions such as movement smoothness and efficiency, as demonstrated in kinematic studies of skill acquisition (Daneault et al., 2023; De Lemos Fonseca et al., 2020). Biological systems exhibit hierarchical control of stability, in which task-specific actions are organized by multi-muscle synergies that can be destabilized to facilitate rapid changes, such as preparatory postural sway in a goalkeeper (Latash, 2017). The redundancy of the musculoskeletal system allows multiple strategies to accomplish tasks, and optimal movement variability, a marker of healthy motor control, can be quantified using linear and nonlinear tools, with applications in physiotherapy

(Harbourne & Stergiou, 2009) and ergonomics (Srinivasan & Mathiassen, 2012a; Mathiassen, 2006).

A central question in human movement science is how work influences motor behavior. Work often shapes trajectories to minimize abrupt changes and conserve energy, particularly when sensory information is insufficient for continuous adjustment (Latash, 2017). This influence is evident in office environments, where prolonged sitting illustrates the trade-off between energy efficiency and postural control (represented in Figure 1). With nearly two in five European workers in sedentary jobs and more than half spending prolonged periods at visual display units (Heredia-Rizo et al., 2022; Peereboom, Langen, & Copsey, 2021), prolonged sitting constitutes a growing concern (Demissie et al., 2024).

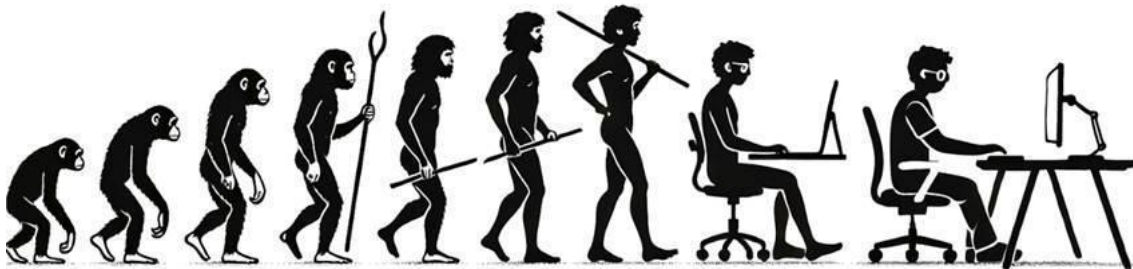


Figure 1. Evolution of human movement and interaction patterns over time, illustrating the shift from free, dynamic activities to predominantly sedentary postures associated with contemporary desk-based work. Source: Author's own illustration.

Chronic spinal pain (CSP), a leading cause of years lived with disability, is influenced by ergonomic inefficiencies such as prolonged sitting, psychological stress, and maladaptive responses to pain (Falla & Hodges, 2017a). These adaptations often include redistribution of muscle activity, altered movement patterns, and reduced force variability (Arvanitidis et al., 2025; Hodges & Tucker, 2011). Individuals with CSP frequently exhibit increased postural sway, reflecting impaired proprioceptive processing and inaccurate estimation of the center of mass, which compromise the compensatory center of pressure adjustments (Arvanitidis et al., 2025; Ruhe et al., 2013; Santos et al., 2010).

Such alterations involve adaptive trunk strategies, including reduced sway velocity (Sung & Lee, 2024).

This thesis investigates movement variability and postural sway in office workers to advance understanding of CSP and inform prevention and management strategies. Chapter 2 provides a state-of-the-art of CSP, exposure assessment methods, and postural movement reasoning. Chapter 3 outlines the methodological considerations, including the rationale for decisions on instrumentation, digital and self-reported outcomes, data analysis, and sitting postural control assessment. Chapter 4 presents Study I, which is a narrative review of human movement variability in office workers. Chapter 5 describes Study II, which introduces a week-long, multimodal data collection protocol that uses wearable sensors and self-reported measures to capture occupational risk factors. Chapters 6 and 7 present the results of the empirical studies. Chapter 6 (Study III) examines real-time variability and complexity in sitting patterns by comparing workers with and without CSP. Chapter 7 (Study IV) investigates postural control and its association with pain intensity in office workers with CSP. Chapter 8 discusses the overall findings and their implications for ergonomics, occupational health, physiotherapy practice, and methodological considerations. Chapter 9 summarizes the main conclusions and identifies directions for future research.

Objectives

The general aim of this thesis was to investigate whether identifiable changes in movement variability occur in office workers with CSP. Specifically, the research sought to quantify and characterize trunk motor variability during occupational tasks, particularly in seated postures, through the use of wearable inertial sensors and advanced analytical approaches.

1. Identify suitable methods for assessing motor variability in occupational contexts, with emphasis on high-risk groups such as office workers.

2. Quantify trunk motor variability in workers with and without CSP during seated tasks, using sway-related metrics such as sway path length and velocity.
3. Assess spinal pain prevalence and characteristics (neck, thoracic, and low back pain) among computer-using office workers, integrating validated questionnaires with sensor-based data.
4. Examine associations between trunk motor variability and clinical outcomes, such as pain intensity, using both linear and nonlinear analytical methods.

Through these objectives, the thesis aims to advance real-time postural data acquisition, integrate novel approaches for variability analysis, and contribute to the development of tools for chronic pain management and occupational risk assessment.

Chapter 2

State-of-the-art

Spinal pain

The human spine is a robust and complex structure. Composed of seven cervical, twelve thoracic, five lumbar, five fused sacral vertebrae, and five coccygeal bones, it forms the vertebral column (Devereaux, 2007; Giron, 2009). The spine provides essential support and mobility, enabling a wide range of movements, including flexion, extension, lateral inclination, and axial rotation, through its 26 degrees of freedom (Calais-Germain, 2006). The spine also houses the spinal cord and nerve roots, crucial for sensory and motor functions. Stability and alignment of the trunk are maintained by layered (poly)articular muscles that facilitate postural control and dynamic movements, even under varied loads (Calais-Germain, 2006). Movement occurs across three planes, namely, sagittal, frontal, and transverse, with mobility differing by region. The cervical and lumbar regions offer greater flexibility compared to the rib-restricted thoracic region (Neumann, 2017).

The muscles of the trunk work together to control posture, stabilize the axial skeleton and protect vital organs. The trapezius muscle, for example, spans the shoulder girdle and attaches to the cervical and thoracic vertebrae, playing a critical role in maintaining upper body posture and stability. Dysfunction in this muscle, whether due to strain, fatigue or injury, can impair movements of the upper extremities and postural control, resulting in discomfort and inefficient motion patterns (Neumann, 2017). Conversely, discomfort may be an early indication of pain related to the biomechanical load placed on the musculoskeletal system (Søndergaard et al., 2010). Imbalances in this system can lead to compensatory strategies that increase the risk of injury (Devereaux, 2007; Neumann, 2017).

The rising prevalence of MSDs globally can be attributed to several key factors, including population growth and the aging workforce, which have increased the

number of individuals affected by these conditions. Additionally, disability associated with musculoskeletal (MSK) conditions has been on the rise and is expected to continue increasing in the coming decades (Bonfiglioli et al., 2022; Wainwright et al., 2022).

MSDs encompass a wide range of diseases affecting bones, joints, ligaments, muscles, and tendons. These disorders can impact various body regions. The main reported are neck and lower back, leading to pain experiences and disability (Bonfiglioli et al., 2022). According to the most recent classification from the International Association for the Study of Pain and the 11th Revision of the International Classification of Diseases, pain is considered a chronic disease (not a symptom) when it becomes recurrent or persists for three months or more (Treede et al., 2019). Data from 2019 report that MSK conditions affected 1.71 billion people globally (Cieza et al., 2020). In the adult population, 20-30% of the subjects (Smart, 2023). In Portugal, 37% of adults were affected, with a higher prevalence in working populations (Azevedo et al., 2012).

Neck Pain

Specifically, neck pain (NP) is increasingly recognized as a prevalent issue among various populations, particularly office workers. The annual incidence of neck disorders in these workers ranges from 17% to 21%, with new-onset NP reported by 34% to 49% of individuals within a year (Chen et al., 2018). The Global Burden of Diseases, Injuries, and Risk Factors Study (GBD), from 2021, projected that NP will affect 203 million people by 2020, with a higher age-standardized prevalence in females than males. This number is expected to rise by 32.5%, reaching 269 million by 2050 (Wu et al., 2024)(GBD 2021 Neck Pain Collaborators, 2024). Jun et al. (2021) reported a one-year incidence of nonspecific NP among office workers of 1.93 (95% CI [1.41, 2.64]) per 100 person-months, highlighting the significant burden of NP in this population across two distinct cultural settings (Jun et al., 2021).

NP not only impacts individual well-being but also has significant repercussions on workplace productivity. A study in Spain suggests that 12.3% of workers missed at least seven days of work over the year due to NP, while a Greek study found that 8.6% of working individuals (aged 15-65 years) missed an average of 4.6 days of work in one month due to this condition (Wu et al., 2023). Furthermore, the biopsychosocial model suggests that NP (as well as thoracic and/or lower back pain) is influenced by a combination of factors. Significant examples of contributors include biomechanical factors, high workloads, and psychological stress (Wu et al., 2023; Briggs, Smith, et al., 2009). Protective factors, on the other hand, include greater cervical mobility, muscle endurance, and higher levels of physical activity (Jun et al., 2021).

Thoracic Spinal pain

A review indicates that spinal pain is highly prevalent, with considerable variation depending on the spinal region and the time frame assessed. Among the general adult population, 12-month and lifetime prevalence estimates for low back pain range from 22-65% and 11-84%, respectively. For neck pain, these estimates are 16.7-75.1% and 0.2-71%, respectively. Thoracic spinal pain, in contrast, shows a 12-month prevalence of 3.5-34.8% and a lifetime prevalence of 15.6-19.5% (Briggs, Bragge, et al., 2009; Briggs, Smith, et al., 2009).

Despite its notable prevalence, thoracic spinal pain remains relatively understudied compared to other spinal regions, with many epidemiological studies combining spinal pain outcomes and obscuring thoracic-specific risk factors. Evidence suggests that individual, physical, and psychosocial work-related factors contribute to thoracic pain, consistent with the biopsychosocial model of musculoskeletal disorders. However, limitations in capturing these exposures underscore the need for targeted research across occupational groups. Prospective studies are particularly warranted to clarify risk factors and inform effective prevention and management strategies for this condition (Briggs, Bragge, et al., 2009).

Lower Back Pain

Lower Back Pain (LBP) is a leading contributor to disability-adjusted life years (DALYs) globally, with its prevalence increasing with age. According to the GBD 2019 study, LBP ranks as the 7th leading cause of DALYs in individuals aged 10-24, 4th in those aged 25-49, and 5th in those aged 50-74. Prevalence ranges from 1%-6% in children, 18% in adolescents, and 28%-42% in individuals aged 40-69 (Knezevic et al., 2021).

Occupational exposures significantly contribute to LBP, accounting for 37% of cases globally, and resulting in 818,000 annual DALYs lost (Punnett et al., 2005). Among office workers, the one-month prevalence of LBP is 23.2% (Hoy et al., 2014). Beyond personal suffering, LBP imposes a heavy societal burden through healthcare costs, absenteeism, and presenteeism, with chronic LBP patients incurring double the healthcare costs of their healthy counterparts (Knezevic et al., 2021; Hong et al., 2013; Schofield et al., 2012).

LBP arises from a complex interplay of nociceptive, neuropathic, and nociplastic pain, often with nonspecific origins. Stressors to lumbar spine structures, such as discs, soft tissues, and joints, contribute to its development. However, specific causes like vertebral fractures or nerve root compression account for only 5%-15% of cases, while the majority (85%-95%) are classified as nonspecific LBP. Emerging evidence suggests that lumbar muscles and fascia may play a role in nonspecific LBP, but their exact contribution remains unclear (Knezevic et al., 2021; La Porta & Tappe-Theodor, 2020).

Diagnostic challenges persist due to multifactorial causes and the limited specificity of imaging. The biopsychosocial model highlights dynamic interactions between social, psychological, and biological factors in LBP's onset and progression (Knezevic et al., 2021). LBP is often related to fearful patients avoiding painful movements or activities, which sets them in a vicious cycle of anxiety, avoidance, disability, and worsening pain (Meinke et al., 2022; Knezevic et al., 2021; Martinez-Calderon et al., 2019).

What drives Chronic Spinal Pain?

Chronic spinal pain (CSP) is a multifactorial disease influenced by a complex interplay of causes and risk factors that influence its pathogenesis, as well as biological, psychological, and social factors (Melzack, 2001), as mentioned above. The biopsychosocial framework is essential for understanding its etiology, progression, and management.

Considerations about the Biopsychosocial Model

The *Biopsychosocial Model*, introduced by George Engel in 1977 (Engel, 1977), was developed to address the limitations of the traditional biomedical model by incorporating psychological and social dimensions into understanding health and disease (Engel, 1981). In 2027, this model will mark its 50th anniversary, highlighting its relevance in biomedical and scientific discourse.

The biopsychosocial model of pain offers a comprehensive framework for understanding, assessing, and managing pain by integrating biological, psychological, and social factors (Van Hecke et al., 2013). As a conceptual rather than mathematical model, it is applicable to both acute and chronic pain, emphasizing the dynamic interplay between biological factors (e.g., genetics, age), psychological factors (e.g., beliefs, behaviors), and social determinants (e.g., workplace conditions, cultural context) (Nicholas, 2022). While immutable factors like age and genetics contribute to pain, modifiable factors such as maladaptive behaviors, fear-avoidance beliefs, and ergonomic risks offer opportunities for targeted interventions (Caneiro et al., 2021; Fitzcharles et al., 2021). However, the application of the biopsychosocial model in physiotherapy research and practice has been criticized for its narrow focus on biological and cognitive-behavioral aspects, often overlooking broader factors such as social and cultural (Mescouto et al., 2022).

Biological Factors

Biological contributors to spinal pain can play a role in the development of MSDs. Biological mechanisms can be divided into two main groups: peripheral

and central, with treatment approaches tailored accordingly. Acute pain is primarily linked to peripheral mechanisms, particularly inflammatory processes, while chronic pain involves factors such as genetic predisposition, age, anthropometry, sex, sleep, hormones, and endogenous opioid systems. Biological processes like homeostasis, resilience, allostasis, drug-induced hyperalgesia, synaptic plasticity, endogenous regulation, centralization, and sensitization further influence these effects (Bonfiglioli et al., 2022; Nicholas, 2022; Knezevic et al., 2021).

An example in which biological factors, such as physical features, are the primary drivers maintaining a patient's chronic pain disorder, includes suboptimal movement and altered patterns of muscle activation (Falla & Hodges, 2017a). In addition, obesity can cause or exacerbate pain via multiple mechanisms, such as mechanically, in terms of stress on the MSK system, as well as chemically, via inflammatory cytokines (Zajacova et al., 2021). Notably, structural causes, including vertebral fractures, disc degeneration, and nerve root compression, account for a minority of cases, while most are “nonspecific”, with muscles and fascia increasingly recognized as significant contributors (La Porta & Tappe-Theodor, 2020).

Psychological Factors

Over time, psychosocial risks have assumed increasing relevance in the study of MSD determinants, though the mechanisms remain under investigation, and no specific psychosocial risk factor has yet been definitively linked to particular MSDs (Bonfiglioli et al., 2022).

Psychological factors are hypothesized to play a critical role in the transition from acute to chronic pain, and may predict the development of chronic pain, with resilience and protective factors counterbalancing psychosocial vulnerabilities. Psychosocial stressors, such as poor sleep quality and perceived stress, are strongly associated with the development and chronicity of spinal pain (Van Bogaert et al., 2024; Chimenti et al., 2018). Mood disturbances (e.g., anxiety, depression), maladaptive thought processes (e.g.,

catastrophizing, fear-avoidance), and limited adaptive beliefs (e.g., low self-efficacy, lack of acceptance), along with behaviors like excessive rest or avoidance, significantly influence the onset, persistence, and disability associated with spinal pain (Kazeminasab et al., 2022; Nicholas, 2022; Chimenti et al., 2018; Falla & Hodges, 2017). These effects are further modulated by environmental contexts (Martinez-Calderon et al., 2019). Moreover, spinal pain often co-occurs with mental health conditions, sharing neurobiological mechanisms that involve brain regions such as the insular cortex and anterior cingulate (De La Rosa et al., 2023).

Social and Occupational Factors

A substantial portion of our lives is spent at work, making occupational and social factors pivotal in understanding the development of CSP. Prolonged sitting, common in office environments, is a notable risk factor, exacerbated by limited job control and dissatisfaction, both of which are strongly associated with higher rates of spinal pain and psychological distress (Skillgate et al., 2021).

Social determinants, such as socioeconomic status, workplace ergonomics, and job satisfaction, play a central role in the severity and persistence of spinal pain (Skillgate et al., 2021; Wainwright et al., 2022). Stressful work environments with high demands and low support intensify pain perception (Falla & Hodges, 2017). Moreover, workplace dissatisfaction and stress can create a detrimental feedback loop, leading to increased pain and disability. Socioeconomic disparities further contribute to inequities in pain management by limiting access to healthcare and ergonomic workplace solutions (Wainwright et al., 2022).

Ergonomic risks such as prolonged postures, repetitive movements, and sustained force exertion are key contributors to MSDs (Hulshof et al., 2021; Ciccarelli et al., 2013; Mathiassen, 2006). Prolonged sitting increases spinal loading and risk of chronic pain (Liu et al., 2022), with NIRS studies showing impaired muscle oxygenation even during low-intensity isometric contractions (McGill et al., 2000). Sedentary behavior and obesity further heighten biomechanical stress and susceptibility to spinal pain (Bonfiglioli et al., 2022;

Knezevic et al., 2021). For LBP, prolonged sitting is associated with an odds ratio of 1.42 (Baradaran Mahdavi et al., 2021).

Ergonomic posture assessment

Prolonged sitting is a common feature of modern lifestyles and is functional, but it has also been linked to spinal pain due to sedentary behavior. It is crucial to understand sitting patterns, as workers spend a significant amount of time performing sedentary activities. However, since sitting is a dynamic action, the "optimal" sitting posture is difficult to maintain in practice. Recent research challenges the concept of an "optimal" sitting posture, emphasizing the importance of posture variation and movement to mitigate spinal pain and promote MSK homeostasis (Tahernejad et al., 2022; Slater et al., 2019; Hey et al., 2017). Building on this research, Mathiassen and his colleagues (Ciccarelli et al., 2013; Srinivasan & Mathiassen, 2012a; Mathiassen, 2006) have highlighted the biomechanical risks of prolonged, monotonous postures and tasks, such as computerized office work. These risks include increased spinal loading and reduced muscle activation.

Due to the diversity of methods, characterizing workplace motor features is a critical consideration in exposure assessment, an aspect addressed by the main methods outlined in the following subsection.

Exposure Assessment Methods

There is a panoply of methods for assessing exposure outcomes in occupational health, particularly in the MSK field (Figure 2). These range from subjective self-reports to highly instrumented systems, encompassing both bulky laboratory setups and lightweight wearable technologies. A significant advancement in this area is the integration of instrumented kinematic methods, which enable the objective, high-resolution quantification of human posture and movement (Anacleto Filho et al., 2024; Donisi et al., 2022; Gonçalves et al., 2022; Odesola et al., 2024). These systems can be used in laboratories or in the field. They capture the kinematics of workers directly, offering temporal and

spatial precision that surpasses and complements traditional approaches (Lim & D'Souza, 2020).

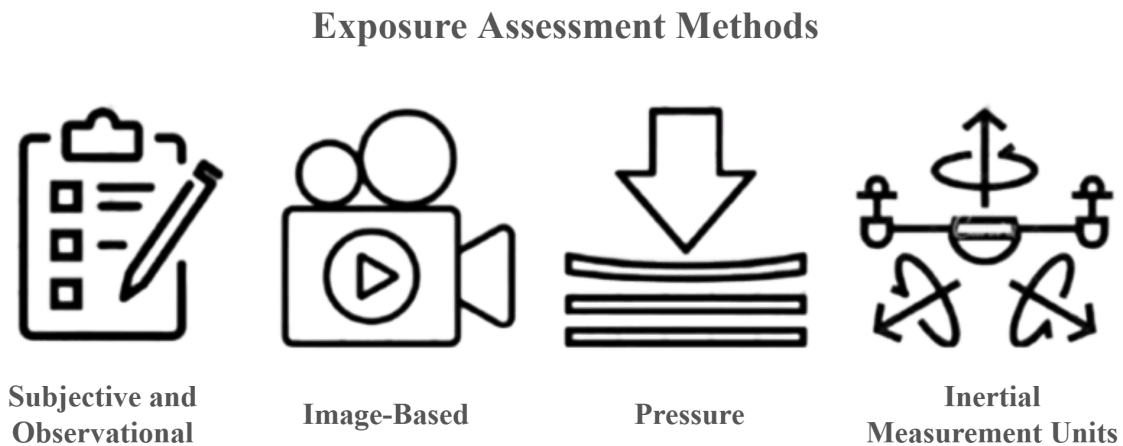


Figure 2. Exposure assessment methods and main categories. Source: Author's own illustration.

Subjective and Observational Methods

Self-reports: Workers' subjective self-reports of their exposure tend to be less accurate and reliable, often due to underestimation and/or overestimating risks (Yang et al., 2024). Even so, these methods allow for the acquisition of current and retrospective exposure data, enabling the assessment of multimodal workplace exposures through (semi)structured interviews, questionnaires, and scales. They are commonly low-cost and scalable, since they do not require any technical equipment, making them suitable for large sample sizes (e.g., questionnaires, interviews). However, they suffer from recall bias and limited temporal resolution (Bonfiglioli et al., 2022; Dane et al., 2002).

Observational tools: Tools such as the Rapid Office Strain Assessment (ROSA) (Sonne et al., 2012), the Rapid Upper Limb Assessment (RULA) (McAtamney & Nigel Corlett, 1993), and the Ovako Working Posture Assessment System (OWAS) (Gómez-Galán et al., 2017) are generally reliable for accurately classifying exposure statuses, particularly those that employ a structured and repeatable approach. These scores reflect changes in risk factors after an ergonomic intervention in an occupational environment.

Consequently, tools like these are used to identify and control risk factors among office workers before and after interventions (De Barros et al., 2022). However, the influence of professional experience and subjective judgment can limit their effectiveness. Additionally, on-site observations are often time-intensive, posing practical challenges to implementation (Bonfiglioli et al., 2022; Gonçalves et al., 2022).

Image-Based Sensors

Optical MoCap Systems: Due to their high spatial and temporal resolution, optical motion capture (MoCap) systems are widely regarded as the gold standard for kinetic and kinematic analysis. These systems use multiple high-speed infrared cameras to track reflective markers placed on anatomical landmarks. This enables highly accurate 3D reconstruction of human movement (Nadeem et al., 2024). However, this method requires the placement of 40-90 reflective markers (or more) on the body of the research subject, depending on the study setup (Ghattas & Jarvis, 2024). Despite their precision, MoCap systems are primarily limited to controlled laboratory settings due to their high cost, complex setup, and limited portability.

Markerless 3D MoCap Systems: Recent advances in computer vision have enabled markerless 3D pose estimation using RGB or RGB-D cameras in combination with deep learning algorithms. A notable example is the ROMP (Monocular, One-stage Regression of Multiple 3D People) algorithm, which allows for accurate 3D human pose estimation from a single RGB camera, even in multi-person and occluded scenarios. When validated against MoCap data, ROMP demonstrated mean joint angle errors of 9.4° and posture classification accuracies of 83.8% (RULA) and 90.7% (OWAS) across 12 ergonomic tasks (Yuan & Zhou, 2023).

RGB and RGB-D Cameras: RGB and RGB-D cameras are increasingly integrated into ergonomic posture assessment systems due to their accessibility, affordability, and suitability for real-world environments. RGB cameras, including smartphone and action cameras such as GoPros, offer

high-resolution imaging and real-time video capture, making them ideal for mobile or field-based applications (Yang et al., 2024; Lee & Lee, 2022). RGB-D cameras, which combine color and depth sensing, enable more robust 3D posture analysis and skeletal tracking, particularly in environments with partial occlusions. Devices such as Microsoft Kinect and ASUS Xtion have been applied across occupational domains, including office ergonomics (Abobakr et al., 2019; Yang et al., 2024; Diego-Mas et al., 2017). However, these systems are sensitive to environmental conditions such as lighting and often require more computational resources, which can limit their usability in real-world scenarios.

Pressure Sensors

Textile-Based Pressure: Textile pressure sensors are designed to capture pressure distribution across contact surfaces such as seat cushions or backrests. Their flexibility, durable, low power consumption, and ability to integrate into soft furnishings make them especially suitable for continuous, non-intrusive posture monitoring in office settings. However, they generally record pressure at discrete points and may not capture full-body load distribution. These sensors are typically moderately priced and relatively easy to implement in real-world environments (Nadeem et al., 2024; Odesola et al., 2024).

Load Cells: These devices provide high-precision measurements of force or weight distribution. They are often embedded in chairs or footrests to monitor postural loading. Load cell sensors convert applied mechanical forces into digital signals that microcontrollers can read. Although they are bulkier and less portable than textile sensors, load cells deliver highly accurate and reliable data. This makes them useful for controlled ergonomic assessments in office environments with fixed installations. Depending on sensor specifications, their cost ranges from moderate to high (Nadeem et al., 2024; Odesola et al., 2024).

Force Platforms: Force platforms and pressure-sensitive mats are used to capture kinetic data such as ground reaction forces, contact pressure

distribution and CoP. These systems typically rely on strain gauge technology or piezoelectric sensors to measure multi-directional forces and moments with high precision. They provide high-fidelity load distribution profiles but are often constrained by high cost, fixed setup, and limited portability. Therefore, their use in typical office environments is rare, but they remain indispensable for comprehensive biomechanical analysis, particularly in validation studies or laboratory settings (Nadeem et al., 2024; Arippa et al., 2022; Madeleine et al., 2021a; Roh et al., 2019; Akkarakittichoke & Janwantanakul, 2017).

Inertial Measurement Unit Sensors

Inertial measurement units (IMUs) represent the predominant sensing technology underlying the majority of wearable systems (Simpson et al., 2019). While alternative technologies, such as strain gauges, flex sensors, fiber-optic goniometers, and inductive sensors, have been explored for posture monitoring, these remain mostly needing clinical validation (Simpson et al., 2019). Given their versatility, maturity, and integration into commercial and research-grade wearable systems, IMUs are the focus of the present thesis.

Generally, IMUs are characterized as compact, self-contained sensors that leverage microelectro-mechanical systems technology to quantitatively assess the orientation and motion of a body or body segment over time (Richards, 2018). These devices typically incorporate a combination of accelerometers (ACC), gyroscopes (GYR), and magnetometers (MAG), thereby facilitating the measurement of linear acceleration, angular velocity, and magnetic field orientation in a three-dimensional (3D) space. A standard IMU integrates three orthogonal units of each sensor type to capture movement along the X (pitch), Y (roll), and Z (yaw) axes (Donisi et al., 2022; Simpson et al., 2019).

Sensor components

ACCs are devices that measure translational acceleration, including gravitational and movement-induced components, based on Newton's second law. In triaxial configuration, these sensors detect linear acceleration in 3D space, thereby enabling estimations of motion and tilt. The acceleration is

deduced from the displacement of a proof mass relative to the sensor casing (Shi et al., 2021; Collin et al., 2019).

GYRs measure angular velocity by leveraging the Coriolis effect. Internal vibrating masses generate forces proportional to the rate of rotation, which can then be integrated over time to estimate angular displacement (Schall et al., 2022; Collin et al., 2019; Richards, 2018). Triaxial gyroscopes allow tracking of rotations across roll, pitch, and yaw (Euler angles).

MAG measures the amplitude and direction of the Earth’s magnetic field in 3D space. Functioning conceptually as digital compasses, they support orientation correction and drift mitigation in dynamic environments (Schall et al., 2022; Richards, 2018).

Measurements from ACC, GYR, and MAG are often fused to enhance the accuracy and robustness of kinematic assessments. Notably, the MAG complements the GYR by providing absolute heading data, while the ACC contributes to tilt correction. This sensor fusion approach exploits the strengths of each sensor to compensate for their respective limitations (Schall et al., 2022).

IMUs commonly employ sensor fusion techniques, such as the rotation vector (RV), to represent orientation more accurately. The RV is a quaternion-based mathematical representation that avoids the singularities associated with Euler angles and enables smooth tracking of orientation changes during complex movements (Shi et al., 2021; Richards, 2018). The fusion of ACC, GYR, and MAG data through filtering algorithms (e.g., Kalman or complementary filters) allows for stable and drift-minimized orientation estimation. Table 1 summarizes the sensor components and concepts used in IMU-based systems.

Table 1. Overview of components and concepts in inertial sensors

Aspect	Description
ACC	Measures linear acceleration in 3D space (X, Y, Z axes). Detects motion, tilt, and gravity components. Units: m/s ² .

GYR	Measures angular velocity (rate of rotation around X, Y, Z axes). Detects rotational motion. Units: rad/s or °/s.
MAG	Measures the Earth's magnetic field in 3D space. Helps determine orientation relative to magnetic north.
RV	Quaternion-based mathematical representation of 3D orientation, combining axis (r_x , r_y , r_z) and rotation angle (θ).

Applications and Validity in Biomechanics and Ergonomics

IMUs have emerged as a powerful tool for advancing research on spine movement, particularly in contexts such as rehabilitation, assessment of MSK disorders, ergonomics, workplace safety, and monitoring of neurodegenerative diseases. Their portability and ability to capture real-time motion data make them suitable for use in both clinical and field settings (Jamshed et al., 2024; Donisi et al., 2022; Baker et al., 2021).

Occupational health researchers have increasingly turned to wearable IMUs to monitor postural risk factors in workplace environments. Commercially available systems offer either proprietary or open-source software and support applications ranging from quantifying joint angles and movement velocity to classifying manual handling tasks and tracking fatigue-induced kinematic changes. IMUs are commonly used, for example, to assess trunk flexion, shoulder elevation, and the smoothness of motion (jerk analysis). These factors are relevant to injury risk and ergonomic intervention planning (Schall et al., 2022).

Importantly, IMUs have demonstrated strong validity and reliability across biomechanical applications. For instance, in measuring lumbar spine movement, IMUs have shown less than 2.4° deviation from gold-standard motion capture systems, with intraclass correlation coefficients (ICC) exceeding 0.84 during dynamic tasks (McClintock et al., 2024). Furthermore, IMUs can effectively distinguish between healthy and pathological populations, including individuals with Parkinson's disease, multiple sclerosis, and CSP (Jamshed et al., 2024; Sheeran et al., 2024). In occupational contexts, IMU-derived

assessments have shown high agreement with those performed by trained clinicians (ICC = 0.84-0.92) (Tanthuwapathom et al., 2025).

Limitations and Considerations

Despite their many strengths, IMUs have limitations. For example, sensor drift, which can be caused by temperature fluctuations, environmental factors, or cumulative integration error, can affect long-term accuracy. Additionally, external magnetic disturbances can bias magnetometer readings. However, modern IMUs incorporate hardware improvements, such as temperature compensation and environmental sealing, as well as signal-processing strategies, such as noise filtering and adaptive fusion algorithms, to mitigate these issues (Richards, 2018). Furthermore, although wearable sensors provide objective, continuous acquisition of biomechanical data, their practical implementation may be limited by device intrusiveness, cost, and the requirement of technical expertise for data interpretation (Yang et al., 2024).

Nevertheless, as IMUs continue to evolve, their integration into wearable systems for spine assessments is expected to increase. When combined with artificial intelligence (AI) algorithms for automated data analysis, IMUs have the potential to advance precision diagnostics and personalized interventions in clinical and workplace environments (Prisco et al., 2025; Helmstetter & Matthiesen, 2023; Bonfiglioli et al., 2022; Donisi et al., 2022; Ghislieri et al., 2019).

Postural control

Posture

Gravity influences life, and posture is maintained through an efficient neuro-MSK system that stabilizes the body against it. This concept, recognized for years, highlights the integration of sensory and motor areas that evolved over millions of years to regulate body orientation in a gravitational field. Antigravity support in humans comes from *passive* bone-on-bone forces, stretched ligaments and muscles, and *active* contractions. Maintaining postural

tone involves complex neural circuitry and cellular processes that generate muscle force and stiffness. Skeletal muscle structure and function enable various activities, from rapid movements to maintaining body orientation against gravity. Different types of muscle fibers allow a variety of muscle contractions and energy production (Ivanenko & Gurfinkel, 2018).

Postural function is closely linked to the interaction between muscle tension. Though postural activity is low, it involves subtle muscle activations in the neck, trunk, and limbs that contribute to resting tension and tone. It requires minimal energy and mainly employs slow-twitch muscle fibers, known for their fatigue resistance. Notably, an individual's postural attitude is influenced by their morphology and low-level muscle activity, which can be impacted by several pathological conditions (Ivanenko & Gurfinkel, 2018).

The system of postural control must manage two tasks simultaneously. One establishes a distribution of tonic muscle activity (“posture”), while the other generates reactive postural adjustments to minimize the effects of internal or external perturbations (“equilibrium”) (Santos et al., 2010). The relationship between posture and movement was described by Sherrington (1906), who stated, “*posture follows movement like a shadow.*” This concept was further refined by Ivanenko and Gurfinkel (2018), who emphasized that posture “*even anticipates movement,*” highlighting the dynamic and anticipatory nature of postural control (Ivanenko & Gurfinkel, 2018).

Postural Sway

Postural sway results from the interaction between the center of mass (CoM), the average position of the body's mass, and the center of pressure (CoP), the point where resultant vertical forces act on the support surface. Balance is maintained when the CoM's vertical projection stays within the base of support, with the CoP dynamically adjusting to counteract deviations. The CoP reflects the combined outcome of the postural control system and gravitational forces and differs from the center of gravity (CoG), which represents the global body

position. In contrast with the CoG, the CoP includes dynamic components associated with the body's acceleration. At sway frequencies below 0.1 Hz, the CoP approximates the horizontal CoG location, or "gravity line," and reliably reflects body sway in these low-frequency ranges. This dynamic CoM-CoP relationship is critical for balance control, as the CoP stabilizes the CoM through neuromuscular feedback, integrating sensory inputs and generating adaptive motor responses (Barfi et al., 2025; Vette et al., 2010; Duarte & Zatsiorsky, 2000).

Even during the maintenance of an apparently "static posture," postural sway is inherently present, characterized by continuous oscillations in both the medial-lateral (M-L) and anterior-posterior (A-P) planes. The CoP of the merged force is frequently utilized to study postural sway (Richards, 2018). Thus, postural sway serves as a critical metric for partially evaluating balance and postural control, with increased sway often indicating impaired stability. Under stable conditions, body segment oscillations typically range within 1-2° of joint motion, while CoP oscillations are about 1-2 cm (Ivanenko & Gurfinkel, 2018). The CoP is defined by X and Y coordinates related to the origin of the sensor (Richards, 2018).

Quantitative posturography typically relies on gold-standard tools, such as force platforms and 3D motion capture systems, which deliver highly accurate data. However, these tools are often limited to laboratory settings due to their high cost, difficulty of transportation, and need for specialized operators. This makes them impractical for clinical or occupational environments (Helmstetter & Matthiesen, 2023; Rashid et al., 2021; Dewan et al., 2019; Ghislieri et al., 2019).

In contrast, IMUs integrated into devices like smartphones offer a small, portable, cost-effective, and user-friendly alternative for assessing postural sway in real-world environments (as mentioned in the previous section). These sensors have been validated against gold-standard systems and reliably measure postural sway under both "static" and dynamic conditions. IMUs enable the measurement of postural sway in diverse settings, tailored to the

specific population under investigation (Helmstetter & Matthiesen, 2023; Lyu et al., 2022; Baker et al., 2021; Rashid et al., 2021; Zhou et al., 2021). For instance, smartphone-based applications have demonstrated excellent reliability and sensitivity in quantifying CoP displacement, sway area, and other postural stability metrics, making them well-suited for remote and field data acquisition in clinical and occupational settings (Doshi et al., 2023; Promsri et al., 2023; Zhou et al., 2021; Dewan et al., 2019; Polechoński et al., 2019).

IMUs capture data on three axes, providing valuable 3D insights into subtle changes in postural sway (Baker et al., 2021). Postural sway is usually measured using CoP metrics, such as displacement (which indicates sway amplitude), velocity (which reflects movement speed and postural responsiveness), acceleration (which measures the rate of change in CoP movement) and sway area (which assesses overall stability). Frequency-domain measures, such as spectral analysis, can differentiate between slow, feedback-driven adjustments and rapid, feed-forward corrections (i.e. high-frequency components). Additionally, advanced measures like sample entropy (SaEn), multiscale entropy (MSE), and fractal analysis (e.g., Hurst exponent) assess the complexity and adaptability of CoP time series. Higher entropy and fractal values indicate greater irregularity and adaptability, while lower values suggest rigidity and reduced postural control efficiency (Promsri et al., 2023; Zhou et al., 2021).

Moving Differently in Pain

As Hodges and Tucker (2011) observed, “people move differently in pain,” although the underlying mechanisms remain under investigation (Hodges & Tucker, 2011). Motor adaptations to pain occur at multiple levels, from single motoneurons to whole-muscle coordination, leading to observable differences in movement patterns between individuals with and without pain. Movement variability, defined as the normal variations in motor performance during repetitive tasks, has become an area of interest for researchers and clinicians (Harbourne & Stergiou, 2009; Srinivasan & Mathiassen, 2012a; Heiderscheit, 2000). While often used interchangeably, variability and complexity are distinct

concepts: variability describes the distribution of a signal (e.g., via statistical variance), whereas complexity captures the temporal organization and interdependence within a signal (Quixadá, 2020).

Reduced movement variability has been linked to discomfort and fatigue, as well as an elevated risk of MSDs, particularly among office workers who maintain prolonged postures with limited motor variation (Arippa et al., 2022; Bontrup et al., 2019). Nonlinear analysis methods such as SampEn reveal that reduced variability and complexity correlate with increased discomfort (Karimi et al., 2021; Søndergaard et al., 2010; Hermann, 2005).

CSP is associated with significant neuromuscular adaptations, including altered motor control and movement variability. Individuals with spinal pain exhibit heterogeneous responses, such as distinct sitting postures (e.g., flexed or extended spine) and variations in muscle activation patterns, which may serve as protective mechanisms, but can lead to maladaptive movement patterns over time (Falla & Hodges, 2017). For example, chronic LBP patients demonstrate reduced movement variability during daily tasks and impaired anticipatory postural adjustments, indicating persistent alterations in neural pathways and somatosensory processing (Jacobs et al., 2009). More, a study by Ringheim et al. (2019) found that chronic LBP patients exhibited lower maximal muscle activation during sustained sitting, with significant post-sitting reductions, highlighting the impact of pain on neuromuscular function (Ringheim et al., 2019a).

Postural control impairments in spinal pain are well-documented, with evidence demonstrating increased CoP displacement, reduced stability, and altered neuromuscular coordination. For instance, Park et al. (2023) performed a meta-analysis demonstrating medium-to-large effect sizes for increased body sway in chronic LBP, especially when visual input is reduced. These findings emphasize sensory integration deficits (Park et al., 2023). Similarly, Van Den Hoorn et al. (2022) found that acute LBP significantly increases CoP displacement during unstable sitting (Van Den Hoorn et al., 2022). Cognitive dual-tasks also influence postural control. For example, patients with LBP

exhibit reduced sway and increased trunk stiffness to maintain stability under cognitive load (Van Daele et al., 2010). A systematic review by Alshehri et al. (2024) highlighted impaired trunk postural control in LBP, with increased linear measures (e.g., RMS displacement, range of motion) and longer stabilization times in nonlinear measures (e.g., critical point coordinates) (Alshehri et al., 2024).

Both nonspecific NP and whiplash-associated disorders are linked to altered postural control. Ruhe et al. (2011) conducted a systematic review that revealed increased CoP excursions in individuals with non-specific NP. Both groups exhibited greater postural stability, characterized by increased sway in the A-P direction. This was correlated with the presence of pain and proprioceptive impairment (Ruhe et al., 2011). Similarly, Silva and Cruz (2012) found that patients with NP or WAD had poorer balance than healthy controls (Silva et al., 2006).

These findings highlight the multifaceted nature of postural control impairments, where both linear measures and nonlinear measures provide valuable insights into motor features.

Sitting Posture (Sway)

While postural sway is extensively studied in standing (Koch & Hänsel, 2019; Park et al., 2023), its application to sitting is less explored. Sitting eliminates lower limb contributions, allowing precise evaluation of trunk control. Studies using unstable sitting paradigms reveal that individuals with LBP exhibit distinct postural strategies, such as reduced sway frequency and increased stiffness, compared to healthy controls (Alshehri et al., 2024; Vette et al., 2010). Sitting is an active, dynamic phenomenon, involving regular spinal movements rather than a static state (Akkarakittichoke & Janwantanakul, 2017). Recent research emphasizes the importance of natural postures, with findings showing that natural sitting involves forward sagittal shifts, increased cervical lordosis, and reduced lumbar lordosis, reflecting energy conservation mechanisms (Hey et al., 2017).

Arippa et al. (2022) analyzed office workers during prolonged sitting and found that those who stood (breakers) maintained consistent trunk sway metrics (path, velocity, and area) and reported lower discomfort than those who remained seated (prolongers) (Arippa et al., 2022). Prolongers exhibited reduced sway variability over time, which correlated with increased discomfort. This finding underscores the biomechanical benefits of periodic standing breaks in mitigating musculoskeletal strain. These findings align with the broader understanding that spinal postural variation is crucial for adapting to task demands and reducing biomechanical workload (Mingels et al., 2021c; Mathiassen, 2006).

Implications for Physiotherapy and Occupational Health

Postural sway assessment is increasingly being applied as a practical tool for physiotherapy and occupational health. In clinical settings, it supports the identification of balance problems and provides an objective way to monitor rehabilitation progress (Asgari et al., 2022; Shahvarpour et al., 2018; Sung & Lee, 2024). In the workplace, it can help understand physical and cognitive demands, fatigue, and environmental stressors that influence stability and safety, which is particularly important for workers with CSP (Arippa et al., 2022; Shanbehzadeh et al., 2022; Leban et al., 2017; Donker et al., 2007; Kincl et al., 2002).

However, real-time assessment of postural control in high-risk occupational groups remains in its early stages. Existing methodologies frequently neglect the synergistic potential of combining linear metrics with nonlinear measures to capture the complexity of postural regulation. Advancement in this domain will depend on the development of wearable systems capable of high-fidelity, continuous data acquisition with minimal disruption to workplace tasks. Equally critical is the validation of standardized, evidence-based assessment protocols that can accurately characterize risk profiles and support targeted interventions for the prevention and management of work-related chronic pain.

Chapter 3

Methodological considerations

This chapter presents the methodological considerations of the studies in this thesis, focusing on the rationale behind the main decisions. Study I employed a narrative review to identify suitable methods for assessing motor variability in office workers, centering on both linear and nonlinear metrics and informing the design of subsequent empirical studies. Study II implemented a week-long, multimodal data collection protocol using wearable sensors and self-reported measures to capture trunk kinematics and occupational risk factors, with a longitudinal design to account for cumulative exposure and temporal fluctuations. Study III quantified real-time variability and complexity of sitting patterns, combining linear measures with nonlinear metrics to explore potential impaired control strategies. Study IV examined associations between trunk motor variability and pain intensity, integrating digital and self-reported outcomes and applying statistical models to assess movement patterns in relation to clinical measures.

Of the 40 workers recruited through a campaign conducted by AT's human resources team, 10 were lost to a technical failure during the first acquisition wave, 5 did not meet the chronicity criterion, 2 had incomplete week-long recordings, and 7 were excluded as outliers that compromised the normality assumption required for the mixed ANOVA. The final sample comprised 16 workers: 10 in the chronic spinal pain group (CSPG) and 6 in the pain-free group (PG); Study IV analysed the CSPG only. Although data were acquired over five consecutive workdays (Chapter 5), Studies III and IV analysed Days 1, 3, and 5. These sample the beginning, middle, and end of the working week while avoiding the redundancy expected between consecutive days. Two constraints reinforced this choice: the intermediate days did not yield sufficient valid seated windows across all participants, and the surrogate-based nonlinear pipeline was computationally demanding.

Across all studies, methodological decisions included the selection of wearable IMUs for unobtrusive, field-based monitoring, complementing sensor data with self-reports to contextualize postural behavior, and applying both linear and nonlinear analyses to characterize sitting postural control comprehensively.

Chapter 4

Human movement variability analysis in office-workers: a review

Abstract: Occupational disorders have not only an effect on mortality worldwide but also a significant impact on the workers' quality of life, in terms of organizational productivity and insurance costs. In specific, work-related musculoskeletal disorders are the most prevalent among office-workers whose occupational exposure presupposes the frequent adoption of maintained postures. Given that there is a close relationship between the state of health of the worker and the human movement system, the monitorization of risk factors associated with the human movement, i.e. of the motor variability in office-workers, has been suggested to prevent or mitigate musculoskeletal complaints. This paper presents a literature review of the existing methodologies and tools that explore the motor variability in office-workers in a sitting position based on linear and nonlinear measures and emphasizes their potential importance in understanding human movement to prevent work-related musculoskeletal disorders.

Keywords: Human movement; occupational health; office-work; motor variability; nonlinear; features extraction.

Introduction

Work-related disorders constitute a public health problem (Bevan, 2015). When focusing on workers within Europe, exposure to several ergonomic risk factors that induce work-related disorders is especially prevalent (Hulshof et al., 2021). These risk factors range from individual and physical to psychosocial, and organizational factors (Hulshof et al., 2021; Mingels et al., 2021d). Office-working activities are performed repeatedly over long periods of time, often in a constrained or “static” sitting posture and capable of generating employees' discomfort, fatigue, perceived tension and/or feeling of pain (Arippa et al., 2022; Srinivasan & Mathiassen, 2012b). Long periods of time in

a sitting position are associated with several conditions, such as musculoskeletal disorders (MSD), diabetes, cardiometabolic diseases and mortality (Arippa et al., 2022; Madeleine et al., 2021). MSDs have a high impact on society and individual workers as these have negative repercussions on their daily life and constrain them in the execution of tasks at work (Arippa et al., 2022; Bevan, 2015). With this in mind, it is essential to encourage workers to adopt more appropriate postures over time.

The variability analysis has been becoming more popular and demonstrates a high impact on quantifying normal variations that occur in motor performance over time (Harbourne & Stergiou, 2009; Stergiou & Decker, 2011a). The motor control strategies are revealed in the structure of motor variability (Latash et al., 2002). Motor variability can be observed and quantified using linear and nonlinear statistical tools in several extensions and tasks (Karimi et al., 2021; Emanuelsen et al., 2019; Giovanini et al., 2017; Karwowski, 2012).

The presented work is part of the Prevention of Occupational Disorders in Public Administrations based on Artificial Intelligence (PrevOccupAI) project, in which the main objective is the promotion of occupational health through the identification of occupational risks. Through non-invasive sensors an estimation of occupational risks for office-workers will be performed, with the goal of minimizing injuries and costs. For this purpose, we have already developed a cross-platform application to assess occupational health and it is prepared to acquire data from self-reports and sensors from a smartphone, a smartwatch and from a wearable device that acquires biosignals such as electromyography (EMG) and movements (inertial measurements) (Silva et al., 2022).

An important aspect of this project is to provide feedback to the workers regarding their health status and how their posture has an influence on it. To assess risk factors in human movement variability, meaningful linear and nonlinear measures should be extracted from these devices using libraries such as Time Series Feature Extraction Library (TSFEL) (Barandas et al.,

2020). It is crucial to decide which measures are more relevant and how they should be combined (see e.g. in (Rodrigues et al., 2021)).

This review is thus focused on the existing linear and nonlinear metrics, and their importance in understanding human movement. The document is structured as follows: Section 2 will make an introduction to the concept of variability and will explain the relevance of occupational variability; Section 3 describes the approach of using the linear and nonlinear tools; Section 4 will cover some research applications of these tools in the context of sedentary work tasks, and Section 5 will conclude with their potential in the context of the PrevOccupAI project.

Variability

Does motor variability matter? To answer this question it is relevant to understand the concept of “repetition without repetition” (Bibbo et al., 2019; Emanuelsen et al., 2019) and why there is valuable information in what was previously considered. Regarding the former, it is essential to understand that, no matter how much we perform a specific task, the way it is executed is never identical. Thus, there is a degree of predictability with high complexity. When it comes to noise, it is interesting to note that previously it was considered an unwanted phenomenon (Latash et al., 2002). However, the so-called noise that we can find among the events of repetitions over repetitions has physiological and motor meaning. The statistical properties that characterize these events over time can differentiate between natural and impaired systems. In other words, the optimal variability does not correspond to a set of repetitions with too much or less variability. There is a specific kind of variability inherent to health systems that can be characterized as optimal variability or complexity (Stergiou & Decker, 2011; Harbourne & Stergiou, 2009).

The model that explains the optimal variability is called the Theoretical Model of Complexity. It describes the relationship that could exist between complexity and predictability. In clinical settings, a healthy pattern presents statistical

properties that correspond to a high level of complexity with some degree of predictability. A flawed system is characterized by a lower degree of complexity and can have either a high or low degree of predictability, that is, its events over time can be random or with equal time spacing between them. When a high degree of predictability is present, the dynamical system is more rigid and periodic. When predictability is low, the relationship among the events that make up the phenomenon is random and independent. That is, too much or too little variability is not desirable. The relevance of this model in terms of health is that in disease, this optimal variability is destroyed, losing its complexity, and becoming more or less predictable. With this in mind, optimal variability has a direct relationship with physiological and motor health. Therefore, variability reflects various options for movement, providing flexible, adaptive strategies that are not reliant on rigorousness for each task or each changing condition encountered (Karwowski et al., 2019; Guastello, 2017; Harbourne & Stergiou, 2009). This natural variability is destroyed with disability as seen during aging and disease (Madeleine et al., 2021; Busa & van Emmerik, 2016; Stergiou & Decker, 2011). In this situation, the events over time become more random, presenting more variability, or turn out close to invariant, that is, showing less variability.

Occupational Variability

It is reasonable to wonder that, if variability can be a biomarker of disability due to aging and disease, other similar conditions that contribute to poor health conditions will show alterations in variability. People spend a considerable time continuously working, namely when performing repetitive work (Emanuelson et al., 2019; Srinivasan & Mathiassen, 2012a). Physiological and inertial measures provide information about changes over time in work conditions that can be used by algorithms for occupational risk estimation at work. Thus, we can define as Occupational Variability the quantification of physiological and inertial variability in the work context for risk stratification.

Interestingly, to avoid exposure to repetitive work or “static” postures for long periods, extrinsic methods such as breaks with rest periods, job rotations, and

task variation have been suggested (Arippa et al., 2022; Srinivasan & Mathiassen, 2012b). However, the use of these measures usually lacks in adjusting individual characteristics of the worker (e.g personal factors, such as previous experience), increasing occupational risk. Therefore, intrinsic variation has been brought to the occupational context (Gaudez et al., 2016; Srinivasan & Mathiassen, 2012b, 2012a).

Motor variability, that is the natural variation that occurs in movements and postures over time while performing a certain task, brings resources of analysis that can explain both general workload risk associated with different workstations and workers' motor strategies to overcome fatigue over time. Thus, refining the definition of occupational variability, we can state that it is the set of natural variations over time, by means of physiological and inertial measures, related to a certain task in a work context.

In this way, task and individual characteristics influence intrinsic motor variability, and its evaluation brings new insights to ergonomics decisions such as workplace design and real-time risk evaluation. Employees working at an unbefitting workstation may suffer from muscle fatigue and musculoskeletal discomfort that can result in work-related MSD (Gaudez et al., 2016). The evolution of wearable devices brings new opportunities that can be explored. To achieve this purpose, a toolkit of options for processing and decision-making can be applied according to signal (time-series) to establish occupational risk metrics.

Linear and nonlinear measures of variability

The two main dimensions to measure variability, depending on the signal and problem under study, are known as linear and nonlinear (Saito et al., 2021; Harbourne & Stergiou, 2009). Both types of measures are valuable and should be used considering the information that is required.

Linear measures are more commonly used in the clinical field for prediction and problem-solving. Besides the relevance of these measures, they fail to

characterize the variability structure because their focus is on only one dimension as a straight line (Harbourne & Stergiou, 2009). However, linear approaches do not appropriately handle physiological and psychological temporal structures (França et al., 2019). For instance, two temporal structures representing a system (time-series) could have the same mean and standard deviation (SD) when they evolve differently over time. Several linear measures are considered in the literature to quantify the amount of variability (e.g., Chen, 2021) such as SD, coefficient of variation, root mean square (RMS), range, interquartile range, and standard error. Such linear analysis is often complemented with nonlinear analysis, as it provides measurements of the pattern of movement over time (Emanuelson et al., 2019; Harbourne & Stergiou, 2009).

Nonlinear measures allow us to understand the adaptability of a biological system to change conditions. These nonlinear tools quantify the variation in how a motor behavior emerges in time scales (Saito et al., 2021). Therefore, nonlinear measures provide further information and allow an understanding of complexity (Harbourne & Stergiou, 2009). Thus, the nonlinear model, often used with the term “dynamics”, can be defined as a system with a nonlinear proportion between its in- and outputs, thus inherently having a higher complexity. In other words, the linear statistical tools reflect the amount or magnitude of variation in movement patterns. Conversely, the nonlinear tools described the temporal organization or structure of the variability (as opposed to amount) (Harbourne & Stergiou, 2009; Saito et al., 2021). Following, the most common nonlinear measures that can be applied to quantify variability are described.

Entropy is the loss of information in a time-series or signal (Yentes et al., 2013). Entropy metrics are commonly pursued to estimate the temporal order of variation in a time-series (Karimi et al., 2021). It is the natural logarithm of a conditional probability, interpreted as the rate of information generation and it estimates the complexity of the underlying system producing the dynamics in question (Yentes et al., 2013; Søndergaard et al., 2010; Costa et al., 2005).

The approximate entropy (ApEn) quantifies the regularity or predictability. Increasing ApEn values reveal more significant irregularity, else ways, lower values reveal a more regular or periodic behavior (Stergiou & Decker, 2011b; Harbourne & Stergiou, 2009). Sample entropy (SampEn) is a unitless, non-negative number describing a time-series' structural irregularity or complexity, which has been used to analyze kinetic or kinematic signals (Emanuelson et al., 2019), more details about this algorithm in Yentes et al. (2013). The multiscale entropy (MSE) measure differs from SampEn and ApEn by including multiple measurement time scales. MSE applies the SampEn algorithm to calculate the entropy value at each time scale. The inclusion of these various measurements allows for distinct benefits such as the overall quantification of the complexity of a system in short and long scales, calculated as the sum of the entropy values of the individual time scales. Combining these features allows researchers to identify the time scales at which the breakdown in complexity occurs and the overall complexity that takes all of the time scales into account. The multiscale approach has been used to identify how physiological changes impact the overall complexity of physiological processes (Karimi et al., 2021; Busa & van Emmerik, 2016; Costa et al., 2005).

The largest Lyapunov exponent (LyE) measures the divergence of movement trajectories, quantifying chaos between two extremes by rating at which nearby orbits converge or diverge (Guo et al., 2015; Harbourne & Stergiou, 2009). The values between random and periodic define complexity or highly variable fluctuations in several physiological processes resembling mathematical chaos. A faster divergence of trajectories represents a higher instability of the system that is measured (e.g. postural stability) (Karimi et al., 2021; Karwowski et al., 2019). The ability to quantify the separation of trajectories makes the LyE also function to measure the average predictability of a system that exhibits nonlinear dynamics (Harbourne & Stergiou, 2009). Two algorithmic options are commonly used: Wolf (Wolf et al., 1985) and Rosenstein (Rosenstein et al., 1993).

The idea beyond Fractal Analysis is that self-similarity is present when an object is broken in smaller scales over and over again, independently of their size they look the same. This concept is applicable in time-series. If we have sequential events over time (e.g., electrocardiogram RR, a direction of postural sway), the time-series that is made up of those events can be divided in different window lengths, known as lags or scales. If their fluctuations at different scales are similar, then the structure of that time-series is fractal (França et al., 2019; Ihlen, 2012; Hausdorff, 2007; Stanley et al., 1999). Detrended Fluctuation Analysis (DFA) was introduced by Peng et al. (1995) to study the presence or not of long-range correlations in nucleotide sequences. The presence of long-range correlations or memory of the time-series means that the events of that time-series are dependent on each other but are not the same. DFA is based on the concept of a fractal time-series as statistical properties that can be described by a power law (Ihlen, 2012). Multifractal Detrended Fluctuation Analysis (MFDFA) assumes that the phenomenon that is measured has a monofractal structure, requiring just a single power law (E. Ihlen, 2012). However, this assumption is overly restrictive for human behavior. Monofractal analysis considers that fractal scaling is independent of time and space. To avoid this assumption, MFDFA operates with different scaling orders revealing information about small and large fluctuations. These spatial and temporal variations can be defined by a multifractal spectrum of power law exponents. These characteristics were identified by Stanley et al. (1999) and the mathematical procedures were developed by Kantelhardt et al. (2002).

Research application

In the following, a closer look will be taken at how linear and nonlinear measures were applied in research applications to measure the motor variability while being seated, with a focus on office-work scenarios and computer tasks. Measures have been extracted using a variety of systems and principally sensors to quantify the center of pressure (CoP) and EMG signals.

Linear measures

Considering linear measures, motor variability has been measured to assess new equipment and at the occupational level, to be associated with cognitive tasks and to evaluate pain.

In terms of equipment analysis, Sardini et al. (2015) developed and validated a T-shirt with integrated inductive sensors, running along the front and the back to assess the sitting posture in the lab and in real-world scenarios. The shirt is able to send data wirelessly to a computer and also contains a vibro-feedback system. The posture is estimated through the change of impedance in the inductive sensor that results from geometric changes occurring when the posture is altered. The output is expressed in the range of motion (ROM) that is based on a reference ROM to ensure comparability between results. When deploying the shirt in a home scenario, they were able to show that it is appropriate to assess posture variability (Sardini et al., 2015).

Chen et al. (2021) analyzed posture variability among participants using three types of chairs (stool, computer chair and gaming chair), associated with the most comfortable sitting postures. The authors recorded 2D markers positions at the head, trunk and knee joint angles using a motion analysis system, which also determines the joint angles to further analysis. Unexpectedly, when the participants sat at a posture that they perceived to be the most comfortable, high variability was found within chairs type and gender (Chen et al., 2021). To evaluate how the posture is affected by cognitive engaging tasks in relation to dynamics and sway, Bibbo et al. (2020) developed a sensorized office chair, without a backrest, equipped with four load cells. From this setup, they calculated the CoP and extracted the mean distance, RMS distance, mean velocity, sway area, 95% confidence circle and ellipse area. They were capable of supporting the hypothesis that tasks that have a higher cognitive demand lead to lower stability in the seated posture (Bibbo et al., 2019).

Studies had been conducted to associate musculoskeletal pain with linear measures extracted from sitting posture during computer work tasks. Recently,

Arippa et al. (2022) aimed to analyze movement patterns during computer work and associate these patterns with musculoskeletal pain. Seat pan pressure and trunk sway parameters were quantified by using a pressure-sensitive mat of two groups: 14 breakers that stoop up at least once during the procedure, and 14 prolongers that remained sitting throughout the process. The linear measures analyzed were associated with CoP: mean position, sway path, sway area, sway velocity, maximum displacement, and in-chair movements. The authors concluded that the trunk sway parameters tend to decrease over time, and breakers have more consistent movement during the procedure and present lower discomfort than prolongers (Arippa et al., 2022).

The relationship between back pain and sitting behavior in call-centre employees was explored by Bontrup et al. (2019). Similar to the previously described study, they used a pressure mat, however in this case, a textile mat connected to a mobile phone application, where data was stored. Four groups of participants were considered to analyze the sitting behavior (no pain, no functional disability, with pain, with functional disability), regarding the features: mean number of movements per working hour, mean number of positional changes per working hour, mean time period of stable sitting, and percentage of transient periods during the whole working period. Although a high variability was found within the groups, chronic low back pain subjects tended to show a more “static” sitting behavior. A sitting position classification based on all pressure values and using a random forest algorithm and Leave-one-out cross-validation achieved an overall classification accuracy of 90% (Bontrup et al., 2019).

Kelson et al. (2019) also assessed pain in computer workers and its association with EMG sensors to record the trapezius muscle activity. To analyze the data, they used the tool exposure variation analysis that expresses continuous exposure-vs-time data in categories defined by exposure amplitude and accumulated time, thus giving way to an understanding of the differences in the temporal structure of exposures at different amplitude levels. They

extracted five amplitude and five duration categories, to compare pain and control groups, concluding that neck-shoulder pain spent less time at low amplitudes and had longer continuous durations of muscle activation. Furthermore, the results of this study suggest that workers with pain have chronic motor control changes occurring in the adaptation of pain (Kelson et al., 2019).

Mingels et al. (2021) used a camera system to make a comparative non-randomized study of the spinal postural variability (SPV) during a computer task of 18 people suffering cervicogenic headaches (CH) and a matched control group (CG). The spinal posture was acquired using 12 infrared Bonita T10 and two video cameras. From the gathered data, left sagittal angles were calculated and significant differences could be observed between both groups. For example, the SPV of the CH group was higher than the CG. Furthermore, they observed that for both groups, the upper spinal variability was generally lower than the lower spinal variability, except for the upper thoracic variability, which was higher for the CH group when compared to the variability of the lower lumbar (Mingels et al., 2021).

Nonlinear measures

Adding complexity to the analysis of motor behavior, some authors considered nonlinear variables to assess different equipment, pain and, at the occupational level, to be associated with cognitive tasks and aging.

Using optical motion capture, Lau et al., (2015) concluded that the movement performance is a multifractal behavior, which can be associated with the multiple strategies behind the motor control, and neural activities, by the analysis of the dynamic properties of spinal curvature during postural sway based on the MFDFA (Lau et al., 2015). Sondergaard et al. (2010) used both linear and nonlinear analysis techniques to measure perceived discomfort during prolonged sitting. Subjects were seated on a force platform with no armrests, nor back and foot support, leaving only a force platform for contact. The mean, SD and SampEn of the CoP displacement in both anterior-posterior

(AP) and medial-lateral (ML) directions were extracted. The resulting amount of variability for both lumbar curvature and CoP displacement increased over time with an increasing perceived discomfort, suggesting a relationship. Further studies explored nonlinear measurements while subjects were performing computer tasks, related to occupational contexts (Søndergaard et al., 2010).

Regarding the dynamics of sitting during cognitive tasks, Madeleine et al. (2019) recorded mental fatigue ratings, overall performance and kinetic, the last using a force and torque 3D transducer on an office chair. Sitting dynamics were analyzed using the average displacement, SD and SampEn values and the displacement of the CoP in AP and ML directions. They concluded that, for their procedure, computer work did not change the dynamics of sitting. However, they observed increased size and structure of variability in the ML than in the AP direction (Madeleine et al., 2019). Still associated with cognitive tasks, Caballero et al. (2021) analyzed differences in motor variability related to the learning rate. Motor variability was recorded via two-axis force sensor (ML and AP) to measure variability structure based on DFA, and motor synergy variability based on good and bad variability ratio (GV/BV). No results were found related to DFA, but higher initial GV/BV was related to greater performance improvements than those with lower GV/BV (Caballero et al., 2021).

Also, with nonlinear measures, EMG was used to study the spatial distribution of upper trapezius muscle activity during computer work as an effect of biofeedback. Samani et al. (2010) extracted two-dimensional maps of RMS, relative rest time and permuted sample entropy (PeSampEn) from EMG. To quantify changes in the spatial distribution of muscle activity, the centre of gravity (CoG) and entropy of maps were also calculated. They used PeSampEn as a measure of temporal heterogeneity and the entropy of RMS as a measure of spatial heterogeneity. The findings of this study suggest that there is a potential benefit of superimposed muscle contraction in relation to

the spatial organization of muscle activity during computer work (Samani et al., 2010).

Madeleine et al. (2021) set out to investigate the sitting dynamics of computer work, and how these differ between age groups. To this end, an instrumented office chair was designed with a 3D transducer using strain gauge technology. This allowed for recording applied forces and moments on the link between the seat pan and chair shaft. The range, velocity, area, SD and SampEn values were extracted using this data. The results contradicted the authors' initial hypothesis regarding changes across the task's duration, as no major changes were observed. Age, however, was shown to play a bigger role: for older subjects, the range and velocity of the CoP displacement were larger. In contrast, complexity was lower among younger users (Madeleine et al., 2021a).

The literature research explored in this paper focuses on the motor variability during sitting posture, more specifically in office-worker scenarios. There are several applications for innovative ergonomics analysis. The major instruments referred to in this review were the plate of force, such as instrumented chairs and also EMG sensors. To our surprise, a well-known nonlinear measure was not used in the office-work studies, the LyE. Although this paper has a focus on the quantification of CoP and EMG signals, an interesting alternative approach would be the use of wearables to provide direct measurements for ergonomics research (Santos et al., 2021).

Conclusions

In this literature review, linear and nonlinear measures to assess motor variability while executing sedentary tasks (i.e. office scenario) were presented. Motor variability assessment remains a challenging task due to the complexity and versatility of human motion. Thus, the presented works used specialized systems like optical motion tracking systems, sensorized office chairs, and wearable fabrics with integrated inductive sensors. While these systems allow for a detailed analysis of human movement they are, in most

cases, only deployable in lab scenarios (e.g. optical motion tracking), are associated with extra costs (e.g. sensorized office chair), or can, to this stage, not be easily produced (e.g. sensorized shirt). Furthermore, the shown systems were mostly tested in limited scenarios.

Therefore, an effort has to be made to develop systems that make use of easily accessible technology like smartphones and smartwatches. Subsequently, these systems need to be tested over long periods of time in real-world scenarios (i.e. offices) while subjects are working in their natural environment. Research has to be carried out on how to extract meaningful linear and nonlinear measures from these devices to comprehensively assess human movement variability in the mentioned scenario. Finally, these measures need to be presented in an easy-to-understand way together with recommendations on what users can do to improve their occupational health and mitigate work-related risk factors.

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Week-long multimodal data acquisition of occupational risk factors in public administration workers

Abstract: Work-related disorders are a growing issue for office workers and represent a significant burden to public health. Work aspects such as sitting for prolonged periods and occupational stress are modifiable risk factors highly associated with occupational disorders in office workers. The PrevOccupAI Project (Prevention of Occupational Disorders in Public Administrations based on Artificial Intelligence) objectively investigates relationships between a variety of occupational risk factors and physiological outcomes. For this purpose, a data acquisition protocol was carried out at the Portuguese Tax and Customs Authority. Physiological, movement, and environmental signals from office workers were acquired during five consecutive workdays using a smartphone, a smartwatch, and two electromyography sensors. Additionally, demographic, occupational, and pain information were collected through questionnaires. The present manuscript provides a detailed description of the PrevOccupAI acquisition protocol. The collected data is used to gather knowledge regarding modifiable factors at the individual and organisational levels.

Keywords: data acquisition, biosignals, intelligent offices, multimodal risk evaluation, occupational health.

Introduction

Occupational disorders, more specifically work-related musculoskeletal disorders (WMDs), constitute a major public health problem (de Kok et al., 2019). These negatively impact workers with physical and mental complications, and stand as the leading cause of decreased productivity and increased absenteeism, generating a considerable medical burden and economic cost to organisations (A. Wu et al., 2020). In total, it is reported that 7.4% of European workers suffered from occupational-related health problems, with a higher prevalence in musculoskeletal, stress, depression, and

anxiety-related problems (Agilis, 2015). These reports also follow the demographic shift of increasing computer and desk-based work and its impact on workers' health due to prolonged sitting, and extended screen (Zerguine et al., 2023; Heredia-Rizo et al., 2022). Due to the complex multifactorial nature of musculoskeletal and mental disorders (Bellosta-López et al., 2021; Dzakpasu et al., 2021), it is necessary to implement goal-oriented prevention strategies that address various factors, such as exposure to physical, psychosocial, and environmental risks (Langella et al., 2021), both at the individual and the organisational level. Smart technologies that can easily be integrated into the workplace could be a promising solution for adequately assessing occupational health risks related to the working environment, desk setup and worker's behaviour. Furthermore, prevention and mitigation strategies could be developed from this, and recommended to workers.

Intelligent or smart offices bring numerous opportunities for delivering prevention and control measures for health issues associated with office work (Zhang et al., 2022). Smart technologies, such as wearables, Internet-of-Things (IoT) or machine learning (ML) models, contribute to the overall development of intelligent office environments that bring more awareness over employees' context. They allow for assessing which are the targeted needs, thus ultimately playing a significant role in integrated health status monitoring systems that enable the application of structural changes by the employee and/or organisation (Giannakakis et al., 2022; Zhang et al., 2022; Chen et al., 2021; Heikkilä et al., 2021; Naranjo-Hernández et al., 2020; Papagiannidis & Marikyan, 2020).

Smart offices constitute a subject of interest for many researchers, some of which are worth highlighting. One of which is *Liu et al.*, (Liu, 2021), who proposed for the development of an intelligent office chair prototype that integrates sensors, micro-controllers, and vibration actuators accompanied by a mobile application, which provide vibrotactile and visual feedback to monitor the user's posture and improve their sitting behaviour. *Aryal et al.* (2019) [(Aryal et al., 2019) investigated intelligent desks, suggesting methods for office

workers' future productivity and well-being. Several aspects were highlighted, consisting of different application modules for improving worker comfort, well-being, and productivity by providing recommended thermal comfort, visual comfort, and sit-stand desks. Sensing and actuation devices can be integrated on different furniture of the office or existing wearables, such as office chairs and smartwatches (Heikkilä et al., 2021; Aryal et al., 2019). The boosts in device capabilities offer many new opportunities for monitoring, momentary ecological assessment, and intervention [(Owen et al., 2020; Tahir et al., 2020).

The mentioned research focuses mainly on systems and strategies that exclusively work either on an individual or on an organisational level. While these approaches are still valid solutions for their respective problems, they are not able to appropriately address the multifactorial nature of occupational diseases (e.g. psychosocial factors such as stress can have influence on the development of WMDs and vice versa). Furthermore, prevention strategies made on an individual level can only have an impact to a certain extent as there may be organisational problems that can not be tackled by individual workers. Similarly, focusing primarily on changes on an organisational level may result in management decisions that are not received favourably by workers. Thus, a comprehensive approach that can identify and assess occupational risk factors on an individual and organisational level is needed to appropriately address occupational risks and provide prevention strategies for both. Implementing such an approach would ultimately lead to an intelligent office environment that results in data-driven decision making that benefits both the workers and the organisation.

The 'Prevention of Occupational Disorders in Public Administrations based on the Artificial Intelligence' (PrevOccupAI) project aims to characterise daily working activities, working conditions, and potential risk factors associated with the occupational environment, on an individual and an organisational level, within the Public Administration. This paper presents the data acquisition procedure used in an ongoing study conducted within the Lisbon Metropolitan Area with workers at multiple locations of Autoridade Tributaria (AT), the

Portuguese Tax and Customs Authority. Acquisitions were carried out for five consecutive work days. The length of the data acquisition was chosen based on two criteria, (1) capturing changes in worker behaviors over multiple days, (2) availability of workers to participate. We included signals like Heart rate (HR), Accelerometer (ACC), Gyroscope (GYR), Magnetometer (MAG), Rotation vector (RV), and ambient noise utilising a smartwatch and a smartphone as well as Electromyography (EMG) using proprietary sensors. Moreover, subjective data was collected through validated questionnaires that address, among others, demographics, workplace conditions, pain intensity, and psychosocial factors.

The main contribution of this paper is to describe the used data acquisition protocol with the principal aim of acquiring multimodal data in real-time in a worker population. Furthermore, we present our reasoning for how the variables measured in the acquisitions were selected and some preliminary population statistics. We conclude the paper with future directions towards our vision for risk assessment in occupational environments.

Methods

Review on Occupational Risk Factors

We conducted a non-systematic literature review to identify multimodal risk factors and instruments to assess WMDs and their essential potential factors. From this review, both intrinsic (i.e., health status) and extrinsic (i.e., environment characteristics) were taken to support an evidence-based WMDs risk assessment tool.

The review process started with collecting information on which demographic variables should be considered in the study. The review showed that variables such as age, body mass index (BMI), and gender were relevant indicators for assessing computer users (Heredia-Rizo et al., 2022; Madeleine et al., 2013).

In a subsequent step the influence of physical activity was found to be relevant as people with sedentary lifestyles are associated with being more prone to

work-related illnesses such as musculoskeletal disorders (Karpenko et al., 2022; Ali Shah et al., 2020; Eanes, 2018; Shrestha et al., 2018). A recent report issued by the European Agency for Safety and Health at Work (EU-OSHA) has concluded that the second most frequently reported risk factor in the EU-27 (61%) was prolonged sitting (Peereboom, Langen, & Copsey, 2021). These results can be seen as a consequence of trends that have been developing over the past 30 years, as physical activity decreased by more than 25% in that time period. In the same time span the number of people working while seated at a desk has increased in several countries (Verbeek et al., 2019).

According to the International Labour Organisation (ILO) (Office, 2012), interventions in the workplace must take into consideration the interaction of multiple elements due to the interdependence to which the worker is subjected, such as leadership issues, job demands, social support, working-time arrangements, work-life balance, and communication, among others [(Briggs, Bragge, et al., 2009), which reinforces the necessity to evaluate the individual at the organisational level. To encompass these aspects, we assessed diverse psychosocial outcomes, ranging from self-efficiency, sleep quality, burnout and specific outcomes of work conditions (Heredia-Rizo et al., 2022; Langella et al., 2021; Collins & O'Sullivan, 2015; Nicholas et al., 2011; Briggs, Bragge, et al., 2009).

Ergonomic interventions include improving the equipment and environment of the workplace. Most office environments do not adequately support office worker health, nor do they maximise work performance. Indoor environmental factors, such as noise, air, lighting, and adjustable furniture, which do not fit the individual's needs or support occupational requirements, can directly affect office workers. Promoting an optimal environment and adequate rest time allows recovery and reduces the risk of long-term damage. Therefore, we include the examination of the occupational setting, such as work arrangements adequacy, privacy, design, and air quality (Zerguine et al., 2023; Heredia-Rizo et al., 2022; Fukumura et al., 2021; Hoe et al., 2018; Paksaichol et al., 2014).

Previous research has suggested that professions involving more physical variation most likely have a reduced risk for the development of WMDs, compared to jobs where similar movements are performed repeatedly (Heredia-Rizo et al., 2022; Shannon et al., 2019; Guastello, 2017; Srinivasan & Mathiassen, 2012b). This is the case for office workers, who often maintain “static” postures and perform repetitive actions throughout their workdays. Thus, the movement variability has been essential to prevent WMDs (Shannon et al., 2019; Srinivasan & Mathiassen, 2012) and pain experiences in office workers (Heredia-Rizo et al., 2022).

In summary, through the review process, we identified as vital to include in our acquisition protocol the following domains: demographics, physical activity, psychological factors, occupational environment factors, and pain experience. The selected domains allow for characterising risks both on an individual and organisational level. To be able to capture all the mentioned risk factors, a comprehensive data collection process is necessary. This process consists of employing both subjective and objective data acquisition strategies. Subjective data collection was realised through the usage of validated structured questionnaires. Objective data was acquired by utilising wearable sensors. By collecting both subjective and objective measures we hope to capture a broad spectrum of rich data that allows for an identification of the aforementioned risk factors. The validated tools and wearable devices used are described in detail in the following two sections.

Questionnaires

For the assessment of subjective measures, validated questionnaires were employed. As such, we used the the International Physical Activity Questionnaire Short Form (IPAQ-SF) (Craig et al., 2003), Copenhagen Psychosocial Questionnaire II (COPSOQ II) (Rosário et al., 2017), Rapid Office Strain Assessment (ROSA) (Sonne et al., 2012) and Numeric Pain Rating Scale (NPRS) (Miguel, 2003; Treede et al., 2019). These assess different dimensions, like physical activity, psychosocial factors, work-related and pain

experience, respectively. Additionally, a questionnaire was developed to retrieve information with regards to demographic variables. The validated tools and the additional questionnaire are described in detail as follows.

Physical Activity: Physical activity (PA) information was evaluated through the IPAQ-SF (Craig et al., 2003)[36], which consists of seven items. These are days and time spent doing vigorous and/or moderate PA, days and time spent walking, and time spent sitting during weekdays. All items are asked with respect to the last seven days. The final score is reported as low, medium, or high as well as level of PA per week through the metabolic equivalents (Chen, O'Leary, et al., 2018). It is an instrument developed for monitoring PA levels among 18 to 65-year-old adults in diverse settings. This tool has been validated and considered reliable (α .80).

Workstation Assessment: ROSA (Sonne et al., 2012) was employed as the ergonomic and biomechanics subjective assessment (e.g., chair, mouse, and overall workstation). ROSA is a questionnaire to quickly quantify risks associated with computer work and provide an action level for change based on reports of worker discomfort (Matos & Arezes, 2015). The risk factors included in ROSA are encoded as increasing scores from 1 to 3, final scores ranging from 1 to 10, with higher scores representing elevating risk factors. In previous studies, it was shown that the final scores obtained with ROSA significantly correlated with body discomfort. Mean discomfort increased proportionally with ROSA scores, with a significant difference between 3 and 5 (out of 10). ROSA's scores give targeted meaningful changes to the office setup that can potentially reduce long-term discomfort and serve as a tool to understand which elements of the individual desk should be changed. This tool has been shown to be an effective and reliable method for identifying computer use risk factors related to discomfort. Moreover, ROSA final scores exhibited high inter-and intra-observer reliability (ICCs of 0.88 and 0.91, respectively).

Psychosocial Factors: The COPSOQ II (Pejtersen et al., 2010)[44] analyses psychosocial risks (e.g., self-efficacy, burnout, and sleep quality). In a previous study, the Portuguese COPSOQ II was validated by issuing it to 745

Portuguese employees from organisations across several economic sectors. The questionnaire was employed twice, once as a baseline and a second time as a follow-up two weeks later. The test-retest reliability estimated by the intraclass correlation coefficient (ICC) showed higher reliability for most scales. Thus, the long Portuguese version of COPSOQ II (C. Silva et al., 2006) is a reliable and validated instrument (Rosário et al., 2017) for assessing psychosocial risks in the workplace. The Portuguese middle version comprises nine domains (demands at work, work organisation and job contents, interpersonal relations and leadership, work-individual interface, values in the workplace, personality, health and well-being, and offensive behaviours), 29 dimensions (also called scales), and 76 items.

Pain Experience: The proposed protocol assesses the three dimensions of pain perceived experience. These are pain intensity, pain-related distress, and pain-related interference. These three dimensions are assessed using the NPRS (Treede et al., 2019). The pain intensity denotes the strength of the subjective pain experience ('how much does it hurt?') for specific body parts (e.g., neck, shoulders, upper dorsal region, among others). For this purpose the NPRS considers a 11-point rating scale ranging from zero to 'no pain' to 10, 'worst pain imaginable' (Treede et al., 2019). The pain intensity is evaluated on a daily basis, using an interface in the application, depicted in Fig. 1, where subjects can draw on a body map the corresponding pain intensity using a predefined color mapping (Lopes et al., 2021). The interface allows for indicating pain ratings from 1 to 10. All uncolored regions are considered to be 0 pain.

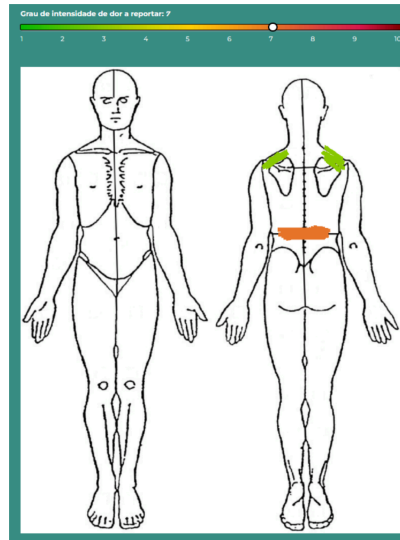


Fig. 1: Pain location and intensity assessment interface.

Pain-related distress is evaluated with regards to the previous week. Here, unpleasant emotional experiences of cognitive, behavioural, emotional, social, or spiritual nature related to recurring pain are assessed based on the same 11-point numerical rating scale. Pain-related interference describes how much the pain interferes with daily activities and participation. Where, the 11-point rating scale ranges from zero 'no interference' to 10 'unable to carry on activities'. Rating is done with regards to interferences over the last week (Treede et al., 2019; Hawker et al., 2011; Miguel, 2003). Using the International Classification of Diseases (ICD-11) temporal criteria, we included a single question to quantify the duration/chronicity (acute <three months or $\geq$ chronic three months) (Lopes et al., 2021; Perrot et al., 2019).

Demographics: To retrieve demographic variables the following questions were compiled into a single questionnaire: age (years), gender (female, male or other), height (cm), mass (kg), dominant hand (right-handed, left-handed or ambidextrous), marital status (single, married, divorced, widowed, unmarried partner), if they have children under the age of 16 (yes/no, and if yes, how many), educational level (elementary school, high school, technical-professional education, university education (bachelor), postgraduate (master or doctoral degree), type of profession, years and months working the

current work position, working hours per week (average) were compiled into a single questionnaire.

Additional Questions: Currently, there are no specific risk assessment questionnaires for WMDs and the risk of developing WMDs, which may potentially progress into chronic symptoms (Langella et al., 2021). Thus, Table I describes all investigated potential risk factors, how they were measured, and how they were coded in the analyses. The possible factors were measured using previously published (Heredia-Rizo et al., 2022; Langella et al., 2021; Da Silva et al., 2019; Jørgensen et al., 2013), and validated questionnaires. Additionally, relevant questions detected in our review by our team of experts were included. These questions are integrated at this stage of the project but will eventually be replaced or removed later based on our validations.

TABLE I: Additional Questions.

Domain	Question/Statement	Answer
Environment	1. The windows, skylights and glassed walls have adequate sun exposure.	Yes/No
	2. The lighting conditions in the workplace are appropriate to execute the tasks that need to be performed.	
	3. Natural lighting conditions are predominantly used at the workplace.	
	4. The natural or artificial air renewal at the workplace does not expose workers to harmful air pollutants and ensures the rapid elimination of these.	
	5. The air temperature and humidity at the workplace are suitable for the health of the workers.	
	6. Is the ambient noise adequate at the workplace?	
	7. How do you feel about the overall design of the workplace?	
Workplace organization	1. Is the workplace (in general) clean and well organized?	Yes/No
	2. Is your personal workspace clean and well organized?	
	3. Is the height of cabinets and their shelves appropriate for your body stature?	

	4. Are the dimensions and the shape of your desk appropriate for the tasks you need to perform? 5. Your workspace is at an adequate distance to your co-workers. 6. Do you have a designated work space where you work? 7. Your workspace is positioned in accordance with your duties (e.g., you work close to the people that are in your team)	
Workplace Privacy	1. Do you consider that the design of the workplace allows you to have enough privacy while working? 2. Is it possible to have confidential conversations at your workplace? 3. Is it possible to work for prolonged periods of time without being interrupted?	Yes/No
Psychosocial Factors	1. I can plan my breaks at work. 2. I can divide my working time. 3. I can decide when to take a break. 4. After breaks I change my work tasks. 5. During breaks, I do not use a computer. 6. After two hours of work I take a break for 10 minutes. 7. I think that my breaks are sufficient.	Always/ Frequently / Sometimes/ Never

Equipment Setup and Placement

The equipment to collect biosignals from the subjects include a smartphone, a smartwatch, and two EMG sensors. The smartphone and a smartwatch were chosen as these are widely available devices that contain a variety of sensors. The EMG sensors were chosen as previous studies have shown its efficacy in the assessment of pain (Naranjo-Hernández et al., 2020) and stress (Da Silva et al., 2019; Wijsman et al., 2013).

Smartphone: ACC, MAG, GYR, RV, and ambient noise were acquired using a Xiaomi Redmi Note 9. The Redmi Note 9 runs the Android operating system. The Android OS restricts the ACC, GYR, and RV to 100 Hz, while the MAG is sampled with 50 Hz. Ambient noise was acquired in decibel using a 1 Hz

sampling rate. The smartphone was placed on the subject's chest using a harness, as shown in Fig. 2a.

Smartwatch: Smartwatch acquisition was done using an OPPO 41 mm watch that was, as illustrated in Fig. 2b, placed on the subject's non-dominant hand. The sensors used in the acquisition were ACC, GYR, MAG, RV, and HR. The sampling rates for ACC, GYR, and RV were 100 Hz, for MAG 50 Hz, and HR is restricted by the android system to 1 Hz. For the HR sensor a separate acquisition scheme was implemented as this sensor depletes the smartwatches battery quickly if it is used continuously. Therefore, the HR sensor was programmed to acquire data every three minutes for one minute.

EMG Sensor: EMG signals were acquired from the left and right trapezius using two muscleBANs (PLUX Wireless Biosignals). The muscleBAN is a wearable sensor unit that in addition to the EMG also contains a tri-axial ACC and a MAG sensor. The placement of the two muscleBANs, shown in Fig. 2c, was done according to the SENIAM guidelines (Hermens et al., 2000). Prior to placing the two muscleBANs, the hair at the placement location was removed, if necessary, and the subject's skin was cleaned with alcohol. The sampling rate of the muscleBANs was set to 1000 Hz for all sensors.

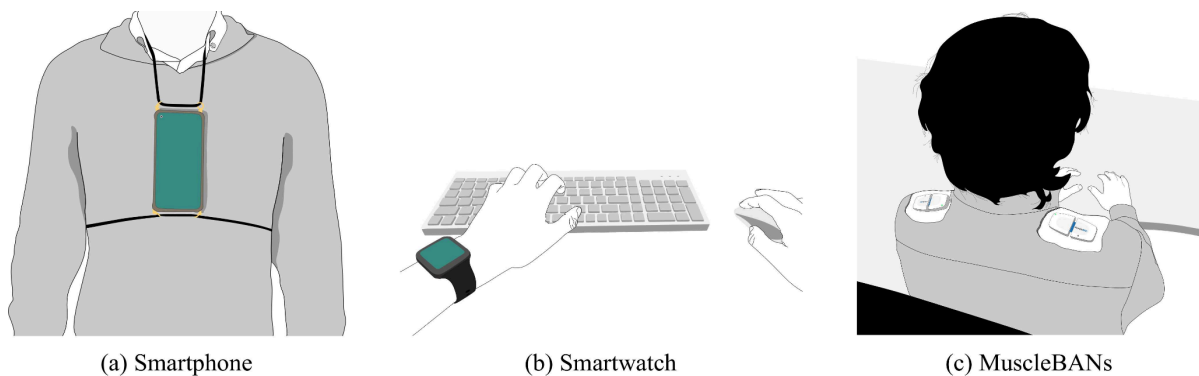


Fig. 2: Equipment placement.

Given the limitations of the smartwatch's and muscleBAN's battery capacity, these devices were scheduled to acquire four times a day for a time span of 20 minutes. The smartphone, on the other hand, acquired data throughout the

entire workday. An overview of the device types, used sensors per device, and the data acquisition procedure is presented in Table II.

TABLE II: Acquisition procedures.

Device Type	Sensors	Acquisition Procedure
Smartphone	ACC, GYR, MAG, RV, ambient noise	Whole workday
Smartwatch	ACC, GYR, MAG, RV, HR*	4 times per day for 20 min (*every 3 min for 1 min within the 20 min)
muscleBAN	EMG, ACC, MAG	4 times per day for 20 min

Participants and Setting

Participants were included when they satisfied the following criteria: Adults 18 years of age and older, without any associated pathology (e.g., neurological, orthopaedic, rheumatic, oncological or cardiorespiratory), and that do not take psychotropic drugs or any other recurring medication.

The present protocol is being carried out as part of an ongoing study in the Lisbon Metropolitan Area, Portugal, on the premises of Autoridade Tributária (AT), which is part of the Portuguese public administration. Workers were recruited randomly through a campaign carried out by the HR team of AT. As an incentive for participation, workers received a detailed analysis of their collected data consisting of a risk analysis utilising appropriate visualisations and recommendations with risk mitigation strategies. The study was approved by the Universidade Nova de Lisboa Ethics Committee (No. CE/FCT/005/2022) (Appendix I). This project was conducted under the Declaration of Helsinki and complied with the General Data Protection Regulation. Personal data like contact information was stored separately on an external hard drive and was only accessible by the principal investigator. All other data (sensors and questionnaires) were pseudonymised. Participants have the right to desist from the study at any time and if requested their data is deleted.

Acquisition Protocol

All data collection was done using the cross-platform application described in (Silva et al., 2022). The application generates user access for each participant. The application allows for filling out questionnaires either on a computer or a smartphone. Furthermore, the smartphone component of the application is able to acquire sensor data from all three device types (smartphone, smartwatch, and muscleBANs). Acquisitions can be scheduled in advance through the application interface. When scheduling acquisitions, it is possible to choose the devices from which data should be acquired, the start time, and the duration of the acquisition.

In a preliminary session that took place prior to the week in which sensor acquisitions were executed, the subjects were informed about the project, its aims, and the acquisitions. After this, subjects gave informed consent and a profile was generated for each subject. Subjects were asked to subsequently fill out all questionnaires, except for the daily pain questionnaires.

For sensor acquisitions, a separate room was prepared at each AT location to which subjects could come in for the placement of the equipment. Participants were asked to come in before starting their workday. First, the participants were asked to fill out the daily pain questionnaire. Then the four 20 min acquisition times at which the smartwatch and muscleBANs would be recording were scheduled in the PrevOccupAI application. Subjects were advised to choose acquisition times at which there is a high chance that they would be working seated at their desks. If possible, two acquisitions were scheduled in the morning and two in the afternoon. For the smartphone, the acquisition was set to start as soon as the workday would begin and was scheduled to stop at the end of the workday. After scheduling the acquisitions, the equipment was placed. Participants then proceeded to go to their offices and executed their usual work tasks until the end of the workday. When the participants came back, the equipment was removed and disinfected. Finally, subjects were asked to fill out the daily pain

questionnaire a second time. The workflow of the acquisition procedure is illustrated in Fig. 3.

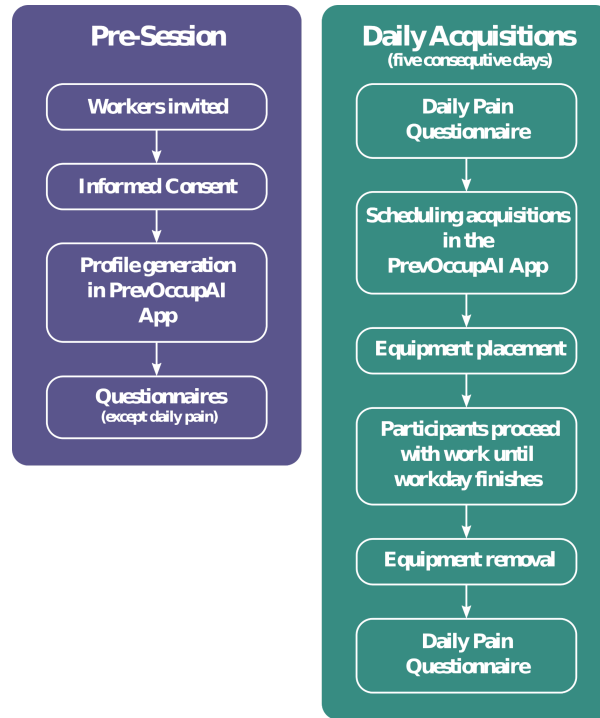


Fig. 3: Acquisition protocol procedure.

Preliminary results

The protocol is currently being used in an ongoing study. For now, data acquisition was undertaken at four AT offices within the Lisbon Metropolitan Area. At each location data was acquired from 10 different subjects for five consecutive days. Thus, a total of 40 participants took part in the study up to now. A fifth acquisition is planned for the near future. Once the acquisitions have been concluded, it is planned to publish the entire database in an open science format.

The preliminary findings of the demographics questionnaire are shown in Table III. The results with normal distribution are present by the mean and standard deviation (SD), and with non-normal distribution, median and interquartile range (IQR).

TABLE III: Preliminary population statistics.

	Age (years)	BMI (kg/m²)	Working hours per week	Years in profession
Mean	58.18	25.34	35.00*	19.64
SD	5.47	4.40	5*	12.32
Min	21	17.47	30	1
Max	63	38.62	60	43

*median and IQR.

Expected results

We expect that the acquired data will contribute with crucial evidence to identifying the relevant risk factors that contribute to occupational diseases. Furthermore, the data acquisition protocol will provide information on workers' responses to the office environment for an entire week, but can also, if necessary, be adjusted to accommodate any arbitrary time periods. Prevention strategies based on the collected data will be promoted for both the workers and AT. The quantification of risk factors for WMDs will help to provide a point of reference for measuring disorders, shifting patterns, delivering policy development data, and guaranteeing that intervention activities at population levels are appraised suitably for effectiveness. Evaluating risk factors will allow for the dissemination of improved, human-centred and safer occupational environments.

The resulting dataset will be used together with data analysis and machine learning models to further develop our platform/app, assess, characterise, and estimate occupational risk factors, and reduce medical leave and costs, thus preventing potential WMDs. Consequently, it contributes to supporting decision-making in the public health perspective. A better understanding of health outcomes related to work, from an individual level perspective, will be crucial to enhancing the approaches in occupational health. This research would provide information to help integrate the risk factor reduction concept for managing WMDs.

The present protocol will allow us to use subjective information to characterise the sample in terms of prevalence. We expect a high occurrence of neck, low back, and shoulder pain in the workers, in line with previous research (Jun et al., 2021; Nunes et al., 2021; Madeleine et al., 2013). Moreover, it will then permit analysis of potential differences, correlations, and relationships, as well as identifying clusters between the multimodal variables and groups of AT via ML methods.

Workplace physical risk factors concerning computer work- stations have been investigated using inertial sensors, including prolonged sedentary hours, and worker posture. Measuring postural behaviour captured by wearable motion sensors may identify a higher risk of an office worker (Jun et al., 2019a)[57]. We hypothesised that the workers with fewer physical activity levels, breaks, posture invariability and reporting more quantity of psychosocial-related complaints and pain should be more prone to WMDs. Analysing the collected data will allow us to investigate the validity of our hypothesis.

Previous studies that used biosignals for stress detection on office workers reported a significant correlation between negative stress ratings and EMG activity during work. For example, high muscle tension is a sign of stress (J. Chen et al., 2021; Naranjo-Hernández et al., 2020). Furthermore, the EMG of trapezius muscle activity is higher when performing computer tasks that demand a high or low mental workload. Neck and shoulder pain induced as the physiological stress response is associated with increased EMG activity in the trapezius muscle and HR (Giannakakis et al., 2022; Korving et al., 2020; Naranjo-Hernández et al., 2020). In addition, HR is the most prominent feature that significantly increases during stress (Giannakakis et al., 2022; Naranjo-Hernández et al., 2020) and mental load (Zargari Marandi et al., 2019). Hence, we expected that multimodal objective information will allow for characterising the essential physiological information previously tested by other researchers and that the fusion of biosignals improves our occupational risk assessment model.

With regards to organisational risk assessment, we expect to use the collected data to find patterns on broader levels (i.e., comparison between different offices). Analysis on an organisational level will ensure that identifying individual participants is impossible (e.g. reporting of group-wise pain statistics, mean noise-levels, mean stress levels, among others). The resulting information will allow us to identify which occupational risks are prevalent throughout the different locations or within the entire organisation and based on that develop appropriate mitigation and prevention strategies.

Our study has some potential limitations that are important to be acknowledged. We are undertaking a cross-sectional study in which the study sample will be recruited from a public company setting and may not represent the characteristics of the general office worker population. Consequently, our observations can only be generalised to office workers attending public administration facilities in Portugal.

Conclusions

The quantification of individual and organisational occupational risk factors for WMDs will help provide a point of reference from the patterns of detected symptoms, deliver data for policy development, and guarantee that intervention activities at population levels are appraised suitably for effectiveness. We also provide a protocol and setup to promote the design of intelligent offices with existing technology, which can be used to monitor occupational variables at the individual and organisational levels. Thus, planning to prevent WMDs in office work requires considering multiple potentially modifiable influences, including factors relevant to the workplace and the individual worker. This research would provide information that would help integrate the concept of risk factor reduction for early screening and prevention.

Finally, it will provide a valuable base for hypothesis generation, longitudinal studies, and randomised controlled trials. It is anticipated that this protocol can be amended and trialled in other national and international occupational care contexts. These findings will be of significant interest to occupational research

and organisations looking to develop more integrated and holistic models. It will help prevent WMDs, increase instructional efficiency, and create an environment for successful outcomes. Key stakeholders and end-users should also be involved through the design, development, and evaluation phases to ensure the risk assessment content and organisational strategies are developed to achieve workers' needs.

Chapter 6

Exploring the real-time variability and complexity of sitting patterns in office workers with non-specific chronic spinal pain and pain-free individuals

Abstract: Chronic spinal pain (CSP) is a prevalent condition, and prolonged sitting at work can contribute to it. Ergonomic factors like this can cause changes in motor variability. Variability analysis is a useful method to measure changes in motor performance over time. When performing the same task multiple times, different performance patterns can be observed. This variability is intrinsic to all biological systems and is noticeable in human movement. This study aims to examine whether changes in movement variability and complexity during real-time office work are influenced by CSP. The hypothesis is that individuals with and without pain will have different responses to office work tasks. Six office workers without pain and ten with CSP participated in this study. Participants's trunk movements were recorded during work for an entire week. Linear and nonlinear measures of trunk kinematic displacement were used to assess movement variability and complexity. A mixed ANOVA was utilized to compare changes in movement variability and complexity between the two groups. The effects indicate that pain-free participants showed more complex and less predictable trunk movements with a lower degree of structure and variability when compared to the participants suffering from CSP. The differences were particularly noticeable in fine movements.

Keywords: movement variability; motor adaptations; chronic pain; spinal pain; biomechanics; signal processing; nonlinear analysis.

Introduction

Chronic spinal pain (CSP), which includes low back pain (LBP), neck pain, and thoracic spinal pain, is a widespread global health issue (Briggs, Bragge, et al., 2009), impacting millions of individuals (Bevan, 2015). CSP is a leading cause of disability, with LBP and neck pain being the most prevalent forms (A.-M. Wu

et al., 2024a; Cohen et al., 2021; Herman et al., 2019; Friedly et al., 2010). Recent research indicates that an estimated 619 million people experienced LBP in 2020, with projections suggesting an increase to 843 million by 2050 (Ferreira et al., 2023). Job roles involving prolonged sitting posture, such as those in tax authorities, have been found to increase the risk of developing CSP due to ergonomic factors (Ferreira et al., 2023; Heredia-Rizo et al., 2022; Issever et al., 2008). Tax authorities are engaged in tasks that necessitate extended periods of sitting posture, leading to heightened discomfort and resulting in changes in motor variability (Baker et al., 2018; Søndergaard et al., 2010; Issever et al., 2008). In addition, tax authority workers experience high levels of stress, which can affect their work performance, leading to reduced job satisfaction, health-related lost productivity, and increased absenteeism. These biopsychosocial risks can contribute to the onset or aggravation of ongoing CSP (Pohling et al., 2016). Hence, there is a growing concern regarding investigating occupational diseases in these workers.

The concept of a singular, correct posture has been challenged, making it imperative to adopt varying positions (Park et al., 2023; Peereboom, Langen, & Copsey, 2021; Slater et al., 2019). Furthermore, the relevance of variation, the study of variability, has become significant as it sheds light on how the motor system adapts to maintaining posture (Noamani et al., 2022; Saito et al., 2021; Stergiou et al., 2006). One of the most effective ways to measure changes in motor performance over time is through variability analysis. This method has gained attention recently due to its ability to identify variations in functional capacity and performance, ranging from healthy states to disability patterns (Stergiou & Decker, 2011). In the field of kinesiology, the complexity of human movement is influenced by the interactions between various physiological systems. Understanding these interactions is crucial for maximizing an individual's ability to function and perform, effectively responding to their environment (Cavanaugh et al., 2017; Stergiou & Decker, 2011; Harbourne & Stergiou, 2009). Human motor variability can be described as the normal variations that occur in motor performance across multiple repetitions of the same tasks (Bernstein, 1967). When executing the same task over multiple

attempts, different performance patterns, including kinematic, kinetic, and muscle activation patterns, can be observed (Latash et al., 2002). This variability is intrinsic to all biological systems and is readily observable. When a person tries to repeat the same movement twice, the two actions will never be identical or independent (Stergiou & Decker, 2011a).

Previous research has revealed that prolonged sitting increases the variability in the displacement of the center of pressure (CoP) and lumbar curvature in the anterior–posterior direction, while decreasing complexity represented by sample entropy, leading to discomfort (Søndergaard et al., 2010). Studies on trunk postural control using an unstable surface indicate that individuals with LBP have inferior control compared to those without LBP, as shown by higher root-mean-square displacement (Alshehri et al., 2024). This impaired postural control may result from delayed or inaccurate corrective responses, increasing seat movements and potential trunk stiffening. A systematic review found that individuals with chronic LBP had delayed muscle onsets in response to perturbations, with inconclusive evidence on CoP or kinematic differences compared to healthy controls (Knox et al., 2018). Additionally, patients with non-specific neck pain or whiplash-associated disorder exhibit greater postural instability, linked to proprioceptive impairment rather than pain duration (Ruhe et al., 2011). Older adults with neck pain show diminished functional performance, as indicated by wavelet analysis (but not for entropy) measures, compared to healthy controls (Quek et al., 2014). It is interesting to note that both experimental and chronic neck–shoulder pain can increase variability in task timing, kinematics, and muscle activation during repetitive arm movement (Madeleine et al., 2008). This suggests that variability plays an important role in motor control and may contribute to the transition from acute to chronic pain. During the acute stage, the central nervous system seeks the least painful biomechanical solution, while in the chronic stage, the chosen solutions are characterized by reduced flexibility of the motor system (Madeleine et al., 2008).

Therefore, it is crucial to understand the motor control of workers who sit for extended periods of time. One potential solution is to use inertial sensors that

are embedded in smartphones to monitor these workers (Z. Wang et al., 2021; Pooranawatthanakul & Siriphorn, 2020; Gizzi et al., 2019; Longo et al., 2018; Sheeran et al., 2012). The present work is part of the Prevention of Occupational Disorders in Public Administration based on the Artificial Intelligence (PrevOccupAI) project. It involves stakeholders from biomedical engineering, health sciences, and public administration (tax authority) in Portugal. The main goal is to promote occupational health by identifying occupational risks. The focus is on characterizing and assessing daily working activities, working conditions, and potential risk factors associated with office work in the assistive technology field. The evaluation encompasses both the individual and organizational levels, utilizing non-intrusive sensing technology and questionnaires to accurately assess workers' potential occupational risks within the tax authority. As part of the PrevOccupAI project, we are interested in studying motor control adaptation in individuals working for tax authorities and investigating CSP presence and perception. To achieve this, we studied the effects on trunk motor variability when working for five consecutive days, following the example of previous investigations that demonstrated changes in motor variability over time (Arippa et al., 2022; Madeleine et al., 2021a; Mingels et al., 2021a; Madeleine, 2012; Søndergaard et al., 2010; Madeleine et al., 2008).

This study aimed to examine the real-time trunk dynamics in individuals with and without CSP while performing sedentary work tasks. The study had two main objectives: (a) to assess individual trunk motor variability of office workers in real time and (b) to test the hypothesis that individuals with and without pain have different responses to office work tasks.

Materials and methods

Design

This cross-sectional study was performed at four locations of the Portuguese Tax and Customs Authority (Autoridade Tributaria e Aduaneira, AT) throughout the Lisbon Metropolitan Area. The study received ethical approval from the

Universidade Nova de Lisboa Ethics Committee (No. CE/FCT/005/2022) (Appendix I). All participants provided written informed consent.

Participants

The participants were selected at random as part of a campaign conducted by AT's HR team. The following inclusion criteria were applied: adults 18 years of age and older without any associated pathology (e.g., neurological, orthopedic, rheumatic, oncological, or cardiorespiratory) and pregnancy.

The pain-free group (PG) (n = 6) was composed of individuals who had no history of back or lower limb pain or injury that restricted their ability to function or required medical attention. On the other hand, the chronic spinal pain group (CSPG) consisted of individuals who experienced non-specific spinal pain that persisted or reoccurred for a minimum of three months without any identifiable underlying cause (n = 10). This definition aligns with the criteria established by the International Association for the Study of Pain (IASP) and the ICD 11 guidelines (Perrot et al., 2019b; Treede, Rief, Barke, Aziz, Bennett, Benoliel, Cohen, Evers, Finnerup, First, & others, 2019).

Demographic information was collected through a single questionnaire to analyze the sample. The collected data included age (in years), gender (male or female), height (in centimeters), and mass (in kilograms), which was then used to calculate the Body Mass Index (BMI) using the formula: $BMI = \frac{mass (kg)}{height (m)^2}$.

The International Physical Activity Questionnaire Short form (IPAQ-SF) (Craig et al., 2003) was included to evaluate physical activity. This survey consists of seven questions about the number of days and the amount of time spent doing vigorous and/or moderate physical activity (PA), walking, and sitting during weekdays. The final score is reported as low, medium, or high, and the level of physical activity per week through the metabolic equivalents (Craig et al., 2003). The participants' characteristics are summarized in Table 1. The data are expressed in terms of mean, standard deviation, or percentage.

Table 1. Participants' characteristics.

Variable	PG	CSPG
Sex (female, %)	50.00	80.00
Age	51.33 (4.41)	54.00 (6.51)
BMI (kg/m²)	28.86 (3.87)	26.75 (6.14)
Years of profession	21.17 (13.64)	18.16 (13.91)
Time working per week (hours)	35.42 (3.32)	41.10 (7.07)
Time sitting per day (week)	8.28 (2.13)	9.20 (3.39)
Time sitting per day (weekend)	3.61 (1.65)	4.18 (1.78)
Physical activity (%)		
Low	33.33	30.00
Moderate	50.00	40.00
High	16.70	30.00

Procedures

A series of data acquisitions were carried out over five consecutive days. Our previous published work (Oliosì et al., 2023) provides a detailed description of the acquisition protocol.

A cross-platform application developed specifically for the project was used for the data collection. The application creates unique user access for each participant, enabling them to complete questionnaires using either a computer or a smartphone. The application interface allows for scheduling acquisitions in advance, specifying the devices from which data should be acquired, as well as the start time and duration of the acquisition. Prior to the week of acquisitions, a preliminary session was held to inform the participants about the project, its objectives, and the acquisitions. Once informed consent was obtained, a profile was created for each participant. They were then given questionnaires, and the acquisition times were scheduled using the PrevOccupAI application, starting at the beginning and ending at the end of the workday. Participants were advised

to schedule acquisitions while seated at their desks, preferably two in the morning and two in the afternoon.

At the beginning of each workday, the researchers attached the equipment to the workers, and the workers went about their daily tasks in their respective offices until the end of the day. After the workday was over, the equipment was removed and disinfected. The manuscript presented here contains part of a comprehensive analysis that collected multimodal information from multimodal sources.

During data collection, three different devices were used: two surface electromyography (EMG) sensors, a smartwatch, and a smartphone. The two EMG sensors (1000 Hz) were placed in the upper trapezius, while the smartwatch, which recorded the heart rate (1 Hz), was placed on the right wrist. The smartphone was positioned on the subject's chest using a harness (Figure 1).

It is important to note that the placement of the EMG sensors and smartwatches did not affect the positioning of the smartphone sensors. Inertial sensors from smartphones were chosen as the most suitable equipment to capture trunk posture data from subjects. The use of smartphones was deemed appropriate due to their widespread availability and the fact that they are equipped with a range of sensors.

Thus, the accelerometer (ACC), magnetometer (MAG), gyroscope (GYR), and rotation vector (RV) data were acquired using a Xiaomi Redmi Note 9. The Redmi Note 9 runs the Android operating system. The Android OS restricts the ACC, GYR, and RV to 100 Hz, while the MAG is sampled at 50 Hz.

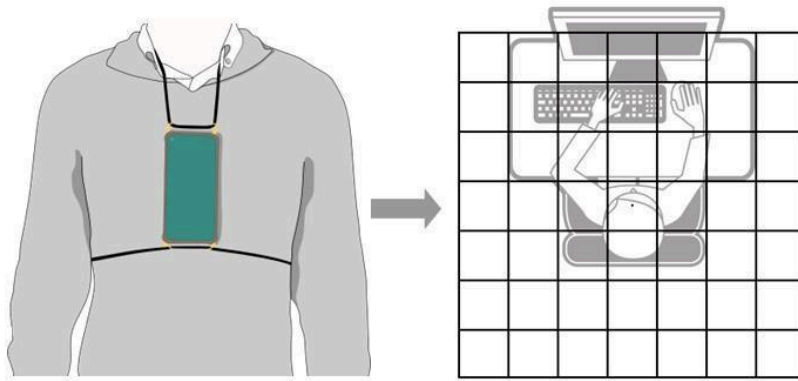


Figure 1. Postural analysis using a smartphone mounted on the chest.

Data Analysis

Data Synchronization

Android's battery-saving mechanisms can cause sensor data to be sampled at different times and with irregular intervals. Due to this reason, the following two-step procedure was performed:

Determining start and stop points: The starting point was defined as the initial timestamp of the last sensor to begin acquisition, and the stopping point as the final timestamp of the first sensor to cease acquisition. All signals were cropped to this range.

Resampling: Each signal was individually resampled to 100 Hz to ensure a consistent and uniform sampling frequency. This was achieved by creating a new time axis with constant intervals. Each component of each signal was then linearly interpolated according to this new time axis.

Accelerometer and Rotation Vector Pre-Processing:

The following pipeline was used to process accelerometer data:

1. High frequencies' removal through a lowpass filter with 10 Hz.
2. Gravity component removal.
3. Detrending by subtracting the mean of the signal from each sample.
4. Moving average smoothing filter with a 150-sample window.

Regarding the rotation vector, a moving average smoothing filter with a window of 5 samples was employed to eliminate noise arising from factors like sensor inaccuracies. This filter reduced the impact of noise by averaging out fluctuations and high-frequency variations in the signal.

5. The signals were segmented due to the large length of the time series (approximately 5 h).

To achieve this segmentation, a 15-min window size was chosen. The central window was labeled as “Lunch” time, with the windows immediately before and after also classified as “Lunch” breaks. The windows before “Lunch” were tagged as “AMx”, where ‘x’ denotes the window number, and the same labeling scheme was applied to the windows following “Lunch”, which were labeled as “PMx” (Table 2).

Table 2. Time series lengths for each window.

Window	Length
AM1	1289
AM2	1167
AM3	1171
PM1	1589
PM2	1126
PM3	1246

An algorithm was used to detect and remove periods when workers were not at their desks or transitioning between postures that were outside the analysis range (Ohlendorf et al., 2020). This algorithm was fed by ACC data and considered a threshold to identify postural changes and walking intervals. The threshold was determined based on the magnitude of acceleration (mag) from the X, Y, and Z axes. The magnitude (mag) represents the combined acceleration value along the x, y, and z axes. In Figure 2, the graph shows the signal with green highlights indicating the segments that were removed.

$$mag = \sqrt{(x^2acc + y^2acc + z^2acc)} \quad (1)$$

The threshold was based on a human walking accelerometry analysis previously documented in (Satkunskiene et al., 2009). A walking velocity of 0.55 m/s was considered as representative of a working scenario. Using acceleration values in the x, y, and z coordinates from an ACC placed on the C7 vertebrae ($a_x = 1.02 \text{ m/s}^2$; $a_y = 1.15 \text{ m/s}^2$; $a_z = 1.41 \text{ m/s}^2$), the following equation calculated the acceleration magnitude threshold:

$$\text{mag} = \sqrt{1.02^2 + 1.15^2 + 1.41^2} \Leftrightarrow \text{mag} = 2.08(\text{m/s}^2) \quad (2)$$

The result presented an acceleration magnitude threshold of approximately 2 m/s^2 . This value was also corroborated by the calculation of the same threshold when establishing the relationship between energy consumption (metabolic equivalent, MET) and acceleration magnitude [44,45] with a MET for walking, gathering things (encompassing the movement that can be considered as postural transitions), and 3 METs for getting ready to leave in occupational situations. The threshold was determined by:

$$\text{MET} = 5.289 * \text{mag} - 8.5548 \Leftrightarrow \text{mag} = \frac{3 + 8.5548}{5.289} \Leftrightarrow \text{mag} = 2 (\text{m/s}^2) \quad (3)$$

Both approaches yielded a similar approximate value for the acceleration magnitude threshold of 2 m/s^2 , and this was the threshold defined for non-seated interval detection. Consequently, the algorithm removed signal intervals exceeding that threshold, preserving only the signal portions containing the sway variability in the postural data for analysis.

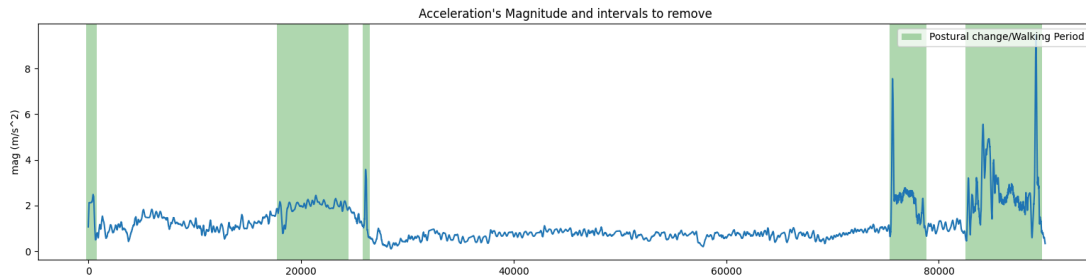


Figure 2. Detection of periods of interest.

Quaternions were utilized to estimate the CoP projection in the xy plane, which was derived from the RV. The algorithm detected and recorded the indexes of

intervals that needed to be removed. The removal of these intervals by their indexes was then applied to the rotation vector signal, synchronizing the data and cleaning the signal of non-seated periods and transitions between postures.

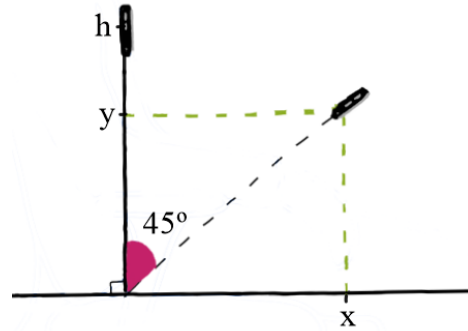


Figure 3. Decomposition-based approach for the projection's calculation of displacement.

Subsequently, the quaternions obtained from the RV were transformed into Euler angles. The median of each Euler angle was subtracted to establish a reference position centered at the origin (0, 0). These angles were then converted into positions in the xz-plane, with the phone placed on the chest near the sternum (Figure 3). This process enabled the estimation of the CoP projection in the horizontal plane that represented the subject's movement during work. The CoP projection comprised two time series, namely CoPx (anterior–posterior) and CoPy (medial–lateral) (Figure 4).

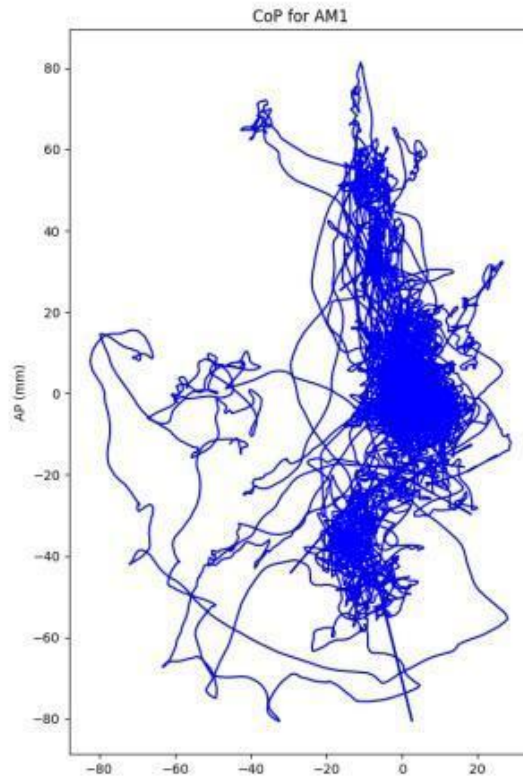


Figure 4. Data from two anatomical axes.

To ensure that all participants were in the same postural sway condition, a limited zone of movement was defined according to the literature (Ohlendorf et al., 2020). An ellipse was created to enclose the postural sway signal, with dimensions of AP radius = 25 mm and ML radius = 18 mm. The signal inside this ellipse was the one extracted for further analysis. After excluding walking periods, the rotation vector time series was used to transform the coordinates into Euler angles. These angles were then converted into projection coordinates to obtain the displacement value in millimeters.

Measures of Variability

Linear Measures

After generating the final dataset containing the CoP time series, we extracted a set of linear measures to evaluate the movement patterns of the trunk and the signal characteristics for each participant. To calculate these linear parameters,

the TSFEL Python package, which is a library described in (Barandas et al., 2020), was utilized. The TSFEL package helped us to compute various metrics that were considered in this analysis. Table 3 provides a comprehensive list of these metrics, along with their interpretations when applied to CoP time series data. Additionally, specific parameters related to postural sway were calculated. Table 4 presents the details of these parameters, including their units and the formulas used for their calculation.

Table 3. Linear parameters of the time series calculated using TSFEL. Adapted from (Barandas et al., 2020).

Parameter	Description	Units
Statistical Domain		
Maximum	Computes the maximum value of the signal.	m/s ²
Minimum	Computes the minimum value of the signal.	m/s ²
Mean	Computes the mean value of the signal.	m/s ²
Standard deviation	Computes the SD of the signal.	m/s ²
Root mean square	Computes the RMS of the signal.	m/s ²
Interquartile range	Computes the IQR of the signal.	m/s ²
Variance	Computes the variance of the signal.	(m/s ²) ²
Temporal Domain		
Autocorrelation	Computes the autocorrelation of the signal.	-
Signal distance	Computes the time series traveled distance.	-

Linear measures of variability are crucial for providing information about the amount of movement and variability around a mean value. However, it is important to note that variability is an inherent characteristic of all biological systems and describes the normal variations that occur in motor performance across multiple repetitions of a task. While traditional linear tools such as standard deviation (SD), coefficient of variation (CV), and range may provide valuable insights, they assume that each cycle of movement is independent of past and future cycles, and that variations between cycles are random. This assumption may not be accurate, and traditional tools may provide different results when compared with nonlinear measures (Stergiou et al., 2006a; Stergiou, 2004).

Table 4. Linear measures to assess the sway variability in trunk movement patterns (Quijoux et al., 2021).

Metric	Formula	Units
	$\sum n X_n + 1 \cdot Y_n - X_n \cdot Y_n + 1 $	
Sway area		mm ²
	$\sqrt{(\max(X) - \min(X))^2 + (\max(Y) - \min(Y))^2}$	
Sway range		mm
	$ \max(X) - \min(X) $	
Sway range (AP)		mm
	$ \max(Y) - \min(Y) $	
Sway range (ML)		mm
	$\sum n \sqrt{(X_n + 1 - X_n)^2 + (Y_n + 1 - Y_n)^2}$	
Sway path		mm
	$\sqrt{\frac{1}{N} \sum n (X^2 + Y^2)}$	
Sway distance (RMS)		mm
	$\frac{fs}{N} \sum n \sqrt{(X_n + 1 - X_n)^2 + (Y_n + 1 - Y_n)^2}$	
Mean sway velocity		mm/s

Nonlinear Measures

To gain a more complete understanding of how a movement pattern changes over time, it is critical to also include nonlinear techniques in the analysis. Traditional linear measures can miss certain valuable insights that nonlinear analysis can provide, which can help us better understand the actual structure of variability (Stergiou, 2004; Stergiou et al., 2006a). When it comes to analyzing trunk movement patterns, it is important to assess complexity using nonlinear parameters. This helps to reveal the variability in the pattern over time by examining the entire time series (Harbourne & Stergiou, 2009). In this study, two nonlinear measures were employed to evaluate the complexity of variability:

Multifractal Detrended Fluctuation Analysis (MDFA): Fractal measures are an effective way to measure the complexity of fluctuations in a system. Multifractal Detrended Fluctuation Analysis (MFDFA) is a method that takes into account both small and large oscillations in a time series, which contain important information. The Hurst exponent (H) is a measure of the correlation among data

points in a time series. The DFA method includes a parameter called “ q ” that allows for the analysis of different statistical moments of the fluctuation function. Each H value for a specific “ q ” order provides insights into how the scaling behavior of the time series changes with different statistical properties of the fluctuations. When considering MFDFA, “ Hq ” represents the Hurst exponent calculated for different orders “ q ”. These values are dimensionless and usually range between 0 and 1. They are scale-invariant measures that describe the fractal nature of the data and do not have units like meters or seconds (França et al., 2019; Kantelhardt et al., 2002; N. M. Lau et al., 2015).

A q -order range spanning from -5 to 5 was employed for the analysis of the time series, utilizing a polynomial order of 0.5 . To enhance the robustness of our analysis, a set of scaling windows was implemented, ranging from 5 to the length of the time series divided by 8 , with linearly spaced steps, resulting in a total of 30 windows.

The calculation of the H and multifractal spectrogram was executed using the Fathon Python library (Bianchi, 2020). Notably, the `countbysteps` parameter in our code determined the number of windows used for computing H values. The determination of the last windows to be included was based on the total length of the time series divided by 8 , resulting in 30 windows. The computation of Hurst exponent values involved varying window sizes. Specifically, we initiated the process with 5 windows and incrementally increased the count by 5 steps until reaching a total of 30 windows (e.g., $5, 10, 15, 20, 25, 30$ windows). This stepwise approach allowed us to comprehensively assess the multifractal characteristics of the time series across different window configurations. The metrics are compiled in Table 5.

Table 5. Nonlinear parameters calculated using Multifractal Detrended Fluctuation Analysis.

Parameter	Description
$H_{qs} = -5$	Computes H for q -order = -5 .
$H_{qs} = 0$	Computes H for q -order = 0 .
$H_{qs} = 2$	Computes H for q -order = 2 .

Hqs = 4.5	Computes H for q-order = 4.5.
Total width	Computes the width of the multifractal spectrum.
Positive width	Computes the left width of the multifractal spectrum.
Negative width	Computes the right width of the multifractal spectrum.
Maximum spectrum	Computes maximum value of the multifractal spectrum.

To ensure that the time series captured the phenomenon of interest and was not derived from a stochastic process, we performed a surrogate analysis. For each time series (3×2 (morning and afternoon) $\times 3$ days), we generated 100 surrogates using the Iterated Amplitude-Adjusted Fourier Transform (IAAFT) algorithm (Venema et al., 2006). $H(q) = 0$ was used since it is the order used in the traditional DFA. We then verified if the value of $H(q) = 0$ for the original time series was inside or outside of the 95% interval of confidence. If the value was outside, we considered genuine fractal characteristics were present in the original time series.

Sample Entropy (SampEn): SampEn is a nonlinear measure to quantify the regularity or unpredictability of time series data. It quantifies the likelihood of finding repeated patterns of a certain length in the data. A higher SampEn value indicates greater irregularity or complexity, suggesting that the time series is less predictable or more disordered. Conversely, a lower SampEn value suggests more regularity or predictability in the data. Similar to the Hurst Exponent, SampEn was computed for the original time series and surrogates, using the EntropyHub Python library (Flood & Grimm, 2021).

The SampEn was calculated with an embedded dimension of 4, as per the recommendation in the literature (Montesinos et al., 2018). It was observed that nearly 98% of the original data points were outside the limit interval. This reaffirmed the fact that the time series exhibited authentic fractal behavior that was absent in the surrogate data.

Statistical Analysis

Descriptive statistics were used to summarize the numerical variables, specifically the mean and standard deviation. The data displayed a normal

distribution, which was confirmed through the Shapiro–Wilk test. A mixed ANOVA (Analysis of Variance) was utilized to compare the average group values of all the calculated measures in order to analyze the impact of the days and periods as independent variables on all the potential dependent variables. Whenever there was a significant difference within or between groups ($p < 0.05$), the effect size of the ANOVA was computed using partial eta squared (η^2_p) and categorized as small (<0.06), medium ($0.06–0.14$), and large (>0.14) (Padulo et al., 2023; Richardson, 2011).

Results

Measures of Magnitude of Variability

Table 6 presents the results of the time series analysis for linear measures, along with the corresponding factors. The table also features the p values resulting from the comparison tests carried out both between and within subjects. Table 7 showcases the results of the ANOVA for linear measures, emphasizing the statistically significant differences, effect sizes, and their interactions.

Results from the statistical analysis conducted on the linear measures showed some interesting findings, indicating significant differences across various metrics, particularly for those with larger effect sizes. Maximum ML (m/s^2) and signal distance AP and ML exhibited significant differences within subjects. Between groups, several metrics showed significant variations, including the minimum value of the signal AP (mm^2), SD AP (m/s^2), variance AP ($(\text{m/s}^2)^2$), RMS ML (m/s^2), and IQR AP (m/s^2). It is noteworthy that most of these values were higher in the PG. The summary of findings is presented in Table 7.

Throughout the week, there were significant differences in the “maximum (ML di- rection)” values of the PG, but not in the CSPG. Specifically, the maximum ML metric displayed a large effect size ($\eta^2_p = 0.149$) with $p = 0.041$ in the PG. On the other hand, the metric minimum AP mm^2 differed notably between the groups, with more negative values in the CSPG, indicating the patterns of most were on the posterior side. The effect size was large ($\eta^2_p = 0.386$) with $p =$

0.010. There were also significant between-group differences in SD (AP), with the CSPG values consistently higher, indicating greater displacement toward the front side. The effect size was large ($\eta^2_p = 0.534$) with $p = 0.001$.

The variance in the AP direction showed a contrasting trend between the PG and the CSPG. The PG tended to decrease over the week, while the CSPG showed an increase. This variation yielded a statistically significant effect size of the group ($\eta^2_p = 0.505$) with $p = 0.002$. The RMS in the ML direction metric also showed a statistically significant effect size of the group ($\eta^2_p = 0.388$) with $p = 0.010$. Moreover, the IQR in the AP direction demonstrated significant differences between groups. In general, there was a decrease in both groups as the week progressed. The effect size was large ($\eta^2_p = 0.398$) with $p = 0.009$.

Table 6. Mean $\pm$ SD values for the calculated linear measures and their comparisons.

	Metrics						Day/Time						WS	BS
	PG						CSPG							
	Day 1		Day 3		Day 5		Day 1		Day 3		Day 5			
	AM	PM	AM	PM	AM	PM	AM	PM	AM	PM	AM	PM		
Sway area	53.98 ±25.9 2	49.52 ±7.05	38.06 ±11.5 4	47.17 ±6.18	51.20 ±22.7 5	44.12 ±15.9 4	49.83 ±18.9 2	60.29 ±28.2 4	45.92 ±21.4 5	45.35 ±14.1 1	53.04 ±20.0 2	47.67 ±23.1 4	0.370	0.610
Sway range	29.80 ±6.26	30.69 ±3.96	28.80 ±3.95	31.14 ±6.23	30.13 ±10.0 7	29.39 ±5.91	25.84 ±6.55	30.17 ±6.63	24.44 ±8.04	29.00 ±9.58	26.87 ±8.38	24.60 ±10.7 3	0.560	0.200
Sway range (AP)	22.79 ±3.80	23.55 ±4.58	22.50 ±3.58	24.21 ±3.82	24.41 ±8.39	22.94 ±7.23	20.73 ±6.25	24.47 ±6.68	19.08 ±6.66	22.03 ±8.28	21.84 ±7.03	19.22 ±8.70	0.610	0.320
Sway range (ML)	17.73 ±6.01	18.38 ±1.76	16.02 ±3.24	18.67 ±5.90	16.54 ±8.03	16.73 ±5.24	14.03 ±4.94	16.87 ±3.63	14.62 ±5.49	17.40 ±6.77	14.36 ±5.79	14.30 ±6.43	0.530	0.200
Sway path	29.80 ±6.26	49.52 ±7.05	28.80 ±3.95	47.17 ±6.18	30.13 ±10.0 7	44.12 ±15.9 4	25.84 ±6.55	60.29 ±28.2 4	24.44 ±8.04	45.35 ±14.1 1	26.87 ±8.38	47.67 ±23.1 4	0.440	0.470
Sway distance	10.09 ±0.85	9.66± 1.38	9.92± 1.78	10.51 ±2.66	10.43 ±3.58	9.31± 2.80	9.88± 3.60	10.51 ±1.42	8.31± 3.06	9.40± 2.34	9.66± 2.24	9.45± 4.00	0.870	0.530

Sway velocity	16.90 ±7.83	15.22 ±2.20	13.51 ±3.45	15.45 ±3.54	14.95 ±6.16	15.04 ±5.81	16.91 ±7.61	19.90 ±9.30	15.24 ±6.42	16.02 ±4.69	16.41 ±6.67	15.08 ±6.89	0.690	0.470
Maximum (AP)	12.39 ±7.66	11.63 ±2.80	9.26± 8.77	8.97± 7.59	10.04 ±6.21	9.77± 7.44	8.58± 4.65	11.45 ±4.56	9.97± 3.27	11.81 ±7.24	14.89 ±4.27	15.12 ±2.20	0.620	0.240
Maximum (ML)	6.83± 3.81	10.90 ±1.99	4.61± 4.15	8.47± 6.08	5.40± 6.37	3.34± 3.20	8.84± 5.05	8.92± 2.38	6.11± 3.62	8.59± 4.29	9.47± 3.93	9.75± 4.46	0.040*	0.110
Minimum (AP)	-8.51± 3.81	-10.60 ±5.89	-8.14± 5.05	-10.58 ±4.58	-7.07± 9.11	-4.52± 7.07	-13.28 ±5.32	-13.81 ±4.84	-12.18 ±3.76	-13.02 ±7.14	-11.32 ±3.87	-9.29± 5.98	0.110	0.010*
Minimum (ML)	-8.27± 1.40	-7.13± 4.55	-8.26± 4.69	-9.77± 3.93	-6.63± 3.46	-6.79± 4.13	-6.76± 6.22	-8.16± 3.55	-10.39 ±4.02	-9.07± 3.34	-7.59± 4.53	-8.51± 2.92	0.460	0.510
Mean (AP)	1.65± 4.37	0.76± 4.32	-0.30± 5.03	0.04± 5.25	1.97± 5.04	3.73± 5.34	-1.90± 4.02	-0.12± 4.28	0.44± 2.94	0.11± 5.64	2.11± 4.36	2.59± 3.37	0.210	0.480
Mean (ML)	-1.59± 1.56	2.11± 3.50	-2.33± 3.04	-0.69± 2.48	0.06± 3.92	-1.38± 2.47	1.55± 5.40	0.08± 2.82	-2.03± 2.50	-0.07± 2.48	0.08± 2.79	0.00± 3.33	0.140	0.440
Standard deviation (AP)	4.10± 1.73	3.78± 0.89	3.13± 2.01	3.52± 1.21	3.12± 1.33	2.32± 1.55	4.39± 1.14	5.09± 0.81	4.01± 0.95	4.75± 1.08	4.99± 1.58	4.72± 1.00	0.220	0.001*
Standard deviation (ML)	2.58± 1.25	2.88± 0.64	1.95± 1.11	2.84± 1.77	2.07± 1.18	1.62± 1.06	2.68± 0.78	2.98± 0.39	2.83± 0.83	2.98± 0.96	3.07± 1.22	3.20± 1.00	0.380	0.070
Variance (AP)	22.21 ±13.9 6	17.22 ±6.44	14.65 ±14.4 1	16.25 ±9.11	15.75 ±10.2 8	9.09± 8.98	24.52 ±11.7 7	32.45 ±8.86	19.41 ±8.22	27.02 ±11.4 0	31.13 ±16.8 2	27.13 ±10.4 1	0.280	0.002*

Variance (ML)	9.12± 8.97	9.85± 3.62	5.46± 4.45	13.02 ±14.5 1	6.40± 4.45	5.07± 6.29	10.23 ±5.04	9.97± 2.71	10.48 ±5.58	10.71 ±6.20	12.60 ±9.12	13.14 ±8.41	0.690	0.250
Root mean square (AP)	6.77± 3.04	6.68± 1.56	5.87± 3.63	6.75± 2.00	6.82± 2.99	7.39± 5.14	7.11± 2.59	8.25± 1.95	7.72± 2.34	8.73± 2.12	8.56± 2.13	7.71± 2.21	0.870	0.060
Root mean square (ML)	5.16± 2.66	6.20± 1.54	4.06± 2.27	4.72± 1.83	4.94± 1.86	3.80± 2.25	6.94± 2.09	5.66± 1.15	4.98± 1.65	5.16± 0.88	5.77± 1.74	5.50± 1.68	0.120	0.010*
Interquar tile range (AP)	5.12± 2.97	4.11± 1.71	3.61± 2.99	4.33± 1.31	3.83± 1.57	2.67± 2.34	6.13± 2.40	7.14± 1.33	5.01± 1.93	6.49± 1.85	6.03± 2.67	6.06± 2.24	0.150	0.009*
Interquar tile range (ML)	3.20± 1.73	3.43± 0.86	2.09± 1.50	3.14± 2.63	2.21± 1.20	1.91± 1.44	3.44± 1.21	3.77± 0.80	3.43± 1.55	3.68± 1.29	3.85± 1.74	4.32± 1.95	0.510	0.060
Autocorr elation (AP)a	7.98± 5.84	7.06± 3.06	7.13± 6.72	7.83± 4.61	8.60± 6.29	11.15 ±10.2 0	7.64± 5.87	10.99 ±5.75	8.77± 4.73	12.54 ±6.94	10.59 ±4.46	8.90± 5.17	0.800	0.230
Autocorr elation (ML)a	4.61± 3.48	6.42± 2.41	3.32± 2.89	3.55± 2.41	4.40± 3.00	3.01± 2.33	7.33± 4.05	4.81± 2.10	4.02± 2.69	4.18± 1.80	4.60± 2.10	4.99± 3.31	0.150	0.130

Signal distance (AP) ^b	11.64 ±1.62	13.54 ±0.41	10.95 ±3.23	12.70 ±1.69	10.31 ±3.23	12.64 ±1.73	12.32 ±0.18	13.44 ±0.14	11.90 ±1.17	13.46 ±0.14	11.95 ±1.26	13.42 ±0.09	0.001*	0.090
Signal distance (ML) ^b	11.57 ±1.60	13.37 ±0.11	10.84 ±3.22	12.68 ±1.74	10.28 ±3.28	12.59 ±1.70	12.28 ±0.17	13.41 ±0.09	11.86 ±1.23	13.39 ±0.11	11.93 ±1.26	13.41 ±0.11	0.001*	0.090

Abbreviations: WS (Within Subjects), BS (Between Subjects). * denotes alpha level at $p < 0.05$. a: $\times 10^4$; b: $\times 10^2$.

There were no significant differences between the PG and CSPG values in both AP and ML components of the signal distance. However, a significant effect was found between the days of the week within groups, with both groups demonstrating an increase in the values as the day progressed. Precisely, signal distance AP (week) had a large effect size ($\eta^2_p = 0.380$) with $p = 0.001$ and signal distance ML (week) had a large effect size ($\eta^2_p = 0.383$) with $p = 0.001$. Lastly, there were no significant differences ($p > 0.05$) in the linear metrics of postural sway between the groups in any direction.

Table 7. Results from Mixed ANOVA for statistically significant calculations.

Metric	Direction	Group	Week	Week × Group
	n			
Maximum	AP	F1,14=1.483, p=0.243	F5,70=0.705, p=0.622	F5,70=1.505, p=0.200
		$\eta^2_p=0.096$	$\eta^2_p=0.048$	$\eta^2_p=0.097$
	ML	F1,14=2.951, p=0.108	F5,70=2.457, p=0.041	F5,70=2.141, p=0.070
		$\eta^2_p=0.174$	$\eta^2_p=0.149$	$\eta^2_p=0.133$
Minimum	AP	F1,14=8.812, p=0.010	F5,70=1.886, p=0.108	F5,70=0.107, p=0.991
		$\eta^2_p=0.386$	$\eta^2_p=0.119$	$\eta^2_p=0.008$
	ML	F1,14=0.451, p=0.513	F3.592,50.282=0.9 02, p=0.462	F3.592,50.282=0.4 56, p=0.748
		$\eta^2_p=0.031$	$\eta^2_p=0.061$	$\eta^2_p=0.032$
Standard Deviation	AP	F1,14=16.012, p=0.001	F5,70=1.431, p=0.224	F5,70=1.429, p=0.225
		$\eta^2_p=0.534$	$\eta^2_p=0.093$	$\eta^2_p=0.093$
	ML	F1,14=3.748, p=0.073	F5,70=1.078, p=0.380	F5,70=1.853, p=0.114
		$\eta^2_p=0.211$	$\eta^2_p=0.072$	$\eta^2_p=0.117$
Variance	AP	F1,14=14.310, p=0.002	F5,70=1.287, p=0.279	F5,70=1.301, p=0.274
		$\eta^2_p=0.505$	$\eta^2_p=0.084$	$\eta^2_p=0.085$
	ML	F1,14=1.474, p=0.245	F5,70=0.722, p=0.609	F5,70=1.821, p=0.120

		$\eta^2p=0.095$	$\eta^2p=0.049$	$\eta^2p=0.115$
Root Mean Square	AP	$F_{1,14}=4.047, p=0.064$	$F_{5,70}=0.365, p=0.871$	$F_{5,70}=0.331, p=0.893$
		$\eta^2p=0.224$	$\eta^2p=0.025$	$\eta^2p=0.023$
	ML	$F_{1,14}=16.506, p=0.010$	$F_{5,70}=1.828, p=0.119$	$F_{5,70}=1.676, p=0.152$
		$\eta^2p=0.388$	$\eta^2p=0.115$	$\eta^2p=0.107$
Interquartile Range	AP	$F_{1,14}=9.262, p=0.009$	$F_{5,70}=1.676, p=0.152$	$F_{5,70}=0.959, p=0.449$
		$\eta^2p=0.398$	$\eta^2p=0.107$	$\eta^2p=0.064$
	ML	$F_{1,14}=4.049, p=0.064$	$F_{5,70}=0.868, p=0.507$	$F_{5,70}=1.788, p=0.127$
		$\eta^2p=0.224$	$\eta^2p=0.058$	$\eta^2p=0.113$
Signal Distance	AP	$F_{1,14}=3.300, p=0.091$	$F_{2.023,28.323}=8.586, p=0.001$	$F_{2.023,28.323}=0.700, p=0.507$
		$\eta^2p=0.191$	$\eta^2p=0.380$	$\eta^2p=0.048$
	ML	$F_{1,14}=3.228, p=0.094$	$F_{2.011,28.156}=8.708, p=0.001$	$F_{2.011,28.156}=0.631, p=0.540$
		$\eta^2p=0.187$	$\eta^2p=0.383$	$\eta^2p=0.043$
Hqs=-5	AP	$F_{1,14}=5.478, p=0.035$	$F_{1.668,23.359}=0.707, p=0.479$	$F_{1.668,23.359}=0.521, p=0.569$
		$\eta^2p=0.281$	$\eta^2p=0.048$	$\eta^2p=0.036$
	ML	$F_{1,14}=4.495, p=0.052$	$F_{1.648,23.067}=0.667, p=0.495$	$F_{1.648,23.067}=0.946, p=0.387$
		$\eta^2p=0.243$	$\eta^2p=0.045$	$\eta^2p=0.063$
Hqs=0	AP	$F_{1,14}=4.837, p=0.045$	$F_{2.167,30.344}=1.651, p=0.207$	$F_{2.167,30.344}=0.375, p=0.707$
		$\eta^2p=0.257$	$\eta^2p=0.105$	$\eta^2p=0.026$
	ML	$F_{1,14}=3.736, p=0.074$	$F_{2.196,30.741}=1.179, p=0.325$	$F_{2.196,30.741}=1.152, p=0.333$
		$\eta^2p=0.211$	$\eta^2p=0.078$	$\eta^2p=0.076$
Hqs=4.5	AP	$F_{1,14}=6.548, p=0.023$	$F_{2.340,32.762}=1.651, p=0.204$	$F_{2.340,32.762}=0.218, p=0.838$
		$\eta^2p=0.319$	$\eta^2p=0.105$	$\eta^2p=0.015$
	ML	$F_{1,14}=4.478,$	$F_{2.842,39.794}=1.2$	$F_{2.842,39.794}=0.7$

		p=0.053	62, p=0.300	64, p=0.514
		$\eta^2p=0.242$	$\eta^2p=0.083$	$\eta^2p=0.052$
Negative Width	AP	F1,14=6.428,	F3.447,48.257=0.8	F3.447,48.257=1.1
		p=0.024	26, p=0.500	74, p=0.332
	ML	$\eta^2p=0.315$	$\eta^2p=0.056$	$\eta^2p=0.077$
		F1,14=6.716,	F3.023,42.325=0.9	F3.023,42.325=0.9
		p=0.021	37, p=0.432	37, p=0.432
		$\eta^2p=0.324$	$\eta^2p=0.063$	$\eta^2p=0.063$

Abbreviations: AP: anterior-posterior; ML: medial-lateral. The values highlighted in bold denote an alpha level at $p < 0.05$.

Measures of Structure of Variability

Table 8 presents the descriptive statistics of 18 outcomes of the time series analysis for nonlinear measures, along with the corresponding factors of days and periods. The table also displays the p values resulting from comparison tests conducted within and between subjects. The ANOVA results for nonlinear measures are shown in Table 7, highlighting the statistically significant differences, effect sizes, and their interactions.

$H(q) = -5$ in the AP direction showed significant differences between groups ($\eta^2_p = 0.281$, $p = 0.035$, large effect size), indicating noteworthy divergence. Similarly, $H(q) = 0$ in the AP direction showed significant differences between groups ($\eta^2_p = 0.257$, $p = 0.045$, large effect size), highlighting distinct patterns in postural dynamics.

Despite a smaller effect size, $H(q) = 4.5$ in the AP direction revealed significant differences along the days of the week within the CSPG compared to the PG ($\eta^2_p = 0.319$, $p = 0.023$), suggesting consequential variations over time in the CSPG.

Both the AP and ML components of negative width showed significant differences between groups (AP: $\eta^2_p = 0.315$, $p = 0.024$; ML: $\eta^2_p = 0.324$, $p = 0.021$, both large effect sizes) (Figure 5). Moreover, within the PG, both components exhibited an increase throughout the day, indicating temporal

trends in CoP dynamics among individuals without spinal pain. Interestingly, both groups displayed similar SampEn values in both directions, and these values did not show statistically significant differences ($p > 0.05$).

Discussion

The main objective of this research was to explore the impact of office work adaptations on the trunk posture in people suffering from non-specific spinal pain in comparison with healthy individuals. The analysis of movement data in individuals with pain (CSPG) versus those without pain (PG) during sitting and working revealed significant differences in both statistical and temporal domain metrics, highlighting variations in movement patterns and intensity between the two groups.

Statistical Domain Metrics

Statistical domain metrics showed distinct differences in trunk movement data distribution and spread. Maximum acceleration values indicated peak movement intensity, with significant differences in the ML direction. Minimum acceleration values were more negative in the CSPG, particularly in the AP direction, suggesting a greater tendency for right-side trunk fluctuations in individuals with pain. The SD of trunk movements, reflecting variability, was higher in the CSPG in the AP direction, indicating more dispersed movements. RMS values, measuring overall movement magnitude, were higher in the CSPG in the ML direction, suggesting more energetic movements. The IQR, representing the middle 50% of the data, was also higher in the CSPG in the AP direction, supporting increased variability in trunk movements. The variance of the signal indicated more consistent and varied movements in the CSPG in the AP direction. The linear metric, SD AP m/s^2 , had the most significant effect size between groups ($\eta^2_p = 0.534$), demonstrating considerable differences between the PG and CSPG across multiple variables related to postural dynamics.

Table 8. Mean $\pm$ SD for calculated nonlinear measures with p values for within and between subjects comparison.

	Metrics						Day/Time						WS	BS
	PG						CSPG							
	Day 1		Day 3		Day 5		Day 1		Day 3		Day 5			
	AM	PM	AM	PM	AM	PM	AM	PM	AM	PM	AM	PM		
<i>Hqs=2</i> (AP)	1.54 ±0.1 8	1.52± 0.11	1.61± 0.15	1.63± 0.16	1.52± 0.10	1.43± 0.15	1.58± 0.15	1.60± 0.11	1.50± 0.18	1.56± 0.12	1.56± 0.18	1.52± 0.17	0.34	0.82
<i>H qs=2</i> (ML)	1.50 ±0.1 9	1.42± 0.16	1.37± 0.18	1.37± 0.15	1.37± 0.11	1.25± 0.18	1.40± 0.12	1.45± 0.11	1.50± 0.16	1.49± 0.16	1.40± 0.09	1.37± 0.12	0.07	0.16
<i>Hqs=-5</i> (AP)	1.98 ±0.2 6	2.06± 0.13	1.83± 0.54	1.95± 0.22	1.76± 0.58	1.92± 0.25	2.19± 0.13	2.15± 0.13	2.13± 0.35	2.15± 0.14	2.11± 0.31	2.49± 1.16	0.48	0.04*
<i>Hqs=-5</i> (ML)	1.95 ±0.2 7	2.04± 0.08	1.80± 0.58	1.93± 0.30	1.73± 0.57	1.89± 0.23	1.94± 0.23	2.06± 0.13	2.20± 0.35	2.13± 0.18	2.09± 0.23	2.48± 1.2	0.50	0.05
<i>Hqs=0</i> (AP)	1.63 ±0.2 0	1.64± 0.08	1.50± 0.46	1.60± 0.21	1.41± 0.45	1.53± 0.19	1.71± 0.12	1.74± 0.08	1.63± 0.23	1.73± 0.09	1.66± 0.21	1.73± 1.00	0.21	0.04*
<i>Hqs=0</i>	1.56 ±0.2	1.62± 0.07	1.43± 0.45	1.52± 0.27	1.35± 0.47	1.43± 0.15	1.57± 0.07	1.60± 0.08	1.60± 0.19	1.67± 0.11	1.59± 0.18	1.64± 0.07	0.33	0.07

(ML)	2													
Hqs=4.5 (AP)	1.36 ±0.2 2	1.40± 0.06	1.29± 0.38	1.36± 0.19	1.21± 0.38	1.30± 0.13	1.50± 0.12	1.50± 0.08	1.37± 0.20	1.45± 0.07	1.38± 0.21	1.48± 0.08	0.20	0.02*
Hqs=4.5 (ML)	1.28 ±0.2 3	1.33± 0.07	1.13± 0.40	1.25± 0.27	1.11± 0.45	1.15± 0.11	1.33± 0.14	1.34± 0.10	1.35± 0.18	1.39± 0.10	1.30± 0.21	1.32± 0.08	0.30	0.05
Total width (AP)	0.94 ±0.2 2	1.01± 0.21	0.80± 0.30	0.87± 0.19	0.79± 0.31	0.92± 0.20	1.01± 0.19	0.95± 0.18	1.08± 0.30	1.01± 0.16	1.05± 0.27	1.33± 1.15	0.57	0.10
Total width (ML)	0.98 ±0.1 7	1.03± 0.08	0.97± 0.31	1.00± 0.26	0.89± 0.30	1.08± 0.34	0.95± 0.22	1.05± 0.12	1.19± 0.34	1.06± 0.13	1.11± 0.23	1.49± 1.26	0.39	0.17
Positive width (AP)	0.45 ±0.1 1	0.43± 0.16	0.36± 0.17	0.40± 0.14	0.33± 0.16	0.39± 0.16	0.38± 0.12	0.40± 0.15	0.48± 0.19	0.46± 0.11	0.46± 0.17	0.70± 0.98	0.59	0.27
Positive width (ML)	0.46 ±0.1 0	0.46± 0.05	0.49± 0.16	0.45± 0.23	0.39± 0.19	0.47± 0.25	0.37± 0.18	0.44± 0.11	0.48± 0.21	0.46± 0.08	0.47± 0.14	0.80± 1.04	0.46	0.52
Negative width (AP)	0.49 ±0.1 3	0.58± 0.09	0.45± 0.13	0.47± 0.07	0.46± 0.17	0.53± 0.12	0.63± 0.12	0.55± 0.10	0.60± 0.15	0.55± 0.10	0.60± 0.13	0.63± 0.18	0.50	0.02*
Negative	0.52	0.57±	0.49±	0.55±	0.50±	0.61±	0.58±	0.61±	0.70±	0.60±	0.64±	0.70±	0.43	0.02*

width (ML)	± 0.15	0.08	0.20	0.09	0.15	0.11	0.10	0.13	0.16	0.10	0.14	0.23		
Maximum spectrum (AP)	1.66 ± 0.20	1.68 ± 0.09	1.53 ± 0.47	1.64 ± 0.21	1.45 ± 0.46	1.57 ± 0.20	1.76 ± 0.12	1.78 ± 0.08	1.72 ± 0.27	1.78 ± 0.09	1.71 ± 0.22	2.06 ± 0.98	0.46	0.06
Maximum spectrum (ML)	1.60 ± 0.22	1.66 ± 0.07	1.47 ± 0.46	1.56 ± 0.27	1.39 ± 0.47	1.48 ± 0.16	1.56 ± 0.20	1.65 ± 0.09	1.70 ± 0.24	1.71 ± 0.12	1.64 ± 0.18	1.98 ± 0.99	0.53	0.09
Sample Entropy (AP)	0.42 ± 0.07	0.46 ± 0.10	0.41 ± 0.13	0.45 ± 0.07	0.39 ± 0.14	0.48 ± 0.13	0.46 ± 0.06	0.45 ± 0.05	0.41 ± 0.06	0.44 ± 0.03	0.40 ± 0.08	0.43 ± 0.06	0.19	0.87
Sample Entropy (ML)	0.43 ± 0.07	0.41 ± 0.06	0.39 ± 0.11	0.42 ± 0.05	0.37 ± 0.11	0.49 ± 0.18	0.48 ± 0.08	0.46 ± 0.05	0.42 ± 0.06	0.46 ± 0.04	0.44 ± 0.08	0.48 ± 0.04	0.08	0.09

Abbreviations: WS (Within Subjects), BS (Between Subjects). * denotes alpha level at $p < 0.05$.

Temporal Domain Metrics

Movement patterns and cumulative aspects over time in the temporal domain metrics were analyzed. The signal's autocorrelation, which measures its correlation with a lagged version of itself, showed no significant differences between groups. This suggests repetitive sitting posture movements were similar in individuals with and without pain. However, the signal distance, reflecting the total trunk movement over time, was significantly different in both directions within subjects. This indicates distinct cumulative trunk displacement between the PG and CSPG, suggesting variations in overall movement patterns during sitting and working.

Signal Structure and Complexity

The structure of the signal signature varied between groups but remained consistent throughout the week. For $H(q) = -5$, emphasizing the smallest fluctuations (Kantelhardt et al., 2002), H was different between groups in the AP direction, with higher values in the CSPG, indicating greater variability in fine trunk movements. For $q = 0$, H was different between groups in the AP direction, indicating higher overall variability in the CSPG. For $q = 4.5$, focusing on the largest fluctuations (Kantelhardt et al., 2002), $H(q)$ was different between groups in the AP direction, highlighting more significant deviations and large-scale movements in the CSPG. In monofractal analysis ($H(q) = 2$), results were equal between groups in both AP and ML directions, suggesting consistent overall trunk movement complexity across scales for both groups. The negative width, indicating fine-scale movement variability, was higher in the CSPG in both directions, supporting more intricate control mechanisms for minor corrections in individuals with pain.

Postural variables derived from CoP provide insights into system complexity through time series analysis. The time intervals displayed a non-random pattern, adhering to an inverse power law distribution ($1/f\alpha$), indicating the presence of pink noise or long-range correlations. Past studies using DFA analysis affirmed the existence of physiological complexity (Larivière et al.,

2013; Lau et al., 2015). Results showed that PG values were closer to 1.5 (indicating Brown noise) compared to CSP values, which were closer to 2.0, suggesting better control over body movements in healthy individuals. CSP individuals showed a tendency to continue moving in the same direction, indicating a persistent trend (Stergiou, 2018). The study also found that H seemed to distinguish between healthy subjects and those with CSP, similar to previous studies with other chronic pain conditions (França et al., 2019). Additionally, the results support previous findings that individuals with CSP tend to have a more static sitting behavior (Bontrup et al., 2019).

The DFA method has recently gained attention for assessing fractal scaling characteristics and identifying long-range correlations in noisy, nonstationary time series. Multifractal analysis characterizes scaling at various statistical moments q . Negative values of q amplify small fluctuations, while positive moments amplify large fluctuations (E. A. Ihlen & Vereijken, 2013). This method has been useful in various fields, including human gait (Hausdorff et al., 2000, 1997), simulated driving tasks (Murata et al., 2018), pain dynamics (Foss et al., 2006), neurological physical therapy (Cavanaugh et al., 2017b), and concurrent motor tasks (Arsac, 2021). One reason to use DFA is to avoid falsely detecting correlations caused by nonstationarities in the time series (Kantelhardt et al., 2002). Previous studies have revealed an array of findings regarding postural sway. For instance, quiet standing in healthy young adults exhibits fractal fluctuations over time scales from 10 s to 10 min in both ML and AP directions, with alpha exponents ranging from 0.68 to 1.47 (Duarte & Zatsiorsky, 2000; Stergiou, 2004).

Delignières et al. found that the short-term slope in quiet stance was AP = 1.65 and ML = 1.70, and the long-term slope was AP = 1.22 and ML = 1.00 in male volunteers (Delignières et al., 2011). The research used a multifractal formalism to study movement control adaptation to dual motor tasks, examining the global (monofractal) scaling related to long-range correlations and long-term memory of the signal in $H(q) = 2$. The degree of multifractality was calculated as $H(q) = -15$ and $H(q) = 15$ to assess scaling differences for small and large fluctuations.

When grouped together, the $H(q) = 2$ scaling exponents were 1.02 ± 0.09 for cycling, 0.59 ± 0.09 for finger tapping, and 0.76 ± 0.11 for circling. The study discovered a significant difference across these motor-task-specific exponents (Arsac, 2021).

In a study conducted by Lau et al. (2012), it was found that patients with neck pain exhibited smaller short-term Hurst exponent values than healthy subjects across all four phases: “self-adopted posture” (neck pain: $H = 0.73$ vs. healthy: 0.78), “upright posture before training” (neck pain: $H = 0.81$ vs. healthy: 0.85), “training stage” (neck pain: $H = 0.76$ vs. healthy: 0.83), and “upright posture after training” (neck pain: $H = 0.82$ vs. healthy: 0.86) (N. Lau et al., 2012). Additionally, data processing techniques appeared to have no effect on the magnitude of variability (SD and RMS), but did affect the structure of variability (DFA α and SampEn) in CoP displacement, as discussed in previous research (Rhea et al., 2015).

Our previous research on office workers indicated significant differences in postural changes based on time of day and day of the week, with fatigue leading to increased movement and postural variability (Mendes et al., 2023). This study’s novelty lies in comparing the CSPG and healthy controls over a week, using smartphone sensors adaptable to other contexts. Smartphones were chosen for their ability to interface with the PrevOccupAI application and collect data from multiple workers simultaneously, creating realistic working conditions.

Implications and Future Research

Contrary findings in CSP patients during seated tasks suggest complex postural adaptations (Willigenburg et al., 2013). CSP’s etiology is multifactorial, with only a portion attributable to sedentary risks (Mahdavi et al., 2021). A recent study distinguished CSP patients from asymptomatic participants using an experimental protocol assessing 72 movement biomarkers (Moissenet et al., 2023). Research employing a two-group design revealed differential effects of cognitive dual-tasks on postural sway in CSP patients versus controls (Van

Daele et al., 2010). Further, CSP impacts postural control, with affected individuals showing divergent trunk muscle activation patterns, influencing tissue loading and requiring further investigation (Viseux et al., 2022; Van Dieën et al., 2019). Mahdavi et al.'s meta-analysis highlighted the heightened CSP risk associated with prolonged sitting and extended driving periods, emphasizing the need for comprehensive CSP research. The present study did not account for uncontrolled variables, such as commuting time, which could impact outcomes (Mahdavi et al., 2021). Future studies should incorporate these variables.

The association between sitting time and CSP has shown inconsistent findings due to variations in study design, measurement methods, and occupational group heterogeneity. This study only included public administration office workers, limiting the generalizability of results to other populations. This study used cross-sectional data, limiting the ability to determine causality between motor control changes, sitting, and CSP. Future research could explore the link between perceived threats and protective responses (Ippersiel et al., 2022). Understanding small posture changes is vital for designing workplace guidelines to prevent injury and validating models of spinal pain risk factors (Karwowski, 2012). Lifestyle interventions, including technology use, motivational counseling, and self-monitoring, have reduced sedentary behavior among individuals with various medical conditions. Addressing sedentary behavior as a risk factor in health education is recommended to reduce CSP prevalence (Mahdavi et al., 2021). Modern ergonomics must evolve to manage complex human-system interactions (Karwowski, 2012). Future research should analyze electromyographic parameters (Naranjo-Hernández et al., 2020; Knox et al., 2018) and categorize patients into different severity risk groups (Abdollahi et al., 2020). Finally, future studies should consider comparing the CoP estimation method. Although based on established physical principles and developed internally by our research team, future investigations should proceed with a validation analysis through comparative studies or external benchmarks.

Conclusions

This study found new evidence linking CSP to trunk posture, especially during pro- longed sitting. Differences were notable in fine movements, indicated by higher negative width in the CSPG. The analysis of the generalized Hurst exponent highlighted the multifractal nature of postural sway in the AP direction, with the CSPG showing higher values across all orders. Further research is needed to determine if the statistically significant differences found are clinically meaningful.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Universidade NOVA de Lisboa, protocol code: CE/FCT/005/2022 (Appendix I).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Chapter 7

Correlation between pain intensity and trunk sway in seated posture among office workers with chronic spinal pain: a pilot field-based study

Abstract: This pilot study examines the relationship between pain intensity and trunk sitting postural control in 10 office workers with chronic spinal pain, using field-based real-time inertial sensors. Pain intensity was assessed with the Numeric Pain Rating Scale (NPRS) before and after work across three non-consecutive workdays, while postural control was evaluated through estimated center of pressure (CoP) displacements. Linear and nonlinear metrics, including sway range, velocity, the Hurst exponent, and sample entropy, were derived from the estimated CoP time series. Pearson correlation coefficients (r) and corresponding p -values were used to analyze the relationship between pain intensity and postural control. Significant correlations, though limited to specific metrics, were found ($r = -0.860$ to 0.855 ; $p < 0.05$), suggesting that higher pain intensity may be correlated with reduced postural variability. These findings provide preliminary insights into the potential link between pain intensity and postural control. Understanding trunk posture dynamics could inform the development of targeted ergonomic interventions to reduce musculoskeletal stress and improve sitting comfort in office environments.

Keywords: musculoskeletal disorders; chronic pain; pain intensity; postural control; variability; inertial sensors.

Introduction

Musculoskeletal disorders (MSDs), particularly chronic spinal conditions such as neck and lower back pain, represent a significant global occupational health challenge. By 2050, low back pain is projected to affect 843 million people, up from 619 million in 2020 (Ferreira et al., 2023), while neck pain, which impacted 203 million in 2020, is expected to rise to 269 million (Wu et al., 2024b). The increasing prevalence of sedentary office work, combined with aging

populations and obesity rates, is expected to exacerbate this problem (Zhang et al., 2024; Ferreira et al., 2023; Collaborators, 2022). Office workers are especially vulnerable due to prolonged sitting, highlighting the urgent need for ergonomic strategies to mitigate the impacts of MSDs (Nunes et al., 2021; Peereboom et al., 2021; Wang et al., 2021; Mathiassen, 2006).

Addressing this issue requires innovative approaches, such as those proposed within the framework of Industry 4.0 and 5.0. These paradigms introduce opportunities to improve workplace health through technology integration and human-centered design. While Industry 4.0 emphasizes automation and digital transformation, Industry 5.0 prioritizes worker well-being and sustainable ergonomics (Bakator et al., 2024; Duggal et al., 2022; Kadir et al., 2019). In this context, addressing the health risks of prolonged sitting is essential. For example, nearly 40% of EU workers report sitting for excessive durations (Peereboom et al., 2021), prompting the EU-OSHA to recommend limiting sitting to less than half of the workday (Peereboom, Langen, Bortkiewicz, et al., 2021).

Movement variability and variation in posture represent complementary ergonomic principles that are particularly relevant in this regard. Movement variability refers to the natural, inherent fluctuations in motor performance across task repetitions (Stergiou & Decker, 2011a). This intrinsic property of biological systems (Stergiou et al., 2006; Stergiou & Decker, 2011) facilitates the redistribution of muscle activity, reducing localized fatigue, and improving activation patterns (Heredia-Rizo et al., 2022). In contrast, variation in posture and movement involves intentional changes in body position, such as alternating between sitting and standing (Toomingas et al., 2012). These postural adjustments are linked to enhancing comfort and productivity by up to 6.5% (Wang et al., 2023).

Recent reviews reinforce the benefits of these principles in workplace settings. Standing interventions have been shown to effectively reduce sedentary behavior without compromising productivity (Sui et al., 2019), while active breaks incorporating postural changes can alleviate pain and discomfort

(Waongenngarm et al., 2018). Advances in technologies, such as inertial measurement units (IMUs), further support ergonomic interventions by enabling the detailed analysis of movement and postural behaviors (Antonaci et al., 2024; Lind et al., 2023; Patel et al., 2022; Lim & D'Souza, 2020; Jun et al., 2019). Together, these findings highlight the critical importance of movement variability as a central component of strategies to reduce back pain and improve workplace well-being.

Despite this growing recognition of the role of movement variability in reducing musculoskeletal discomfort, there remains a limited understanding of how specific aspects, such as trunk posture variability, influence pain intensity. Inconsistencies in kinematic data and a lack of focused studies hinder a comprehensive understanding of the role of movement in the management of chronic spinal pain (Alsubaie et al., 2023; Knox et al., 2018).

This study aims to address these gaps by investigating the relationship between motor variability—measured through linear and nonlinear postural sway metrics derived from the estimated center of pressure (CoP) time series—and pain intensity in office workers with chronic spinal pain, particularly those in tax authorities engaged in computer-based tasks while seated. By utilizing IMUs integrated into smartphones, this research seeks to advance our understanding of motor patterns and contribute to the development of interventions and digital health solutions tailored to this population. Based on the existing literature, the following is hypothesized:

1. Higher pain intensity is associated with reduced variability and complexity in trunk sway (e.g., lower entropy), reflecting increased trunk stiffness and a shift towards a more rigid and predictable postural control strategy. These adaptations likely serve as a compensatory mechanism to minimize movement-related stress and protect the spine during prolonged sitting (Bontrup et al., 2019; Zemp et al., 2016; Asgari et al., 2015; Hodges & Tucker, 2011).

2. Work-related activities modulate postural control and pain perception, leading to increased pain intensity and reduced movement variability in the post-work period (PM) compared to the pre-work period (AM). This effect may be attributed to cumulative biomechanical strain and fatigue associated with sustained "static" postures during prolonged occupational sitting (Zemp et al., 2016; Mingels et al., 2021).

Materials and methods

Study Design

This cross-sectional study, part of the PrevOccupAI Project (Prevention of Occupational Disorders in Public Administrations using Artificial Intelligence), was conducted at offices of the Portuguese Tax and Customs Authority (AT) located in the Lisbon Metropolitan Area. A multidisciplinary team accomplished risk assessments for randomly selected tax enforcement professionals from the AT's Human Resources department. As an incentive to participate in this study, evidence-based recommendations were developed to improve resilience and address occupational health challenges, informed by sources such as the ILO (Office, 2012), the EU-OSHA (Peereboom, Langen, Bortkiewicz, et al., 2021), and Slater et al. (Slater et al., 2019). Ethical approval was granted by NOVA University Lisbon (No. CE/FCT/005/2022) in accordance with the Declaration of Helsinki and GDPR. Informed consent was obtained from all participants.

Participants

A total of 10 workers were eligible to participate in this study. All participants were adults aged 18 years or older, with no history of neurological, orthopedic, rheumatic, oncological, or cardiorespiratory conditions; pregnant women were excluded. To meet the eligibility criteria, participants were required to have a history of non-specific spinal pain lasting at least three months, as defined by the International Association for the Study of Pain (IASP) and the International Classification of Diseases, 11th Revision (ICD-11) (Treede et al., 2019).

Procedures

A standardized data collection protocol was implemented using a dedicated cross-platform application developed within the PrevOccupAI project. This application enabled the acquisition of multimodal biosignals and self-reported questionnaire responses via smartphone and computer interfaces. Data collection spanned one workweek, adhering to protocols established in prior studies (Olios et al., 2023). Each workday began with participants reporting to a designated workplace room for device setup. They first completed a daily pain questionnaire before the recording schedule was configured in the PrevOccupAI application. A smartphone, securely positioned on the chest, continuously recorded inertial sensor data and ambient noise throughout the workday, ensuring the uninterrupted monitoring of postural sway and movement patterns in a real-world occupational setting. Participants engaged in their regular work tasks while the smartphone passively captured movement-related data. At the end of the workday, participants returned for device removal and disinfection, followed by a second pain questionnaire to assess changes in pain perception. This methodology facilitated a comprehensive, ecologically valid evaluation of postural sway dynamics, leveraging smartphone-based sensing for continuous and unobtrusive monitoring.

Demographics

Demographic data, including age, gender, height, and body mass, were captured using an integrated questionnaire module. The Body Mass Index (BMI) was calculated based on the standard formula $BMI = \text{mass (kg)} / \text{height (m)}^2$. Data regarding work (years of work experience, weekly work schedule in hours) were also collected. Subjective assessments were conducted using validated instruments to assess physical activity levels, psychosocial risks, and chronic pain experiences.

Pain Experience

In 2020, the IASP (International Association for the Study of Pain (IASP), 2020) revised its definition of pain to include both physical and emotional dimensions.

Accordingly, pain perception was evaluated along three dimensions: intensity, distress, and interference (Treede et al., 2019).

Pain intensity was assessed daily using the Numerical Pain Rating Scale (NPRS), where participants reported their pain levels at the beginning and end of each workday, ranging from 0 (“no pain”) to 10 (“worst pain imaginable”). Pain-related distress, representing the emotional impact of persistent or recurrent pain, was measured weekly on an 11-point numerical scale, with 0 indicating “no distress” and 10 indicating “extreme pain-related distress”. Pain-related interference, quantifying the extent to which pain disrupted daily activities, was self-reported on a scale from 0 (no interference) to 10 (complete inability to perform activities) (Treede et al., 2019).

To optimize pain assessment, this project’s app integrated a body map tool, which allowed participants to precisely localize pain and quantify symptom distribution (Figure 1). Unmarked regions were assigned a pain intensity value of 0, ensuring a comprehensive and personalized representation of pain across anatomical regions.

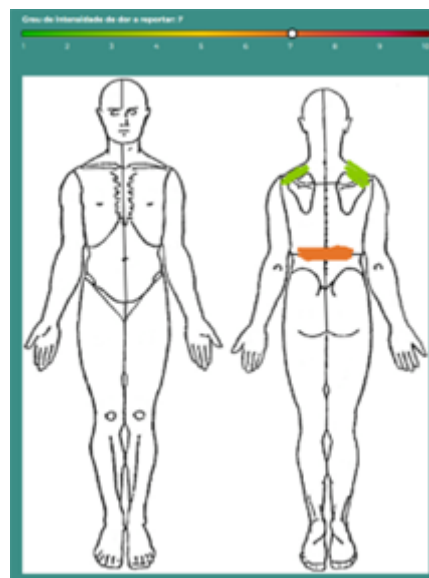


Figure 1. Interface for assessing pain location and intensity.

Physical Activity Levels

The European Portuguese version of the Short-Form International Physical Activity Questionnaire (IPAQ-SF) assessed physical activity, categorizing participants' weekly activity as low, moderate, or high based on metabolic equivalents. This tool, validated for adults aged 18-65, captures vigorous, moderate, walking, and sitting activities over the past week (Craig et al., 2003).

Psychosocial Risks

Workplace psychosocial risks were evaluated using the Portuguese version of the Copenhagen Psychosocial Questionnaire II (COPSOQ II) (Rosário et al., 2017), covering multimodal domains such as work demands, interpersonal relations, and health and well-being (Pejtersen et al., 2010). This tool includes 76 items rated on a 5-point Likert scale. Results were grouped into their domains, expressed as percentages, and used to descriptively characterize the sample population, with input from occupational health stakeholders, management, and worker representatives (Rosário et al., 2017).

Data Collection and Analysis

Data acquisition was performed using a Xiaomi Redmi Note 9 smartphone, which captured signals from the accelerometer (ACC), gyroscope (GYR), magnetometer (MAG), and rotation vector (RV). Sampling rates were constrained by the Android OS, with the ACC, GYR, and RV recorded at 100 Hz and MAG at 50 Hz. Motor biosignals were collected using these integrated sensors within the smartphone, which was securely fixed on the sternum with straps. The CoP displacement time series represented an estimated CoP derived from smartphone inertial sensor data. The collected data were represented in the orthogonal components of the anteroposterior (AP) and mediolateral (ML) directions, reflecting forward–backward (AP) and side-to-side (ML) trunk sway (see Figure 2). This approach provides a reliable method for quantifying postural sway, as supported by previous studies using force plates and smartphone-based inertial sensors to assess postural stability with demonstrated accuracy and consistency (Huang et al., 2023; Onuma et al.,

2023; Karlinsky et al., 2022; Zhou et al., 2021; Barbado et al., 2018; Chung et al., 2014).



Figure 2. Illustration of CoP sway during seated posture.

Linear measures of postural sway were computed from the CoP time series. Key metrics included mean acceleration (in m/s^2), standard deviation (SD) (in m/s^2), sway range (in mm), sway area (in mm), sway path (in mm), and sway velocity (in mm/s). Sway range and area represent the maximum CoP displacement in the resultant (overall) or AP and ML directions, sway path reflects the total CoP distance traveled, and sway velocity indicates the rate of CoP movement, offering insights into postural adjustment speed and variability (Saito et al., 2021; Harbourne & Stergiou, 2009; Prieto et al., 1996). These measures are indicators of centrality, describing magnitude and variability around a central point, and thus characterize movement quantity in data (Stergiou et al., 2016; Deffeyes et al., 2009).

Nonlinear metrics, including Sample Entropy (SaEn) and Multifractal Detrended Fluctuation Analysis (MF-DFA), were used to assess postural control complexity (i.e., to describe the structure within the time series) (Harbourne & Stergiou, 2009). SaEn quantifies sway regularity, where higher values indicate more complex and adaptable movement strategies. It also reflects how physiological health influences postural regulation by identifying signals under stationary

conditions, such as reduced variability in less adaptable postural states. The Hurst exponent, derived from DFA, measures the long-term persistence and fractality of sway behavior. DFA analyzes time series by removing short-term fluctuations (detrending) to reveal long-term correlations, highlighting complex patterns in postural sway. DFA is assessed across different q-orders, which provide varying levels of detail: higher q-orders focus on fine-grained fluctuations, while lower q-orders capture broader trends. This multiscale analysis offers deeper insights into the dynamics and adaptability of postural control across different time scales (Carpena et al., 2021; van Dieën et al., 2010; Harbourne & Stergiou, 2009; Kantelhardt et al., 2002; Richman & Moorman, 2000).

The combination of these features was selected due to their widespread use in studies on seated posture, particularly in ergonomic and occupational contexts (Arippa et al., 2022; Madeleine et al., 2021; Søndergaard et al., 2010; Hermann, 2005).

Data Processing

All acquired signals were synchronized using timestamp alignment and resampled to a uniform frequency of 100 Hz to ensure consistency across modalities. The preprocessing pipeline for the ACC and RV data followed validated methodologies from previous studies (Olios et al., 2024). The ACC data underwent a multi-step processing approach to remove noise and extract movement-related features. A low-pass filter with a 10 Hz cutoff was applied to suppress high-frequency noise and sensor artifacts. The gravitational acceleration component was then removed using an adaptive filtering technique to isolate dynamic movement. Systematic biases were corrected through detrending by subtracting the mean acceleration value from each sample, and a 150-sample moving average filter was used to smooth signal fluctuations. Similarly, RV signals were processed using a 5-sample moving average filter to minimize transient sensor noise and improve orientation stability. Given the extended duration of data collection (approximately 5 h per day), segmentation was performed using a 15-minute windowing approach to facilitate analysis.

Data segments were classified into morning (AM1–AMx), lunch, and afternoon (PM1–PMx) periods.

To ensure that only seated postural sway data were analyzed, an algorithm was implemented to detect and exclude non-seated intervals based on acceleration magnitude thresholds. The magnitude of acceleration (*mag*) was computed as $mag = \sqrt{X^2_{acc} + Y^2_{acc} + Z^2_{acc}}$, with a threshold of 2 m/s² derived from biomechanical analyses and metabolic equivalent (MET) calculations (Mortazavi et al., 2013; Ainsworth et al., 2000)]. This threshold effectively distinguished seated from non-seated activities, ensuring that only relevant data were retained.

Postural sway was quantified by estimating the CoP displacement from inertial sensor data. The RV signal was converted into quaternions and transformed into Euler angles to derive CoP projections in the AP and ML directions. To ensure alignment across participants, the median of each Euler angle was subtracted to establish a reference position at the origin (0,0). The chest-mounted smartphone's orientation was used to project Euler angles into the xz-plane, mapping postural movements throughout the workday (Figure 3). To standardize postural sway analysis, an elliptical boundary was applied based on prior research (Ohlendorf et al., 2020), with an AP radius of 25 mm and an ML radius of 18 mm. Data outside this predefined region were excluded to maintain consistency in postural sway assessment (Olios et al., 2024).

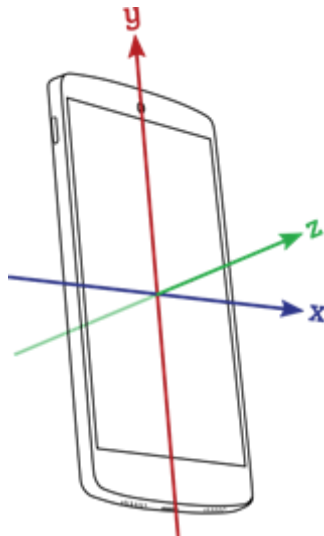


Figure 3. Coordinate system for smartphone-assisted postural analysis.

Previous Reporting on This Dataset

Previous analyses utilizing this dataset have examined how chronic spinal pain influences trunk movement patterns and postural dynamics in office settings. Ref. (Olios et al., 2024) applied a mixed ANOVA to analyze trunk sway, revealing that pain-free participants displayed distinct trunk movement characteristics in certain features compared to those with chronic spinal pain, particularly regarding fine motor adjustments. In another analysis, ref. (Mendes et al., 2023) assessed postural variability among 40 office workers throughout the workday without segmenting by pain status or utilizing nonlinear metrics. The results indicated increased posture variability from morning to afternoon, with a notable rise in positional adjustments later in the day. This paper presents novel analyses focused on the relationship between postural dynamics and pain intensity, specifically within the cohort experiencing chronic spinal pain.

Statistical Analysis

Descriptive and inferential statistics were performed using SPSS 29. Sample demographics and questionnaire scores were used to characterize the participants. For continuous variables, normally distributed data were summarized with the mean and SD, while non-normally distributed data were described using the median and interquartile range (IQR). Categorical variables were reported as counts and proportions. Parametric assumptions were verified for normality using the Shapiro–Wilk test. To examine changes in pain intensity over time, Friedman’s Related-Samples Two-Way Analysis of Variance was applied. For correlations, Pearson’s (r) correlation coefficients were calculated to explore associations between sitting postural control dynamics (trunk displacement features in the AP and ML directions, along with resultant trunk sway time series) and perceived pain intensity (NPRS Sum of neck, upper back, and lower back pain). As Pearson’s r represents both the correlation coefficient and the effect size, it allows for a direct interpretation of the strength of relationships between variables. NPRS scores were summed across spinal

regions to create an NPRS index. Summed pain intensity scores were analyzed for each day (Day 1: Monday; Day 3: Wednesday; Day 5: Friday) and period (AM: pre-work; PM: post-work). A significance threshold of $\alpha = 0.05$ was applied.

Results

The study sample consisted of 10 participants, 80% of whom identified as female. Physical activity levels, as assessed by the IPAQ-SF, indicated that 30% of participants engaged in low physical activity, 40% in moderate activity, and 30% in high activity levels. The mean age of the participants was 54 years (SD = 6.5). The average BMI was 26.75 kg/m² (SD = 6.14), with participants having an average of 18.2 years of work experience (SD = 14.06) and a typical weekly work schedule of approximately 40 h (SD = 4). On average, participants reported spending 9.4 h per day sitting (SD = 3.44), with a reduced average of 4.18 h of sitting on weekends (SD = 1.78). The characteristics of the participants are summarized in Table 1.

Table 1. Sample characterization.

Variable	Outcome
Gender	80% Female (8 Females, 2 Males)
Physical Activity Levels	Low: 30%; Moderate: 40%; High: 30%
Mean Age (years)	54 ± 6.5
Mean BMI (kg/m ²)	26.75 ± 6.14
Work Experience (years)	18.2 ± 14.06
Weekly Work (h)	40 ± 4
Daily Sitting Time (h)	9.4 ± 3.44
Weekend Sitting Time (h)	4.18 ± 1.78

The COPSOQ II results indicated moderate job demands (67.5; SD = 2.7) and neutral perceptions of health and well-being (50.0; SD = 6.1). No offensive behavior was reported (0.0; IQR: 0–10). Social relations and leadership scored

moderately (38.1; SD = 3.5), as did values' alignment within the workplace (31.3; SD = 4.8) and the work–individual interface (42.6; SD = 11.8). Work organization and job content (41.7; SD = 4.6) also received moderate ratings.

Pain Experience

The distribution of reported pain locations among participants revealed that three (30.0%) experienced isolated neck pain, five (50.0%) reported a combination of neck and lower back pain, one (10.0%) had upper back pain, and one (10.0%) experienced pain in both the neck and upper back regions.

The disability levels, assessed using the 11-point NPRS, revealed the following median scores: neck disability, 2.00 (IQR: 0–4); upper back disability, 0.90 (IQR: 0–5); and lower back disability, 0.80 (IQR: 0–5). In terms of classification, 20% of participants reported no disability, 50% reported mild disability, and 30% reported moderate disability for neck pain. For upper back disability, 80% reported no disability, while 20% reported moderate disability. Regarding lower back disability, 70% reported no disability, 10% reported mild disability, and 20% reported moderate disability.

Regarding pain-related distress, also assessed using the NPRS, the median distress scores were as follows: neck distress, 2.50 (IQR: 0–6); upper back distress, 1.10 (IQR: 0–6); and lower back distress, 1.20 (IQR: 0–5). For neck distress, 10% of participants reported no distress, 70% reported mild distress, and 20% reported moderate distress. For upper back distress, 80% reported no distress, and 20% reported moderate distress. For lower back distress, 60% of participants reported no distress, 30% reported mild distress, and 10% reported moderate distress.

Regarding pain intensity, which was assessed both before and after work each day, a detailed description can be found in Table 2. No statistically significant differences were found across days, periods, and pain locations ($p > 0.05$).

Table 2. Pain intensity scores based on the NPRS.

Variable	AM			PM		
	Median	IQR	95%CI	Median	IQR	95%CI
Day 1						
Neck	0.00	4	(-0.26, 3.06)	0.00	2	(-0.61, 3.01)
Upper Back	0.00	1	(-0.47, 2.27)	0.00	1	(-0.55, 2.35)
Lower Back	0.00	5	(0.12, 3.88)	0.00	4	(-0.29, 3.09)
Day 3						
Neck	0.00	3	(-0.27, 2.47)	0.00	3	(-0.22, 2.62)
Upper Back	0.00	0	(-0.63, 1.63)	0.00	1	(-0.55, 2.35)
Lower Back	0.00	0	(0.00, 0.00)	0.00	4	(-0.29, 3.09)
Day 5						
Neck	0.00	3	(-0.23, 2.43)	0.00	3	(-0.30, 2.70)
Upper Back	0.00	1	(-0.37, 1.77)	0.00	5	(-0.02, 3.82)
Lower Back	0.00	3	(-0.17, 2.17)	0.00	4	(-0.09, 3.49)
NPRS						
Day 1	4.0	9	(1.10, 7.50)	2.5	6	(0.54, 6.46)
Day 3	0.0	3	(-0.72, 3.92)	3.5	5	(0.76, 6.24)
Day 5	0.0	6	(-0.32, 5.92)	3.5	8	(0.51, 9.09)

AM: pre-work; PM: post-work; NPRS: Numeric Pain Rating Scale; IQR: interquartile range; CI: Confidence Interval.

Correlations

Daily pain intensity (NPRS Sum) analysis across six assessment points (Day 1 AM/PM, Day 3 AM/PM, Day 5 AM/PM) revealed occasional correlations with postural sway metrics. While most correlations did not reach statistical significance ($p > 0.05$), several moderate- to-strong correlations were observed, indicating potential relationships that merit further investigation. A summary of significant correlations between the NPRS and trunk sway metrics is provided in Table 3, with comprehensive correlation matrices for both linear and nonlinear sway features available in Appendix A.

For linear measurements (Tables A1–A6), significant correlations with the NPRS Sum were observed at different time points. On Day 1 in the morning, the NPRS Sum had a significant negative correlation with overall sway range ($r = -0.688$; $p < 0.05$). In contrast, on Day 1 in the afternoon, the NPRS Sum exhibited a positive correlation with overall sway range ($r = 0.750$; $p < 0.05$) and with range in the AP direction ($r = 0.855$; $p < 0.01$). Additionally, on Day 5 in the morning, a strong negative correlation between the NPRS Sum and the standard deviation in the AP direction (SD AP) was noted ($r = -0.719$; $p < 0.05$).

Nonlinear sway parameters showed varied correlations with the NPRS Sum across time points (Tables A7–A12). On Day 3 in the AM, several strong correlations were observed. The Hurst exponents at the scale $H(0)$ in both the AP ($r = -0.812$; $p < 0.01$) and ML ($r = -0.860$; $p < 0.01$) directions, as well as at the scale $H(4.5)$ in the AP ($r = -0.786$; $p < 0.01$) and ML ($r = -0.780$; $p < 0.01$) directions, were significantly negatively correlated with the NPRS Sum. SaEn in the ML direction also exhibited a significant negative correlation with the NPRS Sum ($r = -0.703$; $p < 0.05$). On Day 3 in the PM, no significant correlations were found between the NPRS Sum and the nonlinear sway parameters. However, on Day 5 in the PM, the NPRS Sum showed a negative correlation with the Hurst exponent at the scale $H(2)$ in the AP direction ($r = -0.722$; $p < 0.05$). Furthermore, moderate to strong positive intercorrelations were found among both linear and nonlinear postural sway parameters (Tables A1-A12).

Table 3. Significant correlations between NPRS Sum and linear/nonlinear metrics.

	Day	Period	Metric	Direction	Correlation
NPRS vs.	1	AM	Overall range	Negative	-0.688*
	1	PM	AP range	Positive	0.855**
	1	PM	Overall range	Positive	0.750*
	3	AM	H(0) AP	Negative	-0.812**
	3	AM	H(0) ML	Negative	-0.860**
	3	AM	H(4.5) AP	Negative	-0.786**
	3	AM	H(4.5) ML	Negative	-0.780**
	3	AM	SaEn ML	Negative	-0.703*
	5	AM	SD AP	Negative	-0.719*
	5	PM	H(2) AP	Negative	-0.722*

Abbreviations: NPRS: Numeric Pain Rating Scale; SD: standard deviation; AP: anteroposterior; ML: mediolateral; H: Hurst exponent. Significance levels: * $p < 0.05$; ** $p < 0.01$.

Discussion

This study investigated the relationship between pain intensity, measured using the NPRS Sum for neck, upper, and lower back pain, and postural sway characteristics in office workers with chronic spinal pain. IMUs were employed for real-time, field-based posture assessment. Both linear and nonlinear sway metrics were analyzed during pre- and post-work periods on Days 1 (Monday), 3 (Wednesday), and 5 (Friday) to assess their potential as objective indicators of pain intensity within occupational settings.

The findings revealed limited and variable correlations between pain intensity and postural sway metrics across different time points, illustrating the intrinsic intricacy of postural control systems in the context of chronic pain.

4.1. Interpretation of Results

Linear metrics, including range (in mm), mean acceleration (in m/s²), SD (in m/s²), velocity (in mm/s), sway path length (in mm), and sway path area (in mm²), were used to assess postural control. Nonlinear techniques, MF-DFA and SaEn, were applied to capture the postural control complexity, reflecting subtle changes that linear metrics might have missed.

Variations in correlations among linear metrics highlighted the nuances of seated postural dynamics. On Day 1, reduced morning sway variability (negative correlation with overall sway range) indicated more rigid postural control, while increased afternoon fluctuations (positive correlations with overall sway range and AP range) suggested compensatory adjustments. By Day 5, greater AP sway variability (negative correlation with SD) was linked to higher pain intensity. These findings are consistent with previous studies. For instance, Søndergaard et al. (Søndergaard et al., 2010), reported positive correlations between discomfort and the standard deviations of CoP displacement in both the AP and ML directions, alongside negative correlations with SaEn. This suggests that increased sway variability and reduced postural control complexity during seated tasks can be associated with greater perceived discomfort. Similarly, Madeleine et al. (Madeleine, 2012) observed that prolonged sitting led to a greater SD and lower SaEn in CoP signals, reflecting decreased postural complexity and increased discomfort. Overall, these findings highlight the link between postural variability degradation and increased discomfort, reflecting the interplay between adaptive posture control and pain perception.

Correlations between nonlinear metrics and pain intensity varied notably across time points. No significant correlations were observed on Day 1 (AM and PM), Day 3 in the PM, or Day 5 in the AM. However, on Day 3 in the AM, strong negative correlations were observed for H(0) (AP and ML), H(4.5) (AP and ML), and SaEn (ML), suggesting a decline in postural sway complexity. On Day 5 in the PM, a significant negative correlation was also found for H(2) in the AP direction, indicating reduced postural adaptability. This reduction in variability aligns with the concept of a more periodic, less adaptive postural strategy,

characterized by the loss of multiscale fractal complexity under pathological conditions (Stergiou & Decker, 2011a; Goldberger, 1997). These findings suggest that higher pain intensity is correlated with diminished variability at both micro-scale fluctuations ($H(0)$) and larger sway deviations ($H(4.5)$), as well as reduced entropy (SaEn), which reflect a shift toward more rigid, less flexible postural control (Stergiou & Decker, 2011b). The absence of consistent correlations across other periods underscores the dynamic and context-dependent nature of postural regulation in response to pain, consistent with theories of adaptive control in motor behavior (Hodges & Tucker, 2011).

Although most postural sway parameters showed weak correlations with the NPRS Sum, specific linear and nonlinear metrics demonstrated moderate to strong correlations at particular time points, indicating pain-related changes in postural stability. Hypothesis 2, predicting stronger evening (PM) correlations, was not supported. Overall, our results suggest a weak link between pain intensity and postural sway dynamics, likely due to the multifactorial nature of chronic pain, influenced by biopsychosocial factors (Bontrup et al., 2019; O'Sullivan et al., 2013; Gatchel et al., 2007). Furthermore, variability in sitting habits and postural adjustments also contributes to inconsistent sway patterns (e.g., “breakers” vs. “prolongers”) (Arippa et al., 2022).

Our findings highlight the potential for the development of personalized ergonomic interventions aimed at protecting office workers from prolonged exposure to postural stress and pain. By understanding trunk posture dynamics, tailored strategies can help reduce MSDs and improve comfort, as optimal postures vary between individuals (Slater et al., 2019).

Limitations and Future Research

Several limitations should be considered. Data were collected from an adult population with an average age of 54 years ($SD = 6.5$), while previous studies emphasize age-related differences in variability (Stergiou et al., 2016; Van Emmerik & Van Wegen, 2000), particularly in office workers (Madeleine et al., 2021). Thus, the kinematic measurements in this study may not reflect those of

other age groups or occupations. The use of smartphone IMUs, while practical, introduced limitations, as placement variability and daily reapplication increased the risk of random errors in postural sway measurements due to inconsistent placement (Davidson & Callaghan, 2025), despite the use of standardized straps and consistent researcher handling.

As this study was conducted in a field setting, variations in cognitive load (e.g., focused computer work) may have influenced postural sway. Prior research suggests that cognitive dual-tasking can reduce postural sway in chronic low back pain, though effects are more pronounced in complex balance tasks (Van Daele et al., 2010). Similar effects were observed in healthy adults, where cognitive demands altered postural complexity without significantly affecting displacement measures (Cavanaugh et al., 2007). Cognitive task difficulty has also been linked to changes in postural variability, particularly in children and older adults, who demonstrate increased sway area and complexity under more challenging conditions (Shafizadeh et al., 2021). Future studies should integrate controlled cognitive-load assessments to better isolate the effects of attentional demands on postural control, such as using EEG (Bibbo et al., 2019).

Customer service roles in public administration and finance face substantial psychosocial risks. For example, 31% of EU workers report suppressing emotions due to customer anger and abuse (Mockała, 2020). In tax offices, depression has been linked to high trait anxiety, workplace conflicts, and low job satisfaction, making tax workers particularly vulnerable to MSDs (Wainwright et al., 2022; Nieminen et al., 2021; Timmers et al., 2019; Issever et al., 2008). These psychosocial hazards limit the applicability of the findings to other office roles, such as programmers and call center staff. However, the non-alarming COPSOQ II results in this study suggest a lower psychosocial risk in the analyzed sample. While our findings suggest a weak correlation between pain intensity and postural sway metrics, they underscore the complexity of chronic pain management. This highlights the need for individualized, multidimensional approaches to postural assessment and ergonomic interventions, where pain intensity is considered alongside other psychosocial and physical factors.

Future interventions may benefit from a combination of sensor data and self-reported measures to provide more accurate assessments of pain and postural dynamics, guiding more effective ergonomic strategies in the workplace.

Although a one-week observation period was chosen to align with this study's primary objectives, future research could benefit from longer observation durations to capture greater variability in postural dynamics and explore potential long-term trends. Additionally, while the small sample size limits the generalizability of the findings, future studies with larger, more diverse samples will offer more robust and conclusive insights. Given the multiple comparisons conducted in this study, the potential for Type I errors must be considered. Future research should apply corrections to account for multiple tests, thereby enhancing the robustness of the findings.

Conclusions

Although postural sway parameters showed weak correlations with pain intensity, specific metrics revealed stronger correlations, suggesting potential links between pain and postural stability. These findings highlight the need for more research on motor variability and pain intensity to inform ergonomic interventions. While our findings were not strongly significant, they contribute to assessing postural sway in real-world settings and provide exploratory insights into how movement-based metrics may inform pain assessment, ergonomic interventions, and future rehabilitation strategies for individuals with chronic spinal pain.

Hypothesis 1 was partially supported, with pain intensity correlated with the reduced complexity of postural sway at specific points, although the effects were inconsistent. Hypothesis 2 was not supported, as work activities did not consistently increase post-work pain or reduce variability, suggesting that other factors may influence postural control and pain intensity. Future research should involve larger sample sizes, longitudinal designs, randomized controlled trials, and consider pain location to better explore these relationships. Furthermore,

utilizing a full range of digital health resources, including wearable sensors, could provide valuable information on postural dynamics and pain management.

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Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of NOVA University Lisbon (protocol code: CE/FCT/005/2022) (Appendix I).

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The data presented in this study are available upon reasonable request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Table A1. Correlation Matrix of Linear Measurements on Day 1 During the AM Period and NPRS Sum (Day 1 AM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	-0.064	-0.348	0.351	0.041	-0.592	-0.461	-0.688 *	-0.552	-0.594	-0.593
Mean AP		0.449	-0.174	-0.013	-0.119	-0.424	-0.253	-0.226	-0.070	-0.073
Mean ML			-0.662 *	-0.099	0.339	-0.112	0.221	0.071	0.057	0.033
SD AP				0.662 *	-0.457	0.257	-0.241	-0.529	-0.383	-0.371
SD ML					-0.328	0.241	-0.168	-0.651 *	-0.580	-0.582
Range AP						0.173	0.904 **	0.612	0.547	0.547
Range ML							0.571	0.475	0.552	0.545
Range Overall								0.706 *	0.700 *	0.698 *
Area									0.956 **	0.954 **
Path										0.999 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$;

**.: $p < 0.01$.

Table A2. Correlation Matrix of Linear Measurements on Day 1 During the PM Period and NPRS Sum (Day 1 PM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	0.007	0.199	-0.196	-0.600	0.855 **	0.143	0.750 *	0.345	0.378	0.393
Mean AP		-0.245	0.152	-0.040	-0.061	-0.138	-0.108	-0.318	-0.304	-0.306
Mean ML			0.322	-0.387	-0.026	-0.688 *	-0.234	0.014	-0.106	-0.053
SD AP				0.247	0.032	-0.220	-0.055	-0.118	-0.212	-0.196
SD ML					-0.341	0.377	-0.174	0.150	0.169	0.171
Range AP						0.467	0.965 **	0.582	0.596	0.594
Range ML							0.678 *	0.628	0.718 *	0.678 *
Range Overall								0.660 *	0.698 *	0.685 *
Area									0.984 **	0.987 **
Path										0.997 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$;

**: $p < 0.01$.

Table A3. Correlation Matrix of Linear Measurements on Day 3 During the AM Period and NPRS Sum (Day 3 AM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	0.148	0.456	0.095	-0.127	-0.006	-0.368	-0.163	-0.047	0.085	0.059
Mean AP		-0.278	-0.447	-0.449	0.039	-0.068	-0.008	-0.306	-0.074	-0.077
Mean ML			0.375	-0.066	-0.072	-0.497	-0.256	0.211	0.009	-0.017
SD AP				0.765 **	-0.377	-0.382	-0.403	-0.136	-0.305	-0.310
SD ML					-0.333	-0.082	-0.240	-0.170	-0.323	-0.313
Range AP						0.695 *	0.947 **	0.743 *	0.914 **	0.915 **
Range ML							0.888 **	0.550	0.720 *	0.732 *
Range Overall								0.721*	0.905 **	0.911 **
Area									0.887 **	0.889 **
Path										0.999 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A4. Correlation Matrix of Linear Measurements on Day 3 During the PM Period and NPRS Sum (Day 3 PM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	0.505	-0.366	-0.011	-0.370	0.573	0.210	0.478	0.214	0.297	0.269
Mean AP		-0.504	0.049	0.031	-0.194	-0.193	-0.236	-0.180	-0.291	-0.279
Mean ML			0.316	0.164	0.067	0.200	0.164	-0.199	-0.088	-0.101
SD AP				0.495	-0.223	0.298	0.026	-0.417	-0.362	-0.373
SD ML					-0.282	0.491	0.024	-0.128	-0.188	-0.139
Range AP						0.588	0.926 **	0.674 *	0.842 **	0.829 **
Range ML							0.843 **	0.433	0.556	0.580
Range Overall								0.591	0.777 **	0.734 **
Area									0.969 **	0.974 **
Path										0.996 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A5. Correlation Matrix of Linear Measurements on Day 5 During the AM Period and NPRS Sum (Day 5 AM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	0.288	-0.085	-0.719 *	-0.054	-0.134	-0.082	-0.112	-0.247	-0.165	-0.173
Mean AP		-0.286	-0.467	-0.115	0.096	-0.218	0.025	0.086	-0.190	-0.191
Mean ML			0.217	-0.449	-0.295	-0.367	-0.351	-0.291	-0.230	-0.219
SD AP				0.506	0.457	0.363	0.435	0.378	0.393	0.410
SD ML					0.546	0.687 *	0.642 *	0.507	0.568	0.579
Range AP						0.637 *	0.957 **	0.855 **	0.743 *	0.748 *
Range ML							0.826 **	0.730 *	0.907 **	0.908 **
Range Overall								0.912 **	0.878 **	0.883 **
Area									0.879 **	0.885 **
Path										0.999 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A6. Correlation Matrix of Linear Measurements on Day 5 During the PM Period and NPRS Sum (Day 5 PM).

	Mean		SD		Range			Area	Path	Velocity
	AP	ML	AP	ML	AP	ML	Overall			
NPRS Sum	-0.229	-0.501	-0.379	-0.391	0.367	0.493	0.429	0.211	0.201	0.182
Mean AP		0.416	0.233	-0.090	-0.254	0.067	-0.162	-0.060	-0.180	-0.197
Mean ML			0.327	0.405	-0.691 *	-0.677 *	-0.717 *	-0.489	-0.501	-0.497
SD AP				-0.116	0.25	0.024	0.182	0.417	0.377	0.397
SD ML					-0.669 *	-0.642 *	-0.680 *	-0.664 *	-0.539	-0.532
Range AP						0.842 **	0.983 **	0.951 **	0.944 **	0.943 **
Range ML							0.926 **	0.759 *	0.806 **	0.775 **
Range Overall								0.918 **	0.929 **	0.916 **
Area									0.941 **	0.944 **
Path										0.996 **

PM: Post-work; NPRS: Numeric Pain Rating Scale; SD: Standard Deviation; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A7. Correlation Matrix of Nonlinear Measurements on Day 1 During the AM Period and NPRS Sum (Day 1 AM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	0.255	-0.100	0.212	-0.107	-0.300	-0.403	0.098	-0.273	0.263	0.378
H(-5) AP		-0.079	0.221	0.116	0.058	-0.218	0.46	-0.120	-0.061	0.057
H(-5) ML			0.462	0.615	0.712 *	0.486	0.22	0.261	0.211	0.016
H(0) AP				0.231	0.625	0.057	0.555	-0.084	-0.388	-0.065
H(0) ML					0.654 *	0.862 **	0.335	0.787 **	-0.029	-0.486
H(2) AP						0.655 *	0.718 *	0.391	-0.487	-0.513
H(2) ML							0.212	0.864 **	-0.260	-0.750 *
H(4.5) AP								0.072	-0.606	-0.397
H(4.5) ML									-0.083	-0.752 *
SaEn AP										0.671 *

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A8. Correlation Matrix of Nonlinear Measurements on Day 1 During the PM Period and NPRS Sum (Day 1 PM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	-0.075	0.278	-0.257	0.153	-0.112	-0.236	-0.366	-0.100	-0.372	-0.437
H(-5) AP		0.462	0.533	0.524	0.671 *	-0.044	0.648 *	-0.090	0.146	-0.201
H(-5) ML			0.338	0.733 *	0.252	0.204	0.463	0.241	-0.068	-0.462
H(0) AP				0.745 *	0.639 *	0.278	0.568	-0.069	0.100	-0.177
H(0) ML					0.42	0.030	0.329	0.169	-0.272	-0.589
H(2) AP						0.320	0.674 *	0.032	0.480	0.134
H(2) ML							0.599	0.281	0.688 *	0.573
H(4.5) AP								-0.063	0.601	0.321
H(4.5) ML									0.348	0.189
SaEn AP										0.856 **

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A9. Correlation Matrix of Nonlinear Measurements on Day 3 During the AM Period and NPRS Sum (Day 3 AM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	-0.631	-0.587	-0.812 **	-0.860 **	-0.330	-0.455	-0.786 **	-0.780 **	-0.451	-0.703 *
H(-5) AP		0.932 **	0.708 *	0.728 *	0.005	0.255	0.542	0.627	0.542	0.613
H(-5) ML			0.569	0.714 *	-0.060	0.409	0.575	0.661 *	0.513	0.49
H(0) AP				0.893 **	0.384	0.451	0.765 **	0.764 *	0.342	0.557
H(0) ML					0.281	0.553	0.770 **	0.885 **	0.454	0.500
H(2) AP						0.522	0.613	0.271	-0.454	0.137
H(2) ML							0.667 *	0.633 *	0.075	0.17
H(4.5) AP								0.778 **	0.072	0.475
H(4.5) ML									0.565	0.462
SaEn AP										0.608

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A10. Correlation Matrix of Nonlinear Measurements on Day 3 During the PM Period and NPRS Sum (Day 3 PM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	-0.195	0.008	-0.207	-0.019	-0.404	0.06	-0.190	0.368	0.26	0.103
H(-5) AP		-0.163	0.923 **	-0.002	0.528	-0.579	0.811 **	-0.207	-0.058	0.365
H(-5) ML			0.099	0.793 **	-0.302	0.179	-0.151	0.53	-0.308	-0.038
H(0) AP				0.219	0.593	-0.562	0.860 **	-0.046	-0.127	0.455
H(0) ML					0.078	0.273	-0.006	0.601	-0.712 *	-0.275
H(2) AP						-0.022	0.780 **	0.014	-0.369	0.285
H(2) ML							-0.257	0.478	-0.331	-0.149
H(4.5) AP								-0.074	-0.012	0.674 *
H(4.5) ML									-0.539	0.023
SaEn AP										0.325

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A11. Correlation Matrix of Nonlinear Measurements on Day 5 During the AM Period and NPRS Sum (Day 5 AM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	-0.012	-0.046	0.129	-0.130	0.129	-0.415	-0.064	-0.308	0.24	0.457
H(-5) AP		0.738 *	0.846 **	0.724 *	0.589	-0.448	0.685 *	0.532	0.35	0.623
H(-5) ML			0.878 **	0.969 **	0.504	0.077	0.848 **	0.755 *	0.176	0.632
H(0) AP				0.888 **	0.550	-0.197	0.856 **	0.728 *	0.388	0.753 *
H(0) ML					0.406	0.085	0.810 **	0.819 **	0.223	0.593
H(2) AP						0.042	0.750 *	0.542	-0.021	0.314
H(2) ML							0.229	0.345	-0.418	-0.442
H(4.5) AP								0.801 **	0.071	0.457
H(4.5) ML									0.283	0.436
SaEn AP										0.769 **

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Table A12. Correlation Matrix of Nonlinear Measurements on Day 5 During the PM Period and NPRS Sum (Day 5 PM).

	H(-5)		H(0)		H(2)		H(4.5)		SaEn	
	AP	ML	AP	ML	AP	ML	AP	ML	AP	ML
NPRS Sum	-0.276	-0.280	-0.215	-0.349	-0.722 *	-0.562	-0.317	-0.506	-0.071	-0.309
H(-5) AP		0.995 **	0.742 *	0.542	0.034	0.136	-0.507	0.132	-0.587	0.005
H(-5) ML			0.745 *	0.596	0.070	0.173	-0.530	0.144	-0.592	-0.017
H(0) AP				0.696 *	-0.004	0.445	-0.453	-0.027	-0.318	0.303
H(0) ML					0.326	0.663 *	-0.426	0.352	-0.333	0.161
H(2) AP						0.649 *	0.309	0.721 *	0.387	0.096
H(2) ML							-0.025	0.530	0.404	0.500
H(4.5) AP								-0.001	0.392	0.502
H(4.5) ML									0.330	-0.069
SaEn AP										0.245

AM: Pre-work; NPRS: Numeric Pain Rating Scale; H: Hurst Exponent; SaEn: Sample Entropy; AP: Anteroposterior; ML: Mediolateral; *: $p < 0.05$; **: $p < 0.01$.

Chapter 8

General discussion

This thesis investigated the quantity and quality of trunk movement among office workers with chronic spinal pain (CSP), aiming to understand postural stability in real-world settings (i.e., office work). Movement data were captured using wearable IMUs, enabling the collection of ecologically valid information beyond laboratory environments. Both linear and nonlinear time-series analyses were applied to quantify postural sway during prolonged sitting.

Chapter 1 established the historical perspectives and motivations underlying this research. Chapter 2 reviewed spinal biomechanics and postural control, as well as the role of movement variability in musculoskeletal disorders within a biopsychosocial framework, with particular emphasis on workplace ergonomics. Chapter 3 outlined the methodological considerations of the thesis, explaining the rationale for key decisions regarding field-based wearable sensors, multimodal data acquisition, movement variability analyses, and the assessment of sitting postural control in office settings. Chapter 4 presented Study I, which examined the complementary roles of linear and nonlinear variability metrics for assessing sitting posture. Chapter 5 described Study II, which implemented a multimodal longitudinal data acquisition protocol to evaluate occupational risk factors for musculoskeletal disorders in public sector office workers, integrating objective data from smartphone-based IMUs, smartwatch-derived heart rate, surface EMG, and subjective questionnaires. Chapter 6 (Study III) compared individuals with CSP to pain-free controls, revealing that postural control in the CSP group was more dispersed but less adaptive. Chapter 7 (Study IV) identified significant correlations between trunk sway metrics and pain intensity, suggesting that greater pain intensity may be associated with reduced movement variability in individuals with CSP.

Although the small sample size limits the generalizability of these findings, this work demonstrates the feasibility of using wearable sensor data to capture

real-world motor behavior in individuals engaged in predominantly sedentary occupations. More importantly, it establishes a methodological foundation for future studies with larger samples and highlights the potential for real-time data collection to inform the development of individualized intervention strategies in office-based occupational health.

Postural stability in office workers with and without chronic spinal pain

To address the thesis research question of characterizing postural sway in office workers with CSP, two empirical studies (III and VI) were conducted. These studies provide moderate evidence that CSP is associated with measurable alterations in both the magnitude and the temporal structure of postural sway during prolonged seated tasks. While linear measures of variability quantify the overall amount of variation in a signal, they do not capture its time-evolving dynamics; both linear and nonlinear analyses are therefore necessary for a comprehensive characterization (Harbourne & Stergiou, 2009).

In Study III, CSP participants exhibited significantly greater sway than controls, characterized by increased SD in the AP direction and elevated RMS in the ML direction. Nonlinear analyses further demonstrated higher multifractal spectrum width and Hurst exponents in the CSP group. These findings align with prior evidence indicating altered postural control in individuals with CSP (Alshahrani et al., 2025; Sung & Lee, 2024; Ruhe et al., 2013). Study VI, reinforced these observations, for example, with pain intensity correlated negatively with sway complexity and positively with sway range. These associations suggest that higher discomfort is linked to reduced adaptability and greater sway amplitude, although the limited sample size and relatively low pain intensity likely constrained statistical power.

Conceptually, these findings support the notion that motor variability is not inherently “good” or “bad,” but context-dependent. Adaptive variability reflects a flexible and responsive control system, whereas excessive regularity or dispersion indicates dysregulation. The observed pattern of increased sway amplitude with reduced complexity in CSP may therefore represent a

maladaptive strategy. This interpretation is consistent with pain theories such as the protective response model, which posits that pain induces changes in motor output (e.g., altered force production, reduced movement amplitude, or load redistribution) that may be beneficial in the short term but, when prolonged, contribute to maladaptive consequences (Hodges & Tucker, 2011; Merkle et al., 2020).

Similar alterations have been reported in other conditions, such as dementia and Parkinson's disease. In these conditions, increased fractal dimensions of movement trajectories have been interpreted as reflecting inefficient motor control (Costa et al., 2022; Quixadá, 2020). Study III moved beyond linear sway descriptors to characterize the scaling properties of CoP dynamics by applying multifractal detrended fluctuation analysis (MFDFA). Elevated generalized Hurst exponents at extreme orders (e.g., $q = -5$, $q = 4.5$) indicated altered persistence and multifractality, which is consistent with the idea that the postural control system is less adaptable. Evidence also supports that CoP regularity indices, such as SampEn, are sensitive to attentional demands during postural tasks (Roerdink et al., 2011). This is consistent with theoretical models proposing that optimal movement variability reflects health and adaptability (Stergiou & Decker, 2011). However, the present research often establishes strong associations between CSP and trunk sway time-series features. From a physiological standpoint, this ambiguity suggests the need for new modeling approaches that can capture the multiscale control mechanisms underlying postural dynamics.

IMUs and Field-Based Biomechanics

As discussed in Chapter II, pain and movement are interconnected aspects of human experience that can be systematically studied in both occupational and clinical contexts. Smartphone-based IMUs provide a practical and scalable tool for collecting biomechanical data in the field. They enable integration of sensor data with questionnaires and repeated assessments and offer sufficient data density for advanced analyses, including nonlinear methods. IMUs are particularly valuable in real-world workplace settings, where privacy concerns,

spatial constraints, and user acceptability often limit the feasibility of video-based motion capture.

Within this thesis, smartphone-based IMUs were applied to characterize the occupationally relevant phenomenon of prolonged sitting in office workers. This approach demonstrates an ecological and scalable method for quantifying spinal kinematics and postural dynamics in daily-life settings, thereby advancing the field of occupational biomechanics. Previous studies have shown that smartphones equipped with gyroscopes can provide valid alternatives to laboratory-based systems for balance assessment, capturing both static and dynamic dimensions of postural control. Traditional methods for evaluating postural stability, such as subjective clinical tests or specialized biomechanical instrumentation, often lack precision or require costly equipment and expert personnel, which limits their widespread application (Polechoński et al., 2019).

Emerging evidence supports the reliability of IMU-based assessments for ergonomic evaluation. For example, Tanthuwapathom et al. (2025) assessed sitting postures and ergonomic risks in office workers by combining physical therapist evaluations using the RULA method with IMU-derived measurements of neck and trunk angles. Their results demonstrated a strong correlation between therapist ratings and IMU-derived data, highlighting the feasibility of integrating traditional ergonomic methods with modern wearable technology (Tanthuwapathom et al., 2025).

Despite these advantages, IMU-based assessments present several challenges, including variability in sensor placement, difficulties in device standardization, and complexities in interpreting biosignals collected in ecological contexts. Future research should aim to integrate IMU-based motion capture with contextual and biopsychosocial information to better address the multifactorial nature of chronic spinal pain in occupational settings.

This thesis contributes novel insights by demonstrating the feasibility of using smartphone-based IMUs for ecological biomechanical assessments. It emphasizes the value of multimodal approaches that combine motor,

contextual, and individual factors to provide a more comprehensive evaluation of occupational postural dynamics.

Implications for Occupational Health and Physiotherapy Practice

This thesis demonstrates that smartphone-based IMUs are a practical and feasible tool for assessing sitting dynamics in occupational contexts. IMUs are well-suited for real-world applications and can identify workers at elevated risk of MSDs due to insufficient postural variation (Mingels et al., 2021; Mathiassen, 2006). These findings could be translated into practice by using IMUs to inform personalized (micro)breaks, promote dynamic sitting strategies, and optimize workstation design to reduce biomechanical workload (Frey et al., 2021; Waongenngarm et al., 2018). According to European occupational health guidelines (Peereboom et al., 2021), sitting should be limited to less than 50% of the workday, and sitting should be alternated with standing or walking and breaks should be taken every 20-30 minutes. Such strategies are consistent with the principles of Industry 5.0, which emphasize human-centered innovation, worker well-being, and sustainable ergonomics (Bakator et al., 2024; Kadir et al., 2019).

From a clinical perspective, capturing postural behaviour in ecological settings creates opportunities for more personalized approaches. For instance, pain and movement are interconnected, with maladaptive compensation frequently observed in CSP (Wildenbeest et al., 2022; Wang et al., 2021; Falla & Hodges, 2017). Neuromuscular adaptations driven by pain may reinforce these maladaptive motor patterns and contribute to the transition from acute to chronic musculoskeletal pain (Merkle et al., 2020). Further, evidence suggests that reduced shifts, and changes in lumbar movement variability are linked to higher pain levels in office workers (De Carvalho et al., 2020; Akkarakittichoke & Janwantanakul, 2017).

Movement variability is generally defined as normal variations that occur during movement performance. However, it can also provide insight into movement behavior and underlying health or functional impairments, thus contributing to

clinical knowledge (Stergiou & Decker, 2011a; Stergiou et al., 2006b). Findings from sitting-pattern research further illustrate these mechanisms. For example, patients with chronic low back pain exhibit lower temporal and similar spatial variability in muscle activity while sitting, despite showing more variable seated postures. Although this did not increase EMG-indicated muscle fatigue, patients reported higher perceived exertion and pain intensity, leading to reduced tolerance for sustained sitting compared to controls (Ringheim et al., 2019b). Similarly, prolonged sitting has been shown to increase discomfort over time, with shifts in postural strategy: in the first two hours, both small and large shifts increase, whereas after four hours, only larger shifts are observed (Waongenngarm et al., 2020).

There are several theoretical models that explain the interplay between pain and motor responses. These include the vicious cycle theory, the strength inhibition theory, the pain adaptation theory, and the protective response theory. Of these, the protective response theory is particularly useful. This theory posits that while pain-related changes in motor output (e.g. altered movement amplitude, force production, or load distribution) may provide short-term protection, they can lead to long-term maladaptive consequences such as increased rigidity or reduced function (Merkle et al., 2020). The model also considers biopsychosocial influences, emphasizing that variability in neuromuscular responses is shaped by cognitive, emotional, and contextual factors, which have direct implications for rehabilitation strategies.

Study Limitations

Several limitations should be noted. The study relied on convenience sampling of Portuguese Tax Authority employees, limiting generalizability to other occupational groups. Participants with CSP reported relatively low intensity and disability compared to prior studies (Alshahrani et al., 2025), reducing sensitivity to detect associations between moderate-to-severe pain and trunk sway.

Sensor- and technology-related factors further constrain methodological precision. IMU performance depends on both embedded algorithms and

hardware quality (Schall et al., 2022). Direct measurement tools like IMUs and EMG provide accurate insights but can be invasive, expensive, and potentially disruptive to natural work activities (Yang et al., 2024). Challenges in sensor placement, number, and wearability remain critical, as improper configuration can compromise data reliability, while ensuring comfort and unobtrusiveness is essential for field adoption (Nadeem et al., 2024).

Finally, broader methodological and analytical limitations of this thesis include the small sample size, the cross-sectional study design, and the lack of evaluation of underlying pain mechanisms. In Study IV, the large number of correlations tested relative to the sample size increases the risk of false-positive findings; the observed associations should therefore be regarded as hypothesis-generating. Additionally, the absence of a standardized international definition of MSDs complicates comparability across studies (Bonfiglioli et al., 2022). Future research should prioritize larger and more diverse cohorts, adopt standardized assessments of pain and disability, and implement protocols that account for temporal influences, such as circadian variation (Forsman et al., 2007).

Future research

This thesis has highlighted the potential of smartphone-based IMUs for characterizing spinal kinematics and sitting behavior in occupational contexts. However, chronic spinal pain remains a multifactorial challenge requiring more comprehensive approaches. Future research should adopt longitudinal and experimental designs with repeated measures to better capture the temporal dynamics of motor variability and its implications for musculoskeletal health. Integrating inertial sensor data with surface EMG (Abboud et al., 2014; Sheeran et al., 2012; Madeleine et al., 2008) may provide deeper insights into neuromuscular adaptations and motor control strategies in individuals with and without chronic spinal pain.

First, studies should target specific subgroups to refine prevention strategies. Investigating younger office workers could identify early risk factors, while

examining diverse occupational groups (e.g., programmers, call-center employees) would clarify how different work demands influence spinal health. Work-life interactions, including sedentary behaviors outside work and recovery practices, warrant exploration to understand cumulative spinal loading and its role in chronic pain development. Furthermore, studies that integrate psychological constructs such as fear of movement (Martinez-Calderon et al., 2019) may advance biopsychosocial models of pain by linking cognitive-behavioral factors with postural variability and motor control.

Second, future research should stratify analyses by pain phenotype (nociceptive, neuropathic, nociplastic) (Nijs et al., 2021; Chimenti et al., 2018) to determine whether variability patterns differ across mechanisms. Spectral analyses of kinematic signals may also reveal underlying control strategies and stability mechanisms. To strengthen clinical applicability, psychometric properties such as the Minimal Detectable Change (MDC) should be established for biomechanical metrics, enabling reliable thresholds to monitor intervention effects.

Third, studies should evaluate whether adherence to occupational health guidelines (Peereboom, Langen, Bortkiewicz, et al., 2021) produces measurable improvements in spinal kinematics. Controlled trials could test whether limiting prolonged sitting, alternating between sitting, standing, and walking, and incorporating 20-30-minute breaks improve temporal dynamics of variability. Individual moderators, including age and BMI, should be considered, as evidence suggests these factors exacerbate postural instability and may shape responsiveness to activity breaks (Alshehri et al., 2024). Embedding IMU-based monitoring into randomized controlled trials would allow unobtrusive assessment of sitting dynamics, supporting causal inference and tailoring recommendations to individual risk profiles. Finally, advances in artificial intelligence could further support this agenda by identifying detrimental postural patterns in real time and delivering personalized feedback, including break reminders and tailored ergonomic recommendations.

Chapter 9

Conclusions

This thesis provides evidence that chronic spinal pain in office workers may be associated with alterations in trunk sway dynamics during seated tasks, indicating that subtle changes in postural control can be quantified using wearable inertial sensors combined with linear and nonlinear analyses. Although sample size and contextual constraints limit generalizability, the findings demonstrate the potential of sensor-based monitoring to capture nuanced aspects of motor behavior in real-world occupational settings. Methodologically, the work establishes a framework for integrating field-based data collection with advanced time-series analyses, enabling the assessment of individualized movement and posture patterns. These results contribute to a more comprehensive understanding of seated behavior, emphasizing that dynamic postural adjustments and variability are relevant factors in maintaining musculoskeletal function. In this context, continuous movement and adaptable postures emerge as essential considerations for spinal health: *“our next posture is the best posture”* (Peereboom et al., 2021).

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Appendix I

Ethics Committee

Consentimento informado, esclarecido e livre para participação em estudos de investigação

Por favor, leia com atenção a seguinte informação. Se achar que algo está incorreto ou que não está claro, não hesite em solicitar mais informações.

Título do estudo: “Aquisição de dados biomecânicos, psicossociais e ambientais para análise de riscos ocupacionais na administração pública”.

Enquadramento: No âmbito do projeto PrevOccupAI (https://novabiosignals.github.io/WebPortal/projects_pages/prevocupai/prevocupai.html), levado a cabo pelo laboratório de biosinais do LIBPhys-UNL, em parceria com o *Comprehensive Health Research Center* da Faculdade de Ciências Médicas da Universidade Nova de Lisboa, a Direção Geral de Saúde e a Autoridade Tributária e Aduaneira.

O(s) investigador(es) responsável(is) [identificar os investigadores e o seu contato] atuará como responsável pelo tratamento dos dados pessoais, no sentido em que tais expressões são mencionadas no Regulamento Geral sobre a Proteção de Dados.

Explicação do estudo: Este estudo envolve a recolha de dados de sensores de movimento e posição a partir do *smartwatch*, *smartphone* e de dois dispositivos *muscleBAN*. A partir do *smartphone* vai ser recolhido o nível de ruído, não sendo detetáveis quaisquer palavras ou sons de fundo que permitam identificar conversas. O sinal de eletromiografia também será recolhido a partir dos dispositivos *muscleBAN*. A aquisição será realizada no local de trabalho dos participantes. As aquisições serão feitas ao longo de 5 dias seguidos, durante todo o dia de trabalho. Será feita uma sessão prévia com os investigadores para apresentação do projeto, preenchimento de questionários

de caracterização da população, relativos a riscos biomecânicos, psicossociais e ambientais no trabalho e esclarecimento de eventuais dúvidas.

Condições: É importante referir que terá toda a liberdade para recusar a participação no estudo ou retirar o seu consentimento, suspendendo a participação em qualquer momento. Ao longo de todo o processo não terá qualquer custo por participar neste estudo. Os participantes neste estudo comprometem-se a cumprir os requisitos abaixo:

- Jovens adultos com idade superior a 18 anos;
- Sujeitos sem patologia associada (neurológica, ortopédica, reumática, oncológica ou cardiorrespiratória);
- Sujeitos que não tomem drogas psicotrópicas;
- Sujeitos não medicados;
- Sujeitos capazes de utilizar o equipamento necessário.

Confidencialidade e anonimato: Os dados pessoais recolhidos serão utilizados apenas no contexto desta investigação, não sendo divulgados em nenhum outro contexto. Dados anonimizados (i.e. bioassinais, dados demográficos e dados de interação com o computador) poderão ser tornados públicos.

Para assegurar que os seus dados pessoais são armazenados apenas durante o período de tempo necessário, e considerando o objetivo da investigação, os seus dados pessoais serão armazenados em segurança durante um período de 5 anos após o fim do estudo.

A qualquer momento, poderá exercer os seus direitos, nomeadamente o direito de solicitar mais informações sobre o tratamento dos seus dados pessoais, o direito de retificação e de apagamento de dados, de remoção do seu consentimento ou de oposição às atividades de tratamento, entre outros, de acordo com o disposto no Regulamento Geral sobre a Proteção de Dados.

Pode exercer os seus direitos contactando Cátia Filipa Mata Cepede de Vela Bastos, c.cepeda@fct.unl.pt. Caso entenda que o tratamento dos seus dados pessoais não cumpre com a legislação aplicável tem, ainda, o direito de apresentar uma reclamação junto da autoridade supervisora competente. Em Portugal, pode contactar a Comissão Nacional de Proteção de Dados (CNPD) em <https://www.cnpd.pt/>.

Participante

Por favor, leia com atenção todo o conteúdo deste documento. Não hesite em solicitar mais informações se não estiver completamente esclarecido(a). Verifique se todas as informações estão corretas. Se concordar com o procedimento descrito e com todas as informações fornecidas acerca do estudo e pretender continuar, por favor, assine em baixo.

Declaro ter compreendido os objetivos que me foram propostos e explicados. Foi-me concedida a oportunidade de esclarecer todas as dúvidas sobre o assunto e para todas elas obtive uma resposta esclarecedora. Tive tempo suficiente para refletir sobre esta proposta, pelo que declaro que autorizo/Não autorizo (riscar o que não interessa) participar no estudo indicado, bem como os procedimentos diretamente relacionados que sejam necessários no meu próprio interesse e justificados por razões fundamentadas. Compreendo que a minha participação no estudo é voluntária e que posso retirar o consentimento em qualquer momento.

Nome: _____

(Assinatura

Legível)

Data: ____/____/____

Universidade Nova de Lisboa granted the ethical approval (No. CE/FCT/005/2022)



COMISSÃO ÉTICA
ETHICS COMMITTEE

REQUERENTES:

Doutora Cátia Filipa Mata Cepeda de Vela Bastos, Investigadora Auxiliar, FCT-NOVA

ASSUNTO:

Projecto – PrevOccupAI (Prevenção de doenças ocupacionais na Administração Pública)

PARECER:

Face à documentação apresentada, a Comissão de Ética da FCT-NOVA não vê qualquer impedimento ético na realização do estudo proposto. Apenas uma pequena nota. No ponto 14., página 15, propõe-se a substituição da frase, "No entanto, isto apenas poderá ocorrer, caso o trabalhador faça", por "No entanto, isto apenas poderá ocorrer, caso o trabalhador o faça".

Esta aprovação presume a prévia autorização livre e esclarecida dos envolvidos e/ou dos seus representantes legais, bem como a aderência aos compromissos assumidos sobre todos os aspetos legais e éticos do estudo. Ressalta, ainda, a necessidade de rigorosa protecção de quaisquer dados pessoais recolhidos.

Caparica, 21 de Outubro de 2022

A handwritten signature in blue ink, appearing to read "Pedro Viana Baptista".

Presidente da Comissão de Ética da FCT-NOVA
Pedro Viana Baptista

A handwritten signature in blue ink, appearing to read "Isabel Maria Amaral".

Membro (vogal) da Comissão de Ética da FCT-NOVA
Isabel Maria Amaral

